UNIVERSITÉ PARIS 13, SORBONNE PARIS CITÉ

Thesis

For the degree of Doctor in Economics

Université Paris 13, Sorbonne Paris Cité

Presented and defended on November 27th 2015 by:

Achraf SEDDIK

CORPORATE BOND VALUATION AND CREDIT SPREADS: LESSONS FROM THE FINANCIAL CRISIS

Supervisor: Dominique PLIHON

Committee members:

Referees	Christophe BOUCHER	Professor at Université Paris Ouest Nanterre La Défense
	Hayette GATFAOUI	Associate Professor at IÉSEG School of Management
Examiners	Ahmed KEBAIER	Associate Professor at Université Paris 13 Sorbonne Paris Cité
	Michel BOUTILLER	Professor at Université Paris Ouest Nanterre La Défense
Supervisor	Dominique PLIHON	Professor at Université Paris 13 Sorbonne Paris Cité

This thesis has been prepared in:

CEPN
Centre d'Économie de Paris Nord
99, Avenue Jean Baptiste Clément
93340 Villetaneuse - Cedex France
Tel: (33)(0)1.49.40.32.55
Fax: (33)(0)1.49.40.33.34
Mail: cepn-secretariat@univ-paris13.fr
Website: http://www.univ-paris13.fr/CEPN

And:

Érasme
Doctoral School,
99, Avenue Jean Baptiste Clément
93340 Villetaneuse - Cedex France
Tel: (33)(0)1.49.40.32.56
Mail: ecoledoc-erasme@univ-paris13.fr
Website: http://www.univ-paris13.fr/ecole-doctorale-erasme/

An expert is a person who has made all the mistakes that can be made in a very narrow field.

Niels Bohr (1885-1962)

On the mountains of truth you can never climb in vain: either you will reach a point higher up today, or you will be training your powers so that you will be able to climb higher tomorrow.

Friedrich Nietzsche (1844-1900)

Remerciements

Mes premiers remerciements vont à mon directeur de thèse Dominique Plihon. Je le remercie de m'avoir ouvert les portes de la recherche et de m'avoir fait confiance pour cette aventure de thèse. Ses critiques ont été pour moi une source d'inspiration constante. Je le remercie également de m'avoir transmis sa conception du travail de recherche et de l'écriture scientifique.

Je remercie Christophe Boucher et Hayette Gatfaoui d'avoir accepté d'être rapporteurs de cette thèse et Michel Boutillier et Ahmed Kebaier d'avoir accepté de faire partie du jury. Je me réjouis à l'avance de pouvoir bénéficier de leurs conseils et de pouvoir débattre avec eux lors de ma soutenance.

Je remercie particulièrement Ahmed Kebaier qui fût mon enseignant lors de nombreux cours à l'Université Paris XIII ou même à HEC Paris. Ses enseignements, toujours très intéressants et stimulants, ont contribué à renforcer mes compétences en mathématiques pour bien entreprendre ce travail de recherche. Le temps qu'il m'a accordé et la bienveillance avec laquelle il a répondu à mes nombreuses questions m'ont permis d'avancer dans les moments de doute.

Cette thèse n'aurait pas été ce qu'elle est aujourd'hui si je n'avais pas eu la chance d'échanger avec de nombreux chercheurs. Je remercie particulièrement Nathalie Rey, Jérôme Mathis, Luciano Campi, Raphael Douadi et Mohammed Ben Alaya d'avoir pris le temps de répondre à mes sollicitations.

Je remercie le CEPN (Centre d'Économie de l'Université Paris Nord) et l'Université Paris 13 de m'avoir offert les conditions nécessaires à la réalisation de ce travail. Les rencontres que j'ai pu y effectuer dans le cadre de mes recherches et de mes enseignements ont été pour moi d'une grande richesse. Bien que je ne puisse tous les remercier individuellement, je tiens à mentionner : Nathalie Rey, Michel Roux, Delphine David, Damien Besancenot, Cédric Durand, Robert Guttmann, Luc Marco, Jean-Jacques Mazier, Francisco Serranito, Pascal Petit, et Didier Borowski.

Je remercie également les enseignants avec lesquels j'ai travaillé dans le cadre de mes fonctions d'attaché temporaire d'enseignement et de recherche à l'université Paris VIII de leur aide et d'avoir partagé avec moi leur expertise de l'enseignement et de la recherche : Jérôme Mathis, Jean-claude Kahané, Véronique de Saint-Giniez, Stéphane Goutte, Lucile chérubin et Florence Machtinger.

Je tiens à saluer mes collègues doctorants, devenus docteurs pour certains : Heger Attaya, Félix Boggio, Jihène Bjeoui, Louison Cahen-Fourot, Matteo Cavallaro, Habib Doggui, Kaouthar Dkhissi, Walid Drira, Ozan Ekin Kurt, Florence Gallois, Serge Herbillon-Leprince, Catherine Le, Luis Reyes, Raquel Ramos, Remy Stieglitz, Zineb Tensaout, Amina Ben Yahya et Hiroki Yokota. Les échanges que nous avons eus ont été pour moi une grande source de satisfaction intellectuelle.

Je remercie également mes camarades du bureau de l'association des doctorants et post-doctorants de Paris 13 (Adepe) : Fatimata Sy, Alexandra Ferreira, Mirza Riskwait, Guillaume Giraud, Elodie Jacquet, Sonia sauce, Benoit Perrin. Les évènements scientifiques et associatifs que nous avons pu organiser ont été d'une grande richesse.

Je profite de cet espace pour saluer mes camarades de l'équipe active du club des jeunes financiers, club qui a beaucoup contribué ma culture économique et financière. En particulier : Christophe Connille, Elyssar Sleiman, Mélanie Mahramadjian, Baptiste Faure, David Rossignol, Sylvain Trébaol, Anne-Audrey Claude, Miguel Nicolas et Ashley Boolell.

Je remercie aussi les personnes qui m'entourent depuis plusieurs années, et qui ont contribué de proche ou de loin à cette thèse. En particulier je souhaite remercier mes chers amis : Heger Attaya, Marylin Rangassamy, Corentin Crémet, Fatimata Sy, Héléna Sallard, Hervé Kobo, Nasreddine M'dimagh, Samed Hajji et Youssef ayari, qui m'ont été d'un grand soutien.

Je tiens évidemment à remercier l'ensemble de ma famille pour leur soutien et leur présence durant toutes ces années. Je remercie tout d'abord mes deux frères Bassem et Taha avec qui j'ai grandi et partagé tant de choses. Un merci tout particulier à Bassem de m'avoir aidé à faire la chasse aux coquilles et pour ses remarques d'expert.

Enfin, je remercie du fond du cœur mes parents, Nejma et Amara, pour leur soutien, leur confiance et leur amour durant toutes ces années. Merci à tous les deux des valeurs que vous avez si bien su m'inculquer et d'avoir fait de moi l'homme que je suis aujourd'hui. Ce travail vous est dédié.

Table of contents

Introduction...**1**

Chapter I. Corporate bonds valuation and credit spreads: a theoretical analysis...**6**

1. Introduction:... 6
2. Basic valuation relations:... 9
3. Merton's model:...10
   3.1. Deriving credit spread:... 11
   3.2. Numerical analysis:... 16
   3.3. Discussion:... 21
4. Black-Cox model:...25
   4.1. Deriving credit spread:... 25
   4.2. Numerical analysis:... 28
   4.3. Discussion:... 31
5. Collin-Dufresne and Goldstein model:...33
   5.1. Deriving credit spread:... 34
   5.2. Numerical analysis:... 38
   5.3. Discussion:... 41
6. Zhou model:...42
   6.1. Deriving credit spreads... 44
   6.2. Numerical analysis:... 47
   6.3. Discussion:... 50
7. Other extensions:...52
   7.1. The impact of incomplete or delayed information:... 52
   7.2. The impact of economic conditions:... 55
   7.3. The impact of liquidity:... 57
8. Conclusion:...59

Chapter II. The corporate bond market during the crisis: a descriptive analysis of credit spreads 64

1. Introduction:..64

2. Data and descriptive statistics:..66

2.1. Data:.. 66

2.1.1 Credit spreads sample: 66

2.1.2 Additional variables:.. 67

2.2. Descriptive statistics:... 68

3. Stylized facts of credit spreads during the crisis:..69

3.1 Higher credit spreads levels during crisis periods: The paradox of tranquility: 70

3.2 Tight connection with economic shocks: the effects of default contagion and systemic risks: 72

3.3 High sensitivity to governments and central banks willingness to help the banking sector:... 75

3.4 Decreasing sensitivity to leverage ratios during stress periods:........... 78

3.5 The effect of the phenomena of "flight-to-quality" and "flight-to-liquidity": 79

3.6 A change in the structure of the factors that affect credit spreads since the beginning of the crisis:.. 80

3.7 Higher financial bonds spreads since the beginning of the crisis: The financial instability hypothesis:... 81

3.8 A change in the relation between credit spreads and time to maturity since the beginning of the crisis: 84

3.9 An increase in the gap between the spreads of the largest and the smallest firms since the beginning of the crisis:..................................... 85

3.10 Increase in the volatility of the spreads of the bailed-out firms after the bailouts: 87

4. Principal component analysis of credit spreads: 90

4.1. Motivation and methodology:... 90

4.2. Results: 91

4.2.1 Full sample analysis: 91

4.2.2 Sub-periods analysis: 95

5. Conclusion: 100

Chapter III. The determinants of credit spread changes during the crisis 104

1. Introduction:..104

2. Related empirical literature: 106

3. Hypotheses on credit spread determinants: 109

3.1. Hypotheses on the structural credit risk component: 109

3.1.1 Negative relationship between firm value and credit spread: 109

3.1.2 Positive relationship between leverage and credit spread: 110

3.1.3 Negative relationship between risk-free interest rate and spread: 110

3.1.4 Positive relationship between volatility and credit spread: 110

3.1.5 Positive relationship between credit spread and the payout rate: 110

3.1.6 Positive relationship between time-to-maturity and spread: 110

3.2. Hypotheses on the market-wide component: 111

3.2.1 Positive relationship between economic slowdown and spread: 111

3.2.2 Positive relationship between default contagion risk, systemic risk and credit spreads: 111

3.2.3 Negative relationship between authorities' actions and spreads: 112

3.3. Hypotheses on the liquidity risk component: 112

3.3.1 Positive relationship between illiquidity and credit spread: 112

3.4. Hypotheses on the delayed information component: 112

3.4.1 The relationship between the delayed information component and credit spread can be either positive or negative: 113

3.5. Hypotheses on the additional factors: 113

3.5.1 Negative relationship between firm size and credit spread: 113

3.5.2 Negative relationship between investors' confidence and spread: 115

4. Data: 115

4.1. Credit spread: 116

4.2. Structural credit risk factors: 116

4.2.1 Leverage: 116

4.2.2 Equity return: 117

4.2.3 Historical volatility: 117

4.2.4 The risk-free rate: 117

4.2.5 The dividend Yield: 118

4.3. Market-wide factors: 118

4.3.1 The slope of yield curve: 118

4.3.2 Business climate indicator: 118

4.3.3 Market return: 119

4.3.4 Market Implied Volatility 119

4.3.5 LTROs: 119

4.4. Liquidity risk factors: 119

4.4.1 Bid-Ask spread: 119

4.4.2 Market liquidity: 120
4.5. Additional factors: 120
4.5.1 Number of employees: 120
4.5.2 Market value: 120
4.5.3 Confidence Index: 120
5. Methodology: 123
6. Results: 125
6.1. Results of the univariate regressions: 126
6.2. Results of the five regression models 128
6.2.1 Structural credit risk factors: 129
6.2.2 Market-wide factors: 133
6.2.3 Liquidity risk factors: 136
6.2.4 Lagged component: 138
6.2.5 Additional variables: 140
6.3. Robustness checks: 144
6.3.1 OLS vs. Fixed-effects regression: 145
6.3.2 Credit spread vs. CDS spread regressions: 146
6.3.3 Principal component analysis of credit spreads changes and regression residuals: 149
6.4. Specification analysis: 153
6.4.1 Maturity sub-samples: 153
6.4.2 Credit worthiness subsamples: 157
6.4.3 Firm-size sub-samples: 160
7. Conclusion: 164

Chapter IV. The term structure of credit spreads with firm rescue: a structural model 169

1. Introduction: 169
2. The term structure of credit spreads with firm rescue: the basic economic framework: 172
2.1. Model assumptions: 172
A.1. Capital structure and firm value dynamics: 172
A.2. The distress barrier: 173
A.3. The bailout negotiation process: 173
A.4. Bankruptcy mechanisms: 174
A.5 Bondholder's payoffs: 175
A.6. The risk-free rate: 176

A.7. Market characteristics:......176
2.2. Deriving credit spread:......176
2.3. Numerical results: 179

3. The term structure of credit spreads with firm rescue: the jump-diffusion dynamics:......184

A.1'. Capital structure and firm value dynamics: 184
3.1. Deriving credit spread:......186
3.2. Numerical results: 187

4. Conclusion: 190

Conclusion......**193**

Bibliography......**203**

Appendices......**215**

Appendix I. About corporate bonds:......216

I.1. Corporate bonds in the primary market: 216

I.1.1. The need for corporate bond issuance:......216

I.1.2. Corporate bond issuers:......216

I.1.3. Corporate bond investors:......217

I.1.4. The corporate bond contract: 217

I.2. Corporate bonds in the secondary market: 220

Appendix II. Credit spread sample and statistics 223

II.1. The corporate bond sample:......210

II.2. Credit spreads: 215

II.3. Descriptive Statistics – Full sample......231

II.4. Unit-root test – Augmented Dickey-Fuller (ADF):......233

II.5. Normality test – summary:......235

II.6. Descriptive Statistics – Pre-crisis period: 237

II.7. Descriptive Statistics – Subprime crisis period:......239

II.8. Descriptive Statistics – Eurozone crisis period: 241

II.9. Correlation Matrix: 243

Appendix III. Credit spread sample and statistics 249
III.1. The corporate bond sample: 249
III.2. Descriptive statistics (changes data): 251
III.3.1. Correlation Matrix (Part 1): 252
III.3.2. Correlation Matrix (Part 2): 253
III.4. The CDS sample: 255
Appendix IV. Proofs of the proposed model: 257
IV.1. Ito calculus for the firm value in $\boldsymbol{T_1}$ and $\boldsymbol{T_2}$: 257
IV.2. Proof of equation (2): 258
IV.3. Proof of equation (3) 260

Introduction

A corporate bond is a transferable debt security that represents a promise on the part of a corporation to make one or more payment(s) to an investor according to a specified agreement[1]. For various reasons, the corporation may end up in a situation where it cannot, or will not, respect the terms of the bond agreement. In particular, the corporate bond investor faces the risk that the corporation: (*i*) makes a delayed or incomplete payment of the face value of the debt or the coupons; (*ii*) makes bankruptcy; or (*iii*) fails to meet some of the other provisions of the bond indenture. The risk that this may happen is generally referred to as credit risk, and has been commonly viewed as one of the major risks of corporate bonds. When assessing actual or potential corporate bond investments, investors need hence to take into account this risk in order to avoid making unconsidered losses. In this context, an extensive literature has emerged over the last forty years with the aim to model this risk and to provide a consistent valuation of corporate bonds.

Broadly speaking, the literature of corporate bond valuation can be divided into two main groups of models: ”structural” and ”reduced-form” models. Initiated by Merton (1974), the structural approach relies mainly on the economic fundamentals of the modeled corporation (i.e. the firm's capital structure) in order to explain default risk and to derive the value of the debt claim. In contrast, the reduced form models (e.g. Jarrow and Turnbull, 1995; Duffie et Singleton, 1999) disregard any economic cause that could trigger default, and use pure probabilistic approaches to model the time of default of the firm and the value of the corporate bond. Despite the numerous shortcomings that they incur, and the apparent discrepancies between their simplifying assumptions and the economic reality, all these models seemed to work well up to a not-so-distant past. Their application has gained popularity over the years, and they have been even declined toward a more general use in credit risk measurement, credit risk management and even for regulatory purposes. Notable examples include Moody's KMV credit analysis tool, Credit Suisse's Credit Underlying Securities Pricing system (CUSP), or the Vasicek (2002) model used in the regulatory framework of Basel II, which build all on the model of Merton (1974). However, the recent economic and financial crisis has put forward the vulnerability of these models. One major illustration of this vulnerability has been the change in paradigm that the overall corporate bonds' credit spreads have showed since the outbreak of the subprime crisis. After

[1] See Appendix I.1 for a more detailed description of the corporate bond contract.

keeping narrow levels and low volatiles in the pre-crisis period, credit spreads soared since July 2007 and maintained relatively higher levels and volatility, which can be still observed up to nowadays[2]. On the one hand, the change in credit spread levels put forward an under-prediction problem of the risks incurred by corporate bonds in the pre-crisis period. Facing a period of tranquil growth and a high market liquidity in the beginning of the 2000s, investors became indeed less risk-averse and took higher levels of risk (i.e. the paradox of tranquility presented by Hyman Philip Minsky, 1975, 1977). One of the facets of this excessive risk-taking has been the under-estimation and even the ignorance of certain risks that corporate bonds may involve (e.g. liquidity risk). Consequently, as the crisis stepped by, the price of risk has been reevaluated and credit spreads soared. On the other hand, the increase in credit spreads volatility since the onset of the crisis catalyzed an increasing uncertainty of market participants about the value of a broad range of debt securities (D. Longworth et al., 2007). This uncertainty has been in fact fuelled by the emergence of many risk factors during the crisis that investors did not know, or at least did not know well, and that have been shown to affect firms in general, and financial institutions in particular (e.g. systemic risk). Above all, these turbulent movements in credit spreads illustrated a certain weakness of the existing corporate bond valuation tools[3]. The vulnerability of the existing corporate bond models was indeed an inherent part of the fragility that risk models in general, and credit risk models in particular, have displayed since the beginning of the crisis. These latter have shown in fact a certain inability to predict credit events (e.g. the defaults on subprime mortgages or corporate bankruptcies); they failed to gauge the risks involved in many financial instruments that were important contributors to the crisis (e.g. Credit Default Swaps, Mortgage-backed Securities and Collateralized Debt Obligations); they were considered as responsible for the spectacular risk management failures that occurred during the crisis, and they were blamed, rightly or not, for the huge losses that financial institutions have undergone since the onset of the subprime crisis[4].

Today, investors and regulators are in need of a better modeling of corporate bonds and a more appropriate assessment of the risks that they entail. Therefore

---

[2] We provide a more detailed evidence about the movements of credit spreads in subsequent chapters.

[3] See the "Senior Supervisors Group" report of October 21, 2009: Risk Management Lessons from the Global Banking Crisis of 2008.

[4] For instance, the April 2009 IMF Global Financial Stability Report puts loan and securities losses originated in Europe (Euro area and UK) at USD 1193 billion, and those originated in the United States at USD 2712 billion (source European commission report 2009). See also Colander, Haas et al. (2008), Rajan et al (2009), D. W. Hubbard (2010), Boucher and Maillet (2011) about the failure of risk models during the crisis.

one question arises: how to improve the valuation of corporate bonds? Dealing with this issue is the goal of this thesis.

Answering this question is indeed all the more important given the significant role that the corporate bond market plays in the funding of the economy (e.g. the outstanding of corporate bonds averaged 169% of the domestic GDP in the developed countries in 2013), and the important amounts outstanding in this market (e.g. for the Euro area alone, the outstanding volume of corporate bonds reached approximatively 1.104bn euros in March 2015)[5]. A more consistent valuation of corporate bonds seems hence necessary in order to stimulate the investment in this market and to enhance its stability.

In order to achieve the goal of this thesis, we propose a framework based on corporate bonds' credit spreads. Credit spread is in fact the difference in yield between a corporate bond and an equivalent risk-free bond (e.g. benchmark AAA-rated government bond). It represents hence the excess return that an investor earns as a compensation for the extra risks of the corporate bond that he bears. As such, credit spread can be seen as a major dimension of corporate bond valuation and, like equity returns in equity analysis, it has a key role in characterizing the risk–return profile of a corporate bond investment and thus its value (Avramov et al. 2007). In addition, a direct correspondence exists between the price of a bond and its credit spread, which makes it possible to switch easily from one to another.[6] Throughout this work, we proceed first to an analysis of the main corporate bond models from the perspective of credit spreads. Afterwards, we analyse the empirical credit spreads in order to draw some lessons from the crisis for the valuation of corporate bonds, before proposing a model for the term structure of credit spreads that captures some of our empirical findings about the spreads.

More specifically, this thesis is structured in four chapters. The **first chapter** will be dedicated to the analysis of the existing theoretical models of corporate bond valuation. In doing so, we chose to concentrate on structural models, as well as some models that present a mixture between the structural and reduced form setups. We carry particularly an extensive analysis of the models of Merton (1974), Black-Cox (1976), Collin-Dufresne and Goldstein (2000) and Zhou (2001). We reformulate these models from the stand point of credit spreads, and then we analyze numerically the term structure of credit spreads they generate in order to bring evidence about their performance. After that, we provide a critical

[5] Sources: IOSCO (2014) from Bank of International Settlement and IMF data; and Creditreform (2015) from European Central Bank data.

[6] More details about the relation between the price of a bond and its credit spread will provided in the first chapter of this thesis.

examination of these valuation frameworks on the basis of their assumptions and the results of their numerical simulation. Finally, we discuss the most recent extensions of these setups that have been proposed by literature, and we try to bring insights about how they can be improved. On top of this analysis, we propose throughout this first chapter to put light on the main credit spread determinants that have been proposed by the theoretical models, along with their relation with the credit spreads. These determinants are then considered empirically in the following two chapters in order to analyze their interaction with credit spreads in the context of the crisis.

In the **second chapter**, we put emphasis on the empirical credit spreads in order to draw some lessons for the valuation of corporate bonds. Our approach consists basically of presenting a descriptive analysis of corporate bonds spreads. We use hence a sample of 71 corporate bonds settled in Euro, as well as a sample of idiosyncratic and market-wide risk proxies, over a ten years period going from July 2004 to July 2014. We proceed our analysis around two main axes. First, starting from the observations and the descriptive statistics of our sample, we identify a set of ten stylized facts about the evolution of the spreads and the factors that affect them during the crisis. This allows us to put light on the different factors that caused the credit spread turbulence that were observed since the onset of the subprime crisis, and that need to be taken in a more consistent corporate bond valuation. Second, we conduct a Principal Component Analysis of credit spreads for different sub-periods including the pre-crisis, the subprime crisis and the Eurozone crisis periods. The aim of this empirical analysis is to bring evidence about a change in the factors that affect credit spreads that may highlight a change in the pricing dynamics inside the corporate bond market.

In the **third chapter,** we try to assess more effectively the factors that lie behind the movements in the credit spreads, together with the changes that these factors have incurred during the crisis. This will allow us to bring evidence about the factors that are relevant for the modeling corporate bonds and how these factors may evolve in a crisis context. To do so, our approach consists of analyzing, by the means of statistical regression techniques, the most significant factors in explaining credit spread changes, for a sample of 70 Euro-settled corporate bonds, over the July 2004-July 2014 period. In light of the theoretical and descriptive analyses that we carry, respectively, in chapters I and II, we propose to explore five major credit spread components. These are: (*i*) credit risk, (*ii*) liquidity risk, (*iii*) macroeconomic and systemic risks (namely, market-wide risks), (*iv*) information asymmetries as well as some (*v*) additional factors such as risk premiums and firm-size factors. A set of idiosyncratic and aggregate risk proxies is chosen in order to reflect accurately these determinants. We organize the empirical analysis proposed in this chapter around three main axes. First, we examine the sensitivity of the spreads to each of the credit spread component presented above, and we specify the changes that this sensitivity has undergone between the pre-crisis, the subprime crisis and the Eurozone crisis periods. Second, we investigate the robustness of our results by assessing, for instance, how well the credit spreads that we propose explain Credit Default Swap (CDS) spreads. Finally, we specify our results for different groups of bond maturities, bond ratings and firm-sizes. In so doing this specification analysis, we put light, for instance, on the risk factors that explain the changes in credit spreads of some of the largest firms in Europe, which are thought to be "Too big to fail".

Based on the theoretical analysis that we present in chapter I, and the lessons of the crisis that we draw in chapter II and III, we propose in **the fourth chapter** of thesis a contribution to the valuation of corporate bonds. More specifically, we start from one of our empirical results according to which credit spreads are impacted by the bailouts that some large firms in general, and large financial institutions in particular have received during the crisis. We develop thus a structural model of corporate bond valuation that builds on the ideas of Merton (1974), Black-Cox (1976), Collin-Dufresne and Goldstein (2000) and Zhou (2001). In doing so, we test two different assumptions for the dynamics of the firm value that are expected to capture either a period of stable economic outlook or crisis. In contrast to the previous structural models (which assume generally that bankruptcy occurs at the first time the firm makes default), we assume in this contribution that, once in distress, the firm has the possibility to negotiate a bailout plan that may allow it to continue its activity. Additionally, by linking the probability of rescue of the firm to its size, we manage to link the credit spreads generated by the model to the size of the firm, in agreement with the empirical observations that we make in chapters II and III. Semi-analytical formulas for the price of the corporate bond and its credit spread are derived in this framework. This work is then extended, as in chapter I, by a numerical analysis of the term structure of credit spreads that the model generates, together with an analysis of the sensitivity of the credit spreads to the main model's parameters.

The final part of this thesis draws general conclusions about this work and proposes several areas for future research in risk modeling and the valuation of corporate bonds.

Chapter I

Corporate bonds valuation and credit spreads: a theoretical analysis

1. Introduction:

Over the last forty years, an extensive literature has emerged with the aim to assess the risks entailed in corporate bonds and to provide a consistent valuation of these latter. While this literature has concentrated traditionally on the excess default risk that corporate bonds carry over government bonds, some recent efforts have been proposed to extend the modelling framework toward other corporate bonds' risks.[1]

[1] According to Moody's "corporate default risk service", default risk on a corporate bond could be defined as one of the following events:

- A missed or delayed disbursement of interest and/or principal, including delayed payments made within a grace period;
- Bankruptcy, administration, legal receivership, or other legal blocks (perhaps by regulators) to the timely payment of interest and/or principal; or
- A distressed exchange occurs where: (*i*) the issuer offers debt holders a new security or package of securities that amount to a diminished financial obligation (such as preferred or common stock, or debt with a lower coupon or par-amount, lower seniority, or longer maturity); or (*ii*) the exchange had the apparent purpose of helping the borrower avoid default.

Indeed, it is hard to give a universally accepted definition of the term "credit risk". According to the Bank of International Settlement (BIS): "credit risk is most simply defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms" (source: BIS consultative document July 1999). This means that credit and default risk could be simply perceived as the same. According to some other sources, however, credit risk encompasses default risk and other risks such as the risk of variation in the credit rating of the bond and the risk of recovery on the bond in case of default. In the frame of this study, we assume, unless otherwise specified, that credit risk and default risk coincide.

Broadly speaking, the literature of corporate bond valuation can be divided into two categories of models: ”structural” and ”reduced-form” models. Reduced-form models (e.g. Jarrow and Turnbull, 1995; Duffie and Singleton, 1999) model default as an exogenous event driven by a stochastic process (e.g. the first jump of a Poisson process). As such, these models disregard any economic cause that could cause default and use pure probabilistic approaches to model the bonds' risk, and accordingly the value of the bond. In contrast, structural models build on the economic fundamentals of the firm (i.e. the firm's capital structure) in order to explain the default arrival time, the riskiness of the firm and the value of the debt claim. In the frame of this theoretical analysis, we chose hence to concentrate on the structural approach since it allows to understand the nature of the factors that lie behind corporate bonds' risks, and to bring some economic content to the valuation of corporate debt securities[2]. That being said, we discuss throughout this chapter some of the recent extensions of the structural approach that account for some of the features of the reduced form models, such as jump process (e.g. the model of Zhou, 2001). These latter can in fact seen as a mixture between the structural and the reduced form setups.

Initiated by Merton (1974), the structural approach consists broadly of assuming that the corporate debt is a contingent claim on the firm's assets. The value of the firm's assets is assumed generally to be the main source of uncertainty that drives default risk. Hence, the model starts by proposing an assumption for the dynamics of the firm value, along with an assumption on the default barrier which triggers default. Default is then assumed to occur at a known or random time (depending on the model assumptions) if the asset value falls below the barrier. The value of the corporate debt and its credit spreads are then derived in the frame of these assumptions. Following Merton's seminal work (which deals with the valuation of a zero-coupon bond issued by a corporation that has a simple capital structure), the structural approach has been extended in several ways in order to consider the different features of corporate bonds and to make the valuation framework closer to reality. For instance, Black-Cox (1976) considered the valuation of a corporate bond containing safety covenants; Collin-Dufresne and Goldstein (2000) considered the valuation of a coupon-paying bond issued by a firm that has a sophisticated capital structure; and Zhou (2001) presented a framework for the valuation of a bond issued by a firm that is subject to idiosyncratic or market-wide shocks. In addition to these studies, which deal mainly with the default risk of corporate bonds, a recent branch of structural models has attempted to consider the introduction of new factors into the

[2] The reduced-form approach does not provide any theoretical insights about the causes or the nature of the risks that corporate bonds entail. Its derivation remains hence beyond the scope of this economic study (for a review of this approach, see for instance M. Jean-Blanc et al, 2009).

valuation of corporate bonds (such as information asymmetry, liquidity risk and economic conditions) in order to improve the valuation of corporate bonds. However, despite all these advances, the relevance of the structural approach is still under question, for instance, due to the numerous simplifying assumptions that the models employ.

In this chapter, we propose to analyze this literature in order to bring some elements of answer about its pertinence in the valuation of corporate bonds. To do so, our approach consists of presenting an extensive analysis of the structural models provided by Merton (1976); Black-Cox (1976); Collin-Dufresne and Goldstein (2000); and Zhou (2001)[3]. We propose first to reformulate these models from the stand point of credit spreads, and then to analyze numerically the credit spreads they generate in order to bring an evidence about their performances[4]. After that, we carry a critical examination of these models on the basis of their assumptions as well as the results of their numerical simulation. Finally, we discuss the extensions of these models that have been already proposed by literature as well as the ones that still need to be made. In addition to this analysis, we propose throughout this work to put light on the main credit spread determinants proposed by the theoretical models and their relation with credit spreads. These determinants will be reconsidered empirically in subsequent chapters in order to analyze their interaction with credit spreads in the context of the recent economic and financial crisis. All this will allow us to draw some conclusions that will be useful in pursuing the objective of this thesis: improving the valuation of corporate bonds.

Furthermore, compared to other surveys that can be found in literature, this study proposes some original features[5]. (*i*) It presents the main corporate bond models from the standpoint of credit spread (whereas the studies that can be found in literature concentrate mainly on bonds' prices or default probabilities). (*ii*) It proposes a numerical analysis of the credit spreads generated by the main valuation models, and tests the sensitivity of the generated credit spreads to the key credit spread determinants. (*iii*) This study analyzes the pertinence of the structural approach from both perspectives of hypotheses and numerical results. (*iv*) This work attempts to bridge the gap between the sophisticated mathematical formulations of the models and the economic reality by providing some economic content to the different formulas and numerical results.

---

[3] The choice of these models stems from the importance of their contributions to the structural approach as well as their relative easiness of presentation. In addition, these models constitute the base of our model developed in chapter IV.

[4] Credit spread is supposed to be here the main catalyzer of the performance of the model.

[5] See for instance the surveys of Elizade (2005) or Gatfaoui (2008c).

The remainder of this chapter is organized as follows: we start in a first section by presenting some of the basic formulas on the relation between bonds' prices, yields and credit spreads. These formulas will be useful for the derivation of the credit spreads of the different models. Afterwards, we analyze extensively the four proposed structural models, before discussing the most recent extensions of these approaches.

2. Basic valuation relations:

We propose first to explicit the relation between a bond's price, yield and credit spread. The formulas that we present here will be used later to derive the credit spread of the models that we aim to analyse.

Theoretically, the value or price of a financial instrument is widely perceived as equal to the present value of its expected future cash flows. The price of a corporate bond can be similarly expressed in terms of its future cash flows, which are the face value of the bond D, and the coupons C in the case of a coupon-paying bond. Assuming a continuous compounding, the price or the present value of a zero-coupon corporate bond at a certain date t can be expressed as follows:

$$P(t,T) = D\, e^{-Y(t,T)(T-t)} \tag{1}$$

Where $Y(t,T)$ is the continuously compound yield to maturity, and $(T-t)$ is the time left until the maturity of the bond. For a coupon-paying bond, the price will naturally take into account the discounted sum of the future coupons that the bond will pay[6]. Assuming that the bond pays a stream of fixed coupons C at times $\{t_i\}$, where $t_1 < t_2 < \cdots < t_n$ and $t_n = T$, the price of coupon-paying corporate bond can be expressed by:

$$P_c(t,T) = \sum_{i=1}^{N} C\, e^{-Y(t,T)(t_i-t)} + De^{-Y(t,T)(T-t)} \tag{2}$$

When comparing corporate bond investments, investors use usually the "yield to maturity" as a measure of the effective return of the bond. The yield to maturity can be indeed perceived as the rate of return (or interest rate) that accounts for the present value of all the future cash flows of the bond. It considers hence the current price of the bond, its face value, the coupons (if any), and the time left until the bond matures. Rewriting from equation (11), the following expression can be provided for the yield to maturity of a discount corporate bond:

---

[6] We concentrate throughout this work on the valuation of ordinary corporate bonds (zero-coupon or coupon paying bonds). Hence we do not survey, for instance, the valuation of convertible bonds, which are beyond the scope of this work.

$$Y(t,T) = -\frac{\ln\left(\frac{P(t,T)}{D}\right)}{T-t} \tag{3}$$

Where ln() is the natural logarithm function[7]. However, for a coupon-paying bond it is not generally possible to provide closed form formulas for the yield to maturity in terms of the bond's price. Numerical techniques need hence to be used in order to approximate the yield $Y(t,T)$ that takes into account the price of the bond provided in equation (2)[8].

Furthermore, by purchasing corporate bonds, investors bear generally higher levels of risk on the return of their investment compared to a typical treasury bond, which is considered theoretically to be risk-free[9]. This risk difference is captured by the notion of credit spread, which can be formulated as follows:

$$S(t,T) = Y(t,T) - r(t,T) \tag{4}$$

Where $S(t,T)$ is the credit spread of a corporate bond of maturity T at a certain date t; $Y(t,T)$ the yield to maturity of the bond defined in equation (3), and $r(t,T)$ the yield of a benchmark government bond of equivalent maturity. Traditionally, credit spread has been viewed as reflecting the higher default risk of a corporate issuer compared to a government issuer. However, as will be discussed later, this risk is not the only component of credit spreads. In what follows, we will use the formulas provided in this sub-section (equations 1-4) to derive and analyze the credit spreads of four main structural corporate bond models.

3. Merton's model:

We start this theoretical analysis by discussing the seminal structural model of Merton (1974). We begin by presenting the key assumptions of the model which will allow us to derive the credit spread presented in equation (4). Afterwards, we

[7] Equation (3) shows the existence of a negative relation between a bond's yield and price over time. More evidence is provided in Figure I.A.1 of Appendix I.

[8] Two main assumptions are made when measuring the yield to maturity of a bond: first, that the bond will be held until maturity, and second that the received coupons (if any) will be reinvested at an interest rate equal to the yield to maturity.

[9] Government bonds are considered to be theoretically default-risk-free because, as opposed to a corporate issuer, the government has the possibility to raise taxes or create additional currency in order to redeem its bonds at maturity. However, it is important to note that there has been cases where a government has defaulted on his debt, such as the Russian government in 1998 or the Greek government since 2010.

analyze numerically the credit spreads generated by the model before discussing its main contributions and drawbacks.

3.1. Deriving credit spread:

In its former structural framework, Merton (1974) assumes first that the firm issuing the bond has a simple capital structure composed by assets V, equities E and a single Zero-coupon bond with face value D and maturity T. Respecting the equality of the assets and liabilities, the capital structure of the firm in this setup can be written as follows:

$$V = E + D \tag{5}$$

Since the value of the firm's assets is not observable, Merton (1974) assumes afterwards that the evolution of the firm's assets over time V_t follows a Geometric Brownian motion with respect to the following stochastic differential equation[10]:

$$dV_t = (r - \kappa)V_t\ dt + \sigma_v V_t\ d\widetilde{\mathbb{W}}_t \tag{6}$$

Where r is the constant risk-free interest rate; κ the constant pay-out rate, σ_v the constant volatility of the of the firm's assets; $\widetilde{\mathbb{W}}_t$ a standard Brownian motion under the risk-neutral measure $\mathbb{Q}$[11]; and $V_0 > 0$ the initial value of the firm's assets. Figure I.1 shows how the firm value evolves under this assumption.

[10] A stochastic process (i.e. a system of random values that evolves over time) V_t is said to follow a geometric Brownian motion if it satisfies the following stochastic differential equation: $V_t = \mu V_t\ dt + \sigma_v V_t\ d\mathbb{W}_t$, where μ is called the percentage drift and σ the percentage volatility; $\mu V_t\ dt$ is called the trend of the stochastic differential equation while $\sigma_v V_t\ d\mathbb{W}_t$ is the random diffusion trajectory.

[11] The standard Brownian motion (or Wiener process) $\mathbb{W}_t$ is a continuous-time stochastic process that satisfies the following characteristics:

- $\mathbb{W}_t$ has independent increments: this means that any increment of the Brownian motion (i.e. the difference between the realizations of the Brownian motion at two successive times) is independent from all the other realizations of the Brownian motion.
- $\mathbb{W}_t$ has stationary and Gaussian increments: this means that the increments of the Brownian motion follows a Gaussian distribution with a zero mean and a variance equal to the time interval of the increment (i.e. for times $0 \leq t_1 \leq t_2$ the increment of the Brownian motion $\mathbb{W}_{t2} - \mathbb{W}_{t1} \sim N(0, t_2 - t_1)$)
- $\mathbb{W}_t$ is almost surely continuous: this means that realizations of the Brownian motion have a probability of 1 of being continuous.
- For a standard Brownian motion the initial value of the process $\mathbb{W}_{t_0}$ is equal to zero.

Furthermore, the Girsanov theorem states that there exists a probability measure $\mathbb{Q}$ under which the discounted value of the expected payoffs of the firm's assets (i.e. the drift of the Brownian motion) becomes equal to the risk-free interest rate (This theorem applies under specific assumptions ensuring the existence of the Itô's integral. See for instance S. Sherve, 2004 for a

Figure I.1 - Firm value path under the geometric Brownian motion assumption

Source: Author's calculations

Assuming that the firm value follows a geometric Brownian motion with a drift $(r - \kappa)$ and a volatility σ_v amounts to saying, on the one hand, that the average change in the firm's value is an increasing function of the risk-free rate r and a decreasing function of the pay-out rate κ; and on the other hand, that the firm faces unpredictable random events that affect its assets' value (following a normal distribution), with a constant volatility rate σ_v. This constitutes one of the key assumptions of the Merton (1974) model since it allows a continuous time modelling of the random values of the firm's assets, and hence, the use of the stochastic calculus techniques employed in the Black & Scholes (1973) option pricing framework.

Merton (1974) assumes afterwards that the ability of the firm to redeem its debt (i.e. the zero-coupon bond) is determined by the value of the firm's assets at maturity T (i.e. the value of the geometric Brownian motion at the maturity of the zero-coupon bond). If at time T the value of the firm's assets V_T is superior

demonstration of the theorem). This probability measure $\mathbb{Q}$ is called the "martingale measure" or the "risk-neutral probability measure". It is in fact a mathematical transformation widely used in financial mathematics (for instance in option pricing) which makes the assumption that market participants are risk-neutral and hence that their risk preferences do not affect the solution of the model. Making the assumption that investors are risk-neutral implies that they do not demand a premium for taking higher risks and hence that the expected return on all assets (here the firm's assets) is equivalent to the risk-free rate. Similarly, in this risk-neutral world, the present value of any future cash-flows can be obtained by discounting the value of the cash flow with the risk-free rate. Using this assumption makes the subsequent calculations (here corporate bond pricing) more tractable and independent from market participants' risk aversion, which is harder to model. This is an important assumption since the corporate bonds prices and yields obtained under this probability measure are different from those obtained through real world probabilities where investors are not risk-neutral. According to Hull (2012) and L. Giordano et al. (2012), the risk-neutrality hypothesis is acceptable for pricing purposes; it is however not acceptable for risk management. See for instance J. Hull (2012), page 333.

to the face value of the debt D, the firm has the capacity to pay its creditors (i.e. the bond holders), and it does so by paying the principal amount of the debt D (the firm's equity here is equal to the remaining value of assets, that is $V_T - D$)[12]. If however at time T the value of the firm's assets V_T is inferior to the face value of the debt, the firm cannot redeem its debt and default occurs. In this situation, the creditors take the residual value of the firm V_T (the firm's equity here is null). In this setup the value of the corporate bond contract at maturity corresponds to the value paid by the firm to its creditors which can be, either the face value of the debt D, or the residual value of the firm's assets V_T, that is formally:

$$P(T,T) = V_T \ \mathbf{1}_{\{V_T<D\}} + D \ \mathbf{1}_{\{V_T \geq D\}} \tag{7}$$

With $\mathbf{1}_{\{\ \}}$ is the indicator function of the events $V_T < D$ and $V_T \geq D$ where the firm pays, respectively, V_T or D. In this framework, the major contribution of Merton (1974) was by viewing the payoff of the creditors at maturity (i.e. the corporate bond contract) as being similar to the situation where creditors sell a European put option written on the assets of the firm, with a strike price equal to the face value of the bond D and with maturity T[13]. That is formally:

$$P(T,T) = \min(V_T, D) = D - \max(D - V_T, 0) \tag{8}$$

Hence in the Merton (1974) setup, the pricing of the corporate bond is reduced to the framework of European options pricing initiated by Black-Scholes (1973). Discounting the right hand side of equation (8) at a date t between the issuance of the bond t_0 and its maturity T, the price of the risky corporate bond can be obtained by:

$$P(t,T) = e^{-r(T-t)}D - Put_{B\&S}(t,T) \tag{9}$$

---

[12] Hence in the Merton (1974) setup, D is assumed to be the default boundary.

[13] In other words, in Merton (1974) setup, the corporate bond investors (i.e. the creditors of the firm) can be viewed as selling a put option to the firm with a strike price D and maturity T. By doing so, they give the firm the right, but not the obligation, to exercise a put option according to the value of the firm's assets at maturity. Hence:

- If at maturity $V_T \geq D$: the firm doesn't exercise its put option (which means that the payoff of the put option $\max(D - V_T, 0)$ is equal to zero) and that the entity $D - \underbrace{\max(D - V_T, 0)}_{0}$ is equal to D; that's what investors receive at maturity in this case.

- If however at maturity $V_T < D$: the firm exercise its put option (which means that the payoff of the put option $\max(D - V_T, 0)$ is equal to $D - V_T$), and the entity $D - \underbrace{\max(D - V_T, 0)}_{(D-V_T)}$ is equal to V_T; that's what investors receive at maturity in this case.

Where $e^{-r(T-t)}$ is the continuous discount factor that takes into account the date of the pricing t, the maturity T, and the constant risk-free rate r[14]; and $Put_{B\&S}(t,T)$ is the payoff of a put option with strike D and maturity T given by Black-Scholes (1973) as follows:

$$Put_{B\&S}(t,T) = \ D\ e^{-r(T-t)}\ N(-d_2) - V_t\ e^{-\kappa(T-t)}\ N(-d_1) \tag{10}$$

Where:

$$\begin{aligned} d_1 &= \frac{\ln\left(\frac{V_t}{D}\right) + \left(r - \kappa + \frac{\sigma_v{}^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}} \\ d_2 &= \frac{\ln\left(\frac{V_t}{D}\right) + \left(r - \kappa - \frac{\sigma_v{}^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}} \\ &= d_1 - \sigma\sqrt{T-t} \end{aligned} \tag{11}$$

And $N(\ )$ denotes the standard Gaussian cumulative distribution function given by:

$$N(x) = \frac{1}{\sqrt{2\pi}} \int_{\infty}^{x} e^{-\frac{t^2}{2}}\ dt \qquad \forall\ x \in \mathbb{R} \tag{12}$$

Replacing back in equation (9), the value of the corporate bond in the Merton (1974) framework is found to be equal to[15]:

$$\begin{aligned} P_{Merton}(t,T) &= e^{-r(T-t)}D - \left(D\ e^{-r(T-t)}\ N(-d_2) - V_t e^{-\kappa(T-t)}\ N(-d_1)\right) \\ &= D\ e^{-r(T-t)}\ N(d_2) + V_t e^{-\kappa(T-t)}\ N(-d_1) \end{aligned} \tag{13}$$

Next, the risky yield-to-maturity of the bond can be obtained by replacing $P_{Merton}(t,T)$ inside equation (3) described earlier. Formally:

---

[14] Using a flat term structure where the risk-free interest rate r is constant and known with certainty at all times consist of another simplifying assumptions of the Merton (1974) model.

[15] The price of the risky debt in Merton (1974) model can be indeed derived in three different ways:

- By using the formulation of a European put option as provided here;
- By using the put-call parity: the firm's equity can be perceived as a European call option on the firm's assets; hence through the Black-Scholes formulations of a European call and the capital structure equality given in equation (5), the same results of equation (13) can be found;
- By using risk-neutral valuation techniques (see for instance S. Sherve, 2004).

$$
\begin{aligned}
Y_{Merton}(t,T) = & -\frac{1}{T-t}\ln\left(\frac{1}{D}\big(P_{Merton}(t,T)\big)\right) \\
= & -\frac{1}{T-t}\ln\left(e^{-r(T-t)}\ N(d_2)+\frac{V_t}{D}e^{-\kappa(T-t)}\ N(-d_1)\right) \qquad (14)
\end{aligned}
$$

Finally, using the formulation that we presented earlier in equation (4), the following closed form formula can be obtained for credit spread in the Merton (1974) framework:

$$
\begin{aligned}
S_{Merton}(t,T) &= Y(t,T) - r \\
&= -\frac{1}{T-t}\ln\left(e^{-r(T-t)}\ N(d_2)+\frac{V_t}{D}e^{-\kappa(T-t)}\ N(-d_1)\right) \\
&\quad - \Big(-\frac{1}{T-t}\ln\big(e^{-r(T-t)}\big)\Big)
\end{aligned}
$$

$$
S_{Merton}(t,T) \;=\; -\frac{\ln\Big(\ N(d_2)+L^{-1}e^{-\kappa(T-t)}\ N(-d_1)\Big)}{(T-t)} \qquad (15)
$$

Where $L = D\ e^{-r(T-t)}/V_t$ is defined as the firm's leverage ratio.

From equations (11) and (15) we note that credit spread in Merton (1974) is a function of the following exogenous factors:

r: The risk-free rate, which affects the grow-path of the firm's assets (given the risk-neutral drift) and the final value of the credit spread (since the risk-free rate is equal to the treasury rate);

σ_v: The volatility of the firm's assets, which represents the incertitude about the firm's activity proxied here by the volatility term of the geometric Brownian motion;

L: The leverage ratio of the firm which is in turn given by: V_t the observable value of the firm's assets at time t; and D the face value of the zero-coupon bond, which represents the total debt of the firm;

$T-t$: The time left until the maturity of the bond T starting from the date of the valuation t;

κ: The payout rate, which represents the portion of the firm's activity that is paid to the firm's shareholders or to the liabilities-holders (e.g. dividends or interest payments).

In what follows, we test numerically the sensitivity of the credit spreads generated from Merton's model to different values of these factors.

3.2. Numerical analysis:

We run next a series of numerical simulations of the credit spreads generated by the Merton model that we represent graphically by the means of the "term structure of credit spreads". To obtain so, we calculate the spreads generated by the models for different values of the time to maturity $(T-t)$, then we represent the obtained values in a scatter plot where $(T-t)$ stands in the horizontal axis. Using this representation allows us, on the one hand, to analyze the relation between credit spreads and time to maturity, and on the other hand, to have a graphical representation of the impact of the different factors presented earlier on credit spreads. We present first the benchmark setup for this numerical analysis of credit spreads before analyzing the impact of each factor on the spreads[16].

Figure I.2 - The term structure of credit spreads

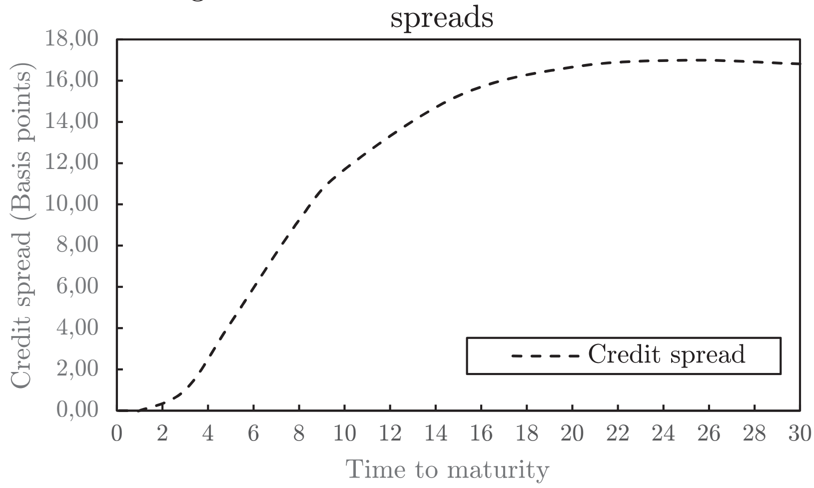


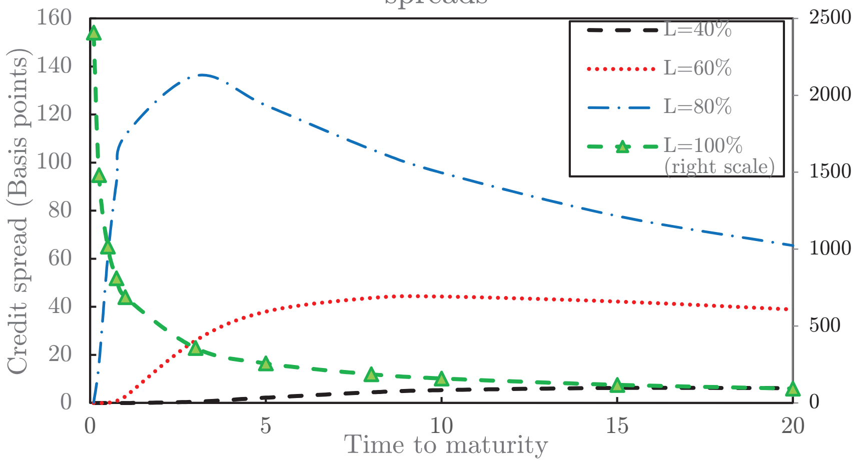
Figure I.2 presents the benchmark setup for the term structure of credit spreads calculated from the Merton (1974) model. To have so, we set in equation (15) the leverage level $L = 40\%$, the asset volatility $\sigma_v = 0.2$, the risk-free rate $r = 0.06$, and the pay-out rate $\kappa = 0.\,03$, and then calculated credit spreads for maturities going from zero to thirty years. Figure I.2 shows importantly that, under these parameters, and keeping everything otherwise equal, the credit spreads obtained from Merton model are low for short maturities (almost zero) while they are substantially higher for longer maturities[17]. The Merton framework implies indeed that a short period of time left until the maturity of the bond is

[16] The numerical analyses are done using Visual Basic for Excel and SCILAB numerical computations' software.

[17] As will be seen later, this observation is typical of the case where the initial leverage of the firm is inferior to 100% (hence the common case in reality).

synonym of low incertitude about the firm's situation and its probability of default, which yields to lower levels of credit spreads. Conversely, longer maturities convey higher incertitude about the firm's activity which is consistently reflected by higher levels of credit spreads[18]. We specify this result in what follows by examining the impact of the variation of the model's parameters on credit spreads and their term structure[19].

Figure I.3 - Impact of Leverage on credit spreads



First, we consider the relationship between credit spreads and the firm's leverage ratio. In fact, no clear consensus rises from literature about the effect of leverage on credit spread in the model of Merton (1974) and we attempt here to bring a more comprehensive understanding of this effect. Keeping everything otherwise constant, we calculate credit spreads for the leverage levels of $40\%, 60\%, 80\%$, and 100%. Figure I.3 shows that higher levels of leverage are consistently associated with higher levels of credit spreads in the Merton model[20]. Indeed, higher levels of initial indebtedness makes the firm much more likely to hit the default boundary at maturity, increases its probabilities of default, and generates, accordingly, higher levels of credit spread.

---

[18] That said, we note that credit spreads show a small decrease for maturities of twenty-eight years and more. Indeed, if the firm does not experience default for a long period of time, its likelihood of default starts decreasing through time, which leads, for these parameters, to a slightly smaller credit spreads for very long maturities.

[19] Note that Merton (1974) provides a brief numerical analysis of the spreads generated by its model. Other studies also attempted to provide an analysis of the spreads generated by the Merton model, but the evidence available to us includes only analyses of the relation between credit spreads and time to maturity (hence doesn't include the effect of the other model parameters). In this study we attempt to provide a more comprehensive analysis of the spreads generated by Merton's model as well as the effect of the different credit spread determinants.

[20] Note that Figure I.3 might be misleading with regard the leverage level of 100% (right scale). In fact, credit spreads generated for this leverage level remain always above the credit spreads generated by the lower leverage levels, even for long maturities (up to 30 years).

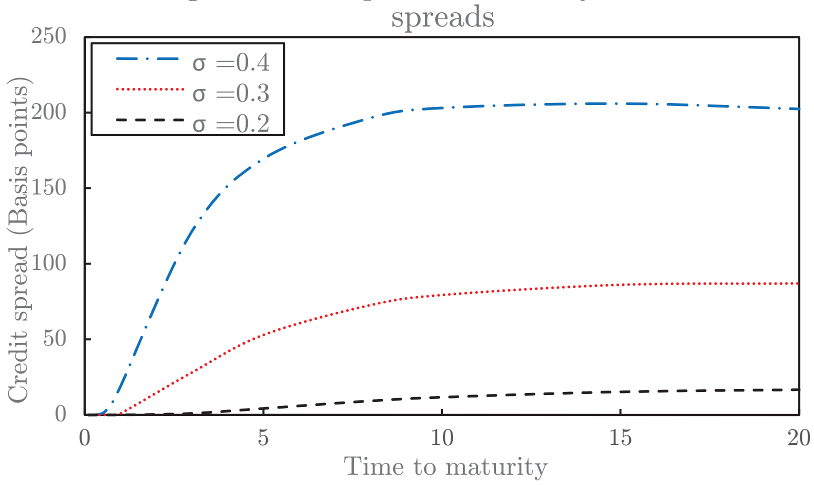
Furthermore, with regard to the structure by term of credit spreads, we note that a high leverage ratio (100% and more) is associated with a downward-sloping term structure (high spreads for short maturities and lower spreads for longer maturities) while a leverage ratio of 80% and less is associated with a hump shaped term structure. In this latter case, the location of the hump on the time axis, and its flattening, change according to the leverage level. The hump comes closer to short maturities for higher leverage ratios and remains flat for a long period of time for lower leverage ratios. The intuition behind this observation is as follows: due to the closeness of its initial asset values to the default boundary (i.e. V_t is close to D), a firm with a high initial leverage ratio has high chances of hitting the default boundary in the short run; this makes its credit spreads reach a high at these maturities (i.e. the observed hump). However, if default doesn't occur in the short run, the firm value will increase inevitably over time (due to the properties of the geometric Brownian motion, which increases exponentially in time), driving the firm away from the default boundary and decreasing gradually its credit spreads. On the other hand, a firm with a low initial leverage has a low probability of crossing the default boundary in the short run; this probability increases slowly as time goes by, which yields to larger credit spreads for longer maturities. That being said, we note from a mathematical point of view that, if the initial leverage ratio is inferior to 100%, the limit of the credit spread, when $T-t$ tends to infinity, is equal to zero[21]. This means that credit spreads will always decrease at very long maturities (here over 30 years), even for firms with low initial leverage. The main reason behind this is again the increasing property of the Brownian motion mentioned previously. Nonetheless, these very long maturities are unlikely to be analysed in practice since corporate bond contracts have generally a maximum maturity of thirty years. We can hence retain the fact that, for firms with low leverage levels, the Merton model implies higher credit spreads for longer maturities.

Finally, it is important to note that the tightening of credit spreads at long maturities for firms of high initial leverage is mainly due to the assumptions of Merton's model. Indeed, in the Merton setup, the firm doesn't have the possibility to issue more debt during the life of the bond contract. Hence, for a constant debt level D and an increasing asset value V_t the firm's leverage ratio will gradually fall over time, implying these low credit spreads. A more realistic scenario needs therefore to include the possibility of the firm to alter its initial capital structure, which would possibly imply a different term structure[22].

[21] However, if the initial leverage ratio is superior to 100%, the limit of credit spread when $(T-t)$ tends to infinity is equal to infinity.

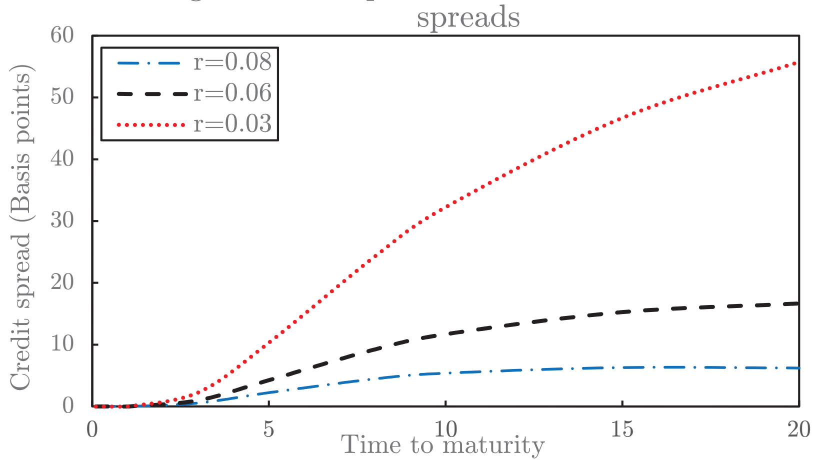
[22] This makes the object of the model of Collin-Dufresne and Goldstein (2000) presented in what fallows and our model presented in chapter IV.

Figure I.4 - Impact of volatility on credit spreads



Next, we consider the relationship between credit spreads and different values of asset's volatility (respectively $\sigma_v = 0.2, 0.3$ and 0.4). As can be seen in Figure I.4, we note that an increase in asset's volatility in Merton's model is largely consistent with an increase in credit spreads. From a theoretical point of view, this relation can be indeed seen in the sense that an increase in assets' volatility is associated with higher incertitude about the firm activity and hence with a higher dispersion in the firm value. This situation makes the firm much more likely to hit the default boundary, reduces the value of the corporate bond and drives consequently the credit spreads up. Hence, according to Merton's model, credit spreads and assets' volatility are positively related.

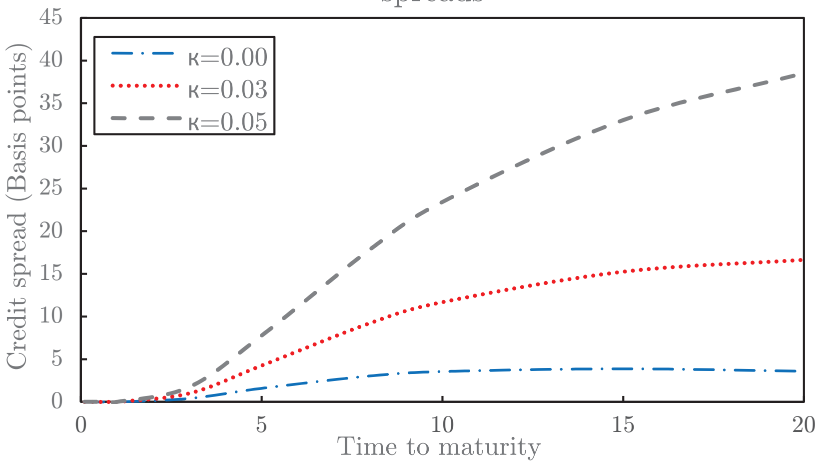
Figure I.5 - Impact of interest rate on credit spreads



Further, Figure I.5 brings insight to the impact of the variation of the risk-free rate on credit spreads in Merton (1973) (we use $r = 3\%; 6\%$ and 8%). We note indeed that a higher level of the risk-free rate is always associated with a lower level of credit spreads (despite how low these are for short maturities). This relation can be explained at least in two different ways. A first way to see this relation emanates from the option pricing theory implied by Merton's model.

Since the debt claim (i.e. the corporate bond) has similar features to being short on a put option, one can see that an increase in the risk-free rate implies a decrease in the value of the put option, and accordingly an increase in the price of the corporate bond[23]. This increase will in turn lead to a fall in the corporate yield (since a bond's price and yield are inversely related) and consequently the credit spread will go down. The second way to see this relation comes simply from the definition of credit spread, which is the excess yield on a corporate bond over the risk free rate. Keeping everything otherwise equal, an increase in the risk-free rate should be associated with a decrease in credit spreads.

Figure I.6 - Impact of the payout rate credit spreads



Finally we consider the impact of different levels of the payout rate on credit spreads and their term structure ($\kappa = 0\%; 3\%$ and 5%). Figure I.6 shows that a positive relationship exists between credit spreads and the payout rate; indeed a higher payout rate is always associated with a higher credit spread in Merton (1974). This relationship can be explained by the fact that the risk-neutral drift of the firm value is negatively related with the payout rate in the Merton framework. Hence the more the firm pays shareholders or liabilities-holders, the closer it is to the default boundary and the higher its credit spreads are.

In sum, these numerical analyses have allowed us to shed light on the joint relation between credit spreads and the main credit spread determinants proposed by the model of Merton (1974). In chapters II and III, we propose to analyze empirically this joint relation in the context of crisis to shed light on the robustness of the statements of Merton (1974). For now, we propose to discuss the theoretical outcomes of this model.

[23] According to the Greeks of option theory (see for instance J. Hull 2012).

3.3. Discussion:

We propose next to discuss the hypothesis and the outcomes of the model of Merton (1974). This will allow us to shed light on the main contributions of this model for the valuation of corporate bonds, and to present its already proposed improvements, as well as the ones that still need to be made. In addition, this will allow us to locate the structural model that we propose in chapter IV in its theoretical context.

As regards the advantages, the model of Merton (1974) presents the convenient feature of making a clear link between the capital structure of a firm and its default risk. This allows an intuitive interpretation of the link between credit spreads and the economic fundamentals of the firm. Furthermore, by using the option pricing framework developed by Black and Scholes (1973), the Merton model proposes closed-form formulas for bond prices and credit spreads, which are relatively easy to calculate and to calibrate. Owing to these appealing features, the model of Merton (1974) constitutes, still today, a benchmark setup for the valuation of default risk and corporate bond among finance professionals and academicians[24].

In spite of these features, the contingent claim framework proposed by Merton (1974) suffers from many shortcomings. These shortcomings stem mainly from the numerous unrealistic assumptions that Merton makes about the corporate bond valuation framework. We summarize in what follows these shortcomings into seven key points, all while presenting the studies that attempted to address these shortcomings.

(i) Perfect market assumption: First, Merton considers in its model of (1974) perfect and frictionless markets with four main characteristics: (a) there are no transactions costs, taxes, or problems with indivisibilities of assets; (b) there is a sufficient number of investors with comparable wealth levels such that each investor believes that he can buy and sell as much of an asset as he wants at the market price; (c) there exists an exchange market for borrowing and lending at the same rate of interest; (d) short sales of all assets, with full use of the proceeds, are allowed. Nonetheless, these assumptions are known to be inconsistent with reality since markets in general, and the corporate bond market in particular, tend to have non-negligible transaction costs, problems in the matching of buyers and sellers, imperfect and asymmetric access to information, along with many

---

[24] The Merton (1974) model is widely used in practice especially through its implementation carried by Moody's-KMV. The Moody's-KMV setup allows the appreciation of the distance to default of a firm, which allowed it to have a great commercial success in the last ten years. These latter implemented the original Merton framework so that it accounts for the empirical observations about the model parameters and default (A. Jorge et al, 2006).

other imperfections[25]. Furthermore, this perfect market assumption implies the agreement with the efficient markets hypothesis (Fama, 1970), which has been seriously questioned in recent years (see for instance B. Guerrien, 2011 and N. Bouleau, 2013).

(*ii*) Continuous time assumption: Second, Merton (1974) assumes that trading in assets takes place continuously in time. This assumption is in fact widely used in mathematical finance literature since it allows using a certain number of mathematical tools (such as the Brownian motion), which are simpler than any other sophisticated tool. According to Merton (1973), well-developed capital markets have small time interval between two successive market openings, which makes the continuous-time assumption a good approximation of reality. However, it is well known that trading in assets takes place only in limited sessions in reality, and that prices can change drastically between two successive market openings (for instance due to adverse news announcements, i.e. the gap risk).

(*iii*) Simple capital structure: Third, Merton (1974) makes the assumption that the modelled firm has a very simple debt structure, which consists of a single zero-coupon issue at a given period. This assumption can be unrealistic since firms have the possibility to issue many debts outstanding at the same time, and their issue may contain features such as coupons, sinking fund provisions or covenants. In addition, Merton assumes that the firm cannot make any modifications on its capital structure as long as the debt is outstanding (e.g. cannot make any new equity sales), which may also be unrealistic.

(*iv*) Unrealistic default mechanisms: Fourth, Merton (1974) makes very simplistic assumptions about the mechanisms of default of a firm. As mentioned earlier, in the Merton framework, debtors take control of the firm at maturity if the value of the firm's assets is inferior to the face value of its debt. This implies, on the one hand, that the firm cannot make default prior to the maturity of the debt (despite how low its value can be), and on the other hand, that default is inevitable in the situation where the face value of debt is superior to the firm's asset. But in reality, the mechanisms of default tend to be much more complex. A firm may indeed make default at any time before maturity if the conditions of default are reunited (e.g. bad financial situation, unpredictable catastrophic events or default as an endogenous decision of the firm). In addition, a distressed firm has several options to avoid default (accordingly bankruptcy). These include,

[25] We test in chapter III the impact of information asymmetries on credit spreads in the secondary market and find evidence for the presence of imperfections in the corporate bond market, especially during the crisis.

amongst others, seeking an external financial support, issuing a new debt, or negotiating the terms of its initial debt[26].

(v) Flat term structure: Fifth, Merton considers a flat term structure where the risk-free interest rate (r) is constant and known with certainty at all times. By itself, the notion of "risk-free rate" is a purely theoretic notion which can be judged inconsistent with reality; indeed, there is no proof that such rate exists in reality[27]. In addition, it is well known that interest rates are not constant over time as it is assumed in Merton (1974). In order to address this shortcoming, many subsequent studies have considered the introduction of stochastic interest rates into the corporate bond pricing framework. These include, Nielsen et al. (1993), Longtsaff and Schwartz (1995), Bryis and de Varenne (1997), Collin-Dufresne and Goldstein (2001), or Hsu et al. (2004).

(vi) The firm value follows a geometric Brownian motion: Another important shortcoming of Merton model arises from the assumption that the dynamics for the firm value can be described by a geometric Brownian motion (see equation 6). In practice, there exist no certitude about the fact that the returns on the assets of a firm follow a Log-normal distribution (as implied by the geometric Brownian motion). In addition, it is not possible to verify that the volatility of a firm's assets is constant over time as assumed in the Merton framework. Furthermore, by assuming that the asset value follows a continuous diffusion process (i.e. the geometric Brownian motion), the default time in the Merton model time becomes a predictable event[28]. Indeed, in this setup, the default event, which is given by comparing the value of the firm's asset to its liabilities, is indicated by the proximity of the asset's value to the default barrier. Accordingly, if the initial firm value is quite far from the default barrier, the continuous diffusion property of the Brownian motion makes it hard for the asset value to hit the default boundary before a certain time. This makes default an almost impossible event in the near run and explains the near-zero credit spreads that the Merton model generates for short maturities (see Figure I.2). In practice, credit spreads are found however to be significantly different from zero (even for

[26] As will be seen in Chapter II, during the crisis many financial institutions took advantage of governments' financial support in order to avoid default. Relaxing this assumption constitutes one of the basic ideas of our model presented in Chapter IV.

[27] From a theoretic point of view, a risk-free rate is a rate of return on a security that will be paid with certainty at a precise date in the future in any possible state of the world. In practice, the assumption of absolute certainty regarding a promised payoff seems unrealistic. Source: ECB (2014) - Euro area risk-free interest rates: Measurement issues, recent developments and relevance to monetary policy.

[28] This issue of predictability of default is endured by all the structural models assuming that the firm value follows a geometric Brownian motion, including the first-passage-time models presented later.

short maturities), which makes the short term credit spreads generated by Merton's model unrealistic[29]. In order to address this question, some subsequent studies considered the introduction of jumps onto the process of firm value or incomplete information about the firm's assets. These studies include mainly the models of Zhou (2001) and Duffie and Lando (2001) will be discussed with more details in subsequent sections.

(*vii*) Risk-neutral valuation: Finally, it is important to underline that the valuation framework proposed by Merton (1974) is based on the risk-neutral probability measure, where it is assumed that all investors have the risk-free rate as an expected rate of return[30]. This assumption excludes indeed any risk premium that can be priced by investors for different levels of risk aversion. In reality however, it is known that investors price different risk premiums according to the risk profile of their investment[31]. Therefore, aside from all the unrealistic assumption mentioned earlier, the results obtained from the Merton risk-neutral setup need to be differentiated from the ones that could be obtained from a real-world probability setup (namely for credit spread). Indeed, an additional adjustment needs to be done on the model in order to meet the risk preferences of investors in real world, which is rather complex. The risk-neutral framework constitutes in fact an interesting theoretic tool for the valuation and the understanding of default risk and credit spreads. Its results need though to be handled with caution. In this sense, Hull (2012) and L. Giordano et al. (2013) argue that the risk-neutral setup is acceptable for pricing purposes but less accurate for risk management purposes.

In summary, this section has attempted to analyse extensively the seminal structural framework of Merton (1974). To do so, our approach consisted of covering this model from the standpoints of hypotheses and numerical results. As regards hypotheses, we note that the model of Merton (1974) employs many unrealistic assumptions, which we summarized in seven main points. In the following sections, we use these seven points to show how the structural models that we present relate to the former Merton setup. As regards the numerical results, we note particularly that the model of Merton (1974) generates near-zero credit spreads for short maturities and presents a term structure that is highly sensitive to the leverage level of the firm.

In what follows, we discuss some of the models that attempted to bridge the gap between the hypotheses of the former Merton model and reality. We start by the model of Black-Cox (1976).

[29] "Real-world" credit spreads are emphasized in Chapters II and III.

[30] The risk-neutral probability measure relies also on the arbitrage-free market conditions.

[31] Chapters II and III shed light on investors risk premiums in the corporate bond market.

4. Black-Cox model:

We turn next to the analysis of another important extension of the structural approach, namely the model of Black-Cox (1976). As mentioned above, Merton (1974) makes the unrealistic assumption that default can happen only at the maturity of the debt (shortcoming (iv)). In reality, however, default can happen at any time between the issuance of the bond and its maturity. The main idea behind the Black-Cox (1976) model was hence to relax this restrictive assumption by allowing the bond pricing framework to take into account the possibility of an early default of the firm. To do so, Black-Cox (1976) consider the introduction of a safety covenant in the corporate bond contract which sets the rule for the early default. Through safety covenants, the bondholders may in reality prevent the firm from falling behind a certain level of performance in order to protect their debt claim[32]. If the firm falls behind this level, the creditors may force the firm into default or reorganization, and may take the control of the firm and the remaining value of its assets (hence equal to the pre-set default barrier). Similarly, in the Black-Cox (1976) framework, the early default is allowed by the means a default barrier set inside the bond covenant on the value of the firm. At the first time the asset value (V_t) hits this default threshold, the early default is triggered; if however, the firm value does not hit this boundary through the life of the bond, default happens at maturity according to the same terms as the Merton framework (namely by comparing the firm value to the face value of debt).

4.1. Deriving credit spread:

Technically, Black-Cox (1976) start first by assuming that the firm value follows a geometric Brownian motion under the risk-neutral measure, in the same vein as Merton (1974) (see equation 6). Similarly to Merton, Black-Cox assume a constant volatility for the firm value (σ_v), a constant interest-rate (r), and a constant payout ratio (κ) with a continuous compounding as a function of the firm value[33].

Afterwards, Black-Cox (1976) set the standard for the low performance of the firm that is stipulated by the bond covenant, namely the default boundary. In order to make an early default, the firm value (V_t) must cross the following deterministic and time-dependent barrier, denoted $\hat{b}(t)$:

$$\hat{b}(t) = \; Ke^{-\gamma(T-t)} \qquad\qquad \forall \; t \in [0, T[\tag{16}$$

[32] See section 2.1.3 for more details about bond covenants.

[33] Black-Cox (1976) keep otherwise all the former Merton (1974) assumptions: i.e. perfect market assumption, continuous time trading, simple debt structure and flat term structure.

With the constants K and γ have pre-specified arbitrary levels[34]. Black-Cox postulate judiciously that the value of the barrier $\widehat{b}(t)$ (which is also the payoff of the creditors in the case of an early default) must not exceed the discounted value of the face value of the bond D, so that the payoff to bond holders at default will not exceed the value of their debt claim (formally, $\widehat{b}(t) \leq De^{-r(T-t)}\ \forall\ t \in [0,T]$). If default doesn't happen before maturity, the default barrier becomes, as in Merton (1974), the face value of the debt D. In sum, the overall default boundary in the Black-Cox framework (denoted b_t) can take two different values: $\widehat{b}(t)$ before maturity, and D at the maturity.

Next, in order to set the bond valuation equation the default times must be considered. In the Black-Cox (1976) setup, default happens indeed at the first time $t \in [0,T]$ at which the firm value V_t hits the overall default boundary b_t. This default time, denoted henceforth by "τ", can be in turn divided into an early default time denoted "$\hat{\tau}$" and a default time at maturity denoted "$\check{\tau}$". The pricing function of the zero-coupon corporate bond for each time "t" between the issuance and maturity can be hence written by the following expectations:

$$P(t,T) = \mathbb{E}^{\mathbb{Q}}\left(\underbrace{De^{-r(T-t)}\ \mathbf{1}_{\{\hat{\tau}\geq T\ ;\ V_T>D\}}}_{(i)}|\mathcal{F}_t\right) + \mathbb{E}^{\mathbb{Q}}\left(\underbrace{V_T e^{-r(T-t)}\ \mathbf{1}_{\{\hat{\tau}\geq T;\ V_T<D\}}}_{(ii)}|\mathcal{F}_t\right)$$

$$+\ \mathbb{E}^{\mathbb{Q}}\left(\underbrace{\widehat{b}(t)e^{-r(T-t)}\ \mathbf{1}_{\{t<\hat{\tau}<T\}}}_{(iii)}|\mathcal{F}_t\right) \tag{17}$$

Where the entity (i) corresponds to the payoff of the bond in the joint event where the firm doesn't make an early default and doesn't make default at maturity (hence bondholders receive at maturity the face value of the Debt D); entity (ii) corresponds to the payoff of the bond in the case where the firm doesn't make an early default but makes default at maturity (hence the bondholders receive the remaining value of the firm assets V_T); and finally the entity (iii) correspond to the payoff of the bond in the case where the firm makes an early default (hence the bondholders receive the value of the default barrier $\widehat{b}(t)$.[35]

[34] This makes the default boundary in the Black-Cox (1976) setup completely exogenous. Note that if $\gamma = 0$, the early default boundary is equal to the constant K.

[35] Equation (17) takes into account the conditional expectations with respect to the information filtration $\mathcal{F}_t$. $\mathcal{F}_t$ is the σ-algebra that contains all the information about the path of the Brownian motion $\mathbb{W}_t$ up to the time t. In other words, at the date of the valuation t, the investor is supposed in this context to have a complete information about the path of the firm value up to this time t. In reality however, this is a complicated issue, if not impossible, because only the managers of the firm have a complete information about the assets of the firm in reality. This complete information about the firm value makes default a predictable event in the structural models that use the geometric Brownian motion assumption for the dynamics of the firm assets.

In order to solve equation (17), one need to compute, on the one hand, the joint probability distribution of $\hat{\tau}$ and V_t (for the first two expectations), and on the other hand, the probability distribution of the first time the firm value process crosses the barrier $\hat{b}(t)$ (for the last expectation)[36]. This yields to the following explicit solution:

$$\begin{aligned} P_{B\&Cox}(t,T) = {} & De^{-r(T-t)}\Big(N(z_1) - \ R_t^{2\theta-2}\ N(z_2)\Big) \\ & + \ V_t e^{-\kappa(T-t)}\Big(N(z_3) + R_t^{2\theta}\ N(z_4) + R_t^{\theta+\zeta} e^{\kappa(T-t)}\ N(z_5) \\ & + R_t^{\theta-\zeta} e^{\kappa(T-t)}\ N(z_6) - R_t^{\theta-\eta}\ N(z_7) - R_t^{\theta-\eta}\ N(z_8)\Big) \end{aligned} \tag{18}$$

Where[37]:

$$R_t = \ \hat{b}(t)/V_t \quad ; \quad \delta = (b-\gamma)^2 + 2\sigma_v^2(r-\gamma)$$

$$b = r - \kappa - \frac{\sigma_v^2}{2} \quad ; \quad \theta = (r - \kappa - \gamma + \frac{\sigma_v^2}{2})/\sigma_v^2$$

$$\zeta = \sqrt{\delta}/\sigma_v^2 \quad ; \quad \eta = \sqrt{\delta - 2\sigma_v^2\ \kappa}/\sigma_v^2$$

And:

$$z_1 = \frac{\ln\left(\frac{V_t}{D}\right) + b(T-t)}{\sigma\sqrt{T-t}} \quad ; \quad z_2 = \frac{\ln\left(\frac{V_t}{D}\right) + 2\ln(R_t) + b\,(T-t)}{\sigma\sqrt{T-t}}$$

$$z_3 = \frac{\ln\left(\frac{D}{V_t}\right) - (b+\sigma_v^2)(T-t)}{\sigma\sqrt{T-t}} \quad ; \quad z_4 = \frac{\ln\left(\frac{V_t}{D}\right) + 2\ln(R_t) + (b+\sigma_v^2)\,(T-t)}{\sigma\sqrt{T-t}}$$

$$z_5 = \frac{\ln(R_t) + \zeta\ \sigma_v^2\ (T-t)}{\sigma\sqrt{T-t}} \quad ; \quad z_6 = \frac{\ln(R_t) - \zeta\ \sigma_v^2\ (T-t)}{\sigma\sqrt{T-t}}$$

$$z_7 = \frac{\ln(R_t) + \eta\ \sigma_v^2\ (T-t)}{\sigma\sqrt{T-t}} \quad ; \quad z_8 = \frac{\ln(R_t) - \eta\ \sigma_v^2\ (T-t)}{\sigma\sqrt{T-t}}$$

Next, replacing like previously in equation (3), we obtain the following formula for the risky yield of the zero-coupon bond:

[36] These are well known results in stochastic calculus literature, designed generally by the first passage time probability. See for instance the demonstration provided by Musiella and Rutkowski (2006), page 649.

[37] The formulas for R_t, δ, θ, η, ζ, b and z_i $(i = 1, \ldots, 8)$ are only shorthand formulas to reduce the length of equation (18). They are all function of the same variables, $V_t, D, \sigma_v, r, \kappa, (T-t)$, and $\hat{b}(t)$.

$$
\begin{aligned}
Y_{B\&Cox}(t,T) = -\frac{1}{T-t}\ln\Bigg(& e^{-r(T-t)}\Big(N(z_1) - \ R_t^{2\theta-2}\ N(z_2)\Big) \\
&+ \frac{V_t}{D}e^{-\kappa(T-t)}\Big(N(z_3) + R_t^{2\theta}\ N(z_4) + R_t^{\theta+\zeta}e^{\kappa(T-t)}\ N(z_5) \\
&+ R_t^{\theta-\zeta}e^{\kappa(T-t)}\ N(z_6) - R_t^{\theta-\eta}\ N(z_7) - R_t^{\theta-\eta}\ N(z_8)\Big)\Bigg)
\end{aligned}
\tag{19}
$$

Finally, using the relation in equation (4), we propose the following formulation for the credit spread of the Black-Cox (1976) model:

$$
\begin{aligned}
S(t,T) &= Y_{B\&Cox}(t,T) - r \\
&= -\frac{1}{T-t}\ln\Bigg(\Big(N(z_1) - \ R_t^{2\theta-2}\ N(z_2)\Big) \\
&\quad + \ L^{-1}e^{-\kappa(T-t)}\Big(N(z_3) + R_t^{2\theta}\ N(z_4) + R_t^{\theta+\zeta}e^{\kappa(T-t)}\ N(z_5) \\
&\quad + R_t^{\theta-\zeta}e^{\kappa(T-t)}\ N(z_6) - R_t^{\theta-\eta}\ N(z_7) - R_t^{\theta-\eta}\ N(z_8)\Big)\Bigg)
\end{aligned}
\tag{20}
$$

Where L is the firm's leverage ratio, defined in the same way as Merton (1974). Similar to Merton (1974), credit spread in the Black-Cox (1976) is expressed as a function of the leverage ratio L, the asset volatility σ_v, the fixed risk-free rate r, the pay-out rate κ, and the time left for the bond until maturity $(T-t)$. In addition to these variables, and as can be seen in formulas (18), (19) and (20), credit spread is represented in the Black-cox framework as a function of a new variable: the default boundary that is stipulated by the bond covenant "$\hat{b}(t)$". This brings indeed light to the fact that yield spreads can be theoretically affected by *bond-specific* factors such as safety covenants. In what follows, we analyze numerically the term-structure of the credit spreads calculated from the Black-cox (1976) model while focusing on the impact of this bond-specific factor.

4.2. Numerical analysis:

We lead next a series of numerical simulations of the credit spreads generated from the Black-Cox (1976) model[38]. As mentioned earlier, the Black-Cox setup extends Merton (1974) by allowing the bond pricing framework to take into account the possibility of an early default of the firm. These two models share hence the same proprieties with regard to the impact of: leverage, asset volatility, risk-free rate, pay-out rate and time-to-maturity on credit spreads[39]. Since the

[38] To our knowledge, no previous studies have attempted to analyze the outcomes of the Black-Cox model from the standpoint of its term structure of credit spreads.

[39] These properties are also common to all the structural models that will be discussed later.

impact of these parameters on credit spreads has been addressed in previous sections, we focus mainly here on the specific features of the Black-Cox model, namely the impact of the default barrier on credit spreads and their term structure.

First, we recall that Black-Cox (1976) stipulate in their model that the early default boundary $\hat{b}(t)$ must not exceed the discounted value of the debt D for all maturities[40]. All the formulations provided earlier hold indeed only in the case where $Ke^{-\gamma(T-t)} \leq De^{-r(T-t)}, \forall\ t \in [0,T]$. Second, with regard to the values of the default boundary, an interesting choice proposed by Black-Cox is to set the level of the boundary $\hat{b}(t)$ as a constant fraction of the discounted value of the debt for all maturities. Formally, one must specify the levels of K and γ so that $Ke^{-\gamma(T-t)} = \rho\ De^{-r(T-t)}$, where $0 \leq \rho \leq 1$. For numerical analysis clarity, we follow the Black-Cox suggestion by setting $\gamma = r$ so that the entities $e^{-\gamma(T-t)}$ and $e^{-r(T-t)}$ become equal and the fraction $\rho = K/D$ becomes constant for all maturities. Afterwards, we set in equation (20) the same benchmark parameters used earlier in the Merton's analysis (i.e. $L = 40\%$, with $D = 40$; $r = \gamma = 0.06$; $\sigma_v = 0.2$; and $\kappa = 0.03$) and we calculate the credit spreads generated from the Black-Cox model for different values of K (of the default boundary, accordingly) and $(T-t)$. Results of these simulations are presented in Figure I.7:

Figure I.7 - Impact of the default boundary level on credit spreads

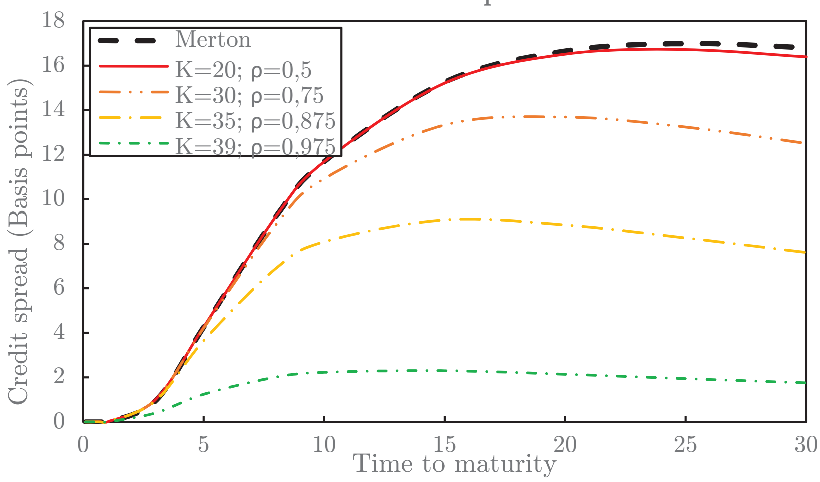


Figure I.7 presents the term structure of the credit spreads calculated from the Black-cox (1976) model for the levels of $K = 20; 30; 35$ and 39. For comparison, we include in the same graphic the term-structure of credit spreads calculated from Merton model for the same parameters. It shows interestingly that a higher level of the default boundary is consistently associated with lower

[40] See the specifications provided with equation (16).

credit spreads in the Black-Cox model. Indeed, as the values of K approach those of D, the values of credit spreads tend toward zero. This can be explained by the fact that a higher level of the default boundary makes the corporate bond more safe, and reduces the loss of the bondholders in the case of default (since they are assured to receive at least the amount specified in the covenant), which drives in turn credit spreads down.

Conversely, Figure I.7 shows that lower levels of the default boundary are consistently associated with higher levels of credit spreads in the Black-Cox model. These spreads remain however, in all cases, below, or equal, to the credit spread generated from the Merton model. Indeed, as K (and accordingly the boundary level $\widehat{b}(t)$) approaches zero, the Black-Cox framework becomes similar to the Merton setup (where no-safety covenant is specified in the bond contract). Hence, the term structures of the two models become closer. Further, Figure I.7 shows that, similarly to Merton (1974), the Black-Cox model generates near-zero credit spreads for short maturities. Under the same model parameters, we find that the difference between the credit spreads generated from the two setups becomes visible (here superior to 10^{-4}) only for maturities of 3 years and more. This suggests that under these structural setups, the presence of a safety covenant in the bond corporate is almost negligible on the short run.

These near-zero short term spreads are again a direct consequence of the assumption that asset value follows a geometric Brownian motion. As a matter of fact, even in this first-time-passage setup, the default event is announced by the proximity of the firm value to the default barrier, which makes default a predictable event[41]. Therefore, since the initial firm value is far from the default boundary (i.e. low initial leverage ratio), the continuous diffusion path of the geometric Brownian motion makes it hard for the firm value to cross the default boundary before a certain time. Consequently, the probability that the firm defaults in the short run will be very low, and credit spreads will maintain near-zero levels. This observation is thus found to be common to most of the structural models making the same assumption about the process of the firm value.

[41] In mathematical terms, this refers to the notion of predictable stopping times of a continuous and adapted process. Indeed, if τ is the first time at which the continuous process V_t is equal to some value $\widehat{b}(t)$, then it is announced by the sequence $\tau\ n$, where $\tau\ n$ is the first time at which V_t is within a distance of $1/n$ of $\widehat{b}(t)$). With this regard, τ (which is here the default event) is said to be a predictable event.

4.3. Discussion:

In their paper of (1976), Black-Cox provide an interesting extension of the contingent claim approach initiated by Merton (1974). They consider the effect of some of the specific provisions that can be found in the bond indenture (i.e. safety covenants) on the value of zero-coupon corporate bonds and credit spreads[42]. By doing so, Black-Cox allowed, for the first time, the corporate bond valuation framework to take into account the possibility of an early default of the firm (i.e. at any time between the issuance and maturity), which constituted one of the major shortcomings of the original Merton model (Merton shortcoming (iv)). This set indeed the standards for a whole strand of structural models that emerged in the following years, designed as the "first-passage-time approach"[43]. Furthermore, despite the relative complexity of its derivation, the model of Black-Cox provides closed-form solutions for the price of the corporate bond prices and credit spreads, which are relatively easy to handle. As such, this model can be seen as a benchmark framework for the valuation of zero-coupon bonds with covenants.

In spite of all these advantages, the model of Black-Cox (1976) suffers still of many shortcomings. Many of these shortcomings were indeed incurred by the former Merton setup, such as the assumptions of a flat term structure, perfect and frictionless markets, and the simple capital structure of the firm. In addition, the numerical simulations of this model show that it generates, similarly to Merton (1974), near zero credit spreads for short maturities, which makes the default boundary setup quite useless in the short run. Further, as previously mentioned, the main innovation of the Black-Cox setup consists in considering more realistic default mechanisms (Merton shortcoming (iv)). However, even at this level some improvements can still be made in order to make the valuation framework closer to reality. First, Black-Cox (1976) assume that the ownership of the firm goes directly to the bondholders at the first time the firm's value crosses the default boundary, which means that the firm is liquidated at the first time it makes default. This hypothesis may be indeed a restrictive one since the firm may not be liquidated as soon as default happens (e.g. due to the social consequences of liquidation, to legal delays, to the possibility of reorganization of the firm or renegotiation of the bond contract).

---

[42] Black-Cox (1976) investigate the effect of two other bond indenture provisions: subordination arrangements and restrictions on the financing of interest and dividend payments. They found that each of these provisions increase the value of the corporate bond (hence decrease their credit spreads). This brings support to the significant effect that bond specific features may have on the value of corporate bonds and by extension credit spreads.

[43] A non-exhaustive list of these studies includes Longstaff and Shwartz (1995); Leland and Toft (1996) or Hsu, Saa-Requejo and Santa-Clara (2004).

Many subsequent studies tried hence to relax this assumption by considering more realistic liquidation mechanisms. For example, Francis and Morellec (2004) assume that, after default (i.e. the first moment at which the firm value crosses the default boundary) the firm is liquidated only if the value of its assets remain a certain time below the default boundary; otherwise, it continues normally its activity[44]. Similarly, Moraux (2004) considers that liquidation occurs when the total cumulative time where the asset value remains below the default threshold exceeds a certain period. Galai, Raviv and Wiener (2005) propose a model in which liquidation is triggered by the severity and the proximity of the default episodes (they use a state variable that accumulates with time and severity of distress).

Second, the exogenous time-dependent default boundary proposed by Black-Cox (1976) can be extended towards a more sophisticated and realistic default boundary. For instance the default boundary can be set as random (e.g. the model of Collin-Dufresne and Goldstein presented in what follows), or can be derived endogenously inside the model (For instance, in order to maximize the welfare of the shareholders). This latter idea was considered, by Mello and Parsons (1992), Nielsen et al. (1993), Leland (1994), Anderson and Sundaresan (1996), Leland and Toft (1996), Mella-Barral and Perraudin (1997) or Francis and Morellec (2004). Finally, the absolute priority rule (bondholders are the priority claimants) can be deviated to consider some different priority rules observed in reality (for instance toward shareholders or for bondholders of a different debt claim), which has been considered for instance by Anderson and Sundaresan (1996), Unal, Madan et al. (2003) or Pyo and E. Thompson (2007).

In summary, the model of Black-Cox (1976) extends the model of Merton (1974) by taking more realistic default mechanisms. Analysing the model's hypotheses shows that many improvements can still be made in order to make the default mechanisms even more realistic. The numerical analysis of the model shows, on the one hand, that the safety covenant feature proposed by Black-Cox (1976) allows for a reduction in the credit spreads generated by the model, and on the other hand, that the model generates similar term structure of credit spreads to Merton (1976). Analysing the outcomes of this model was indeed of particular interest since we reproduce in our model presented in chapter IV the idea of a safety covenant in the bond contract. In what follows, we present another extension of the structural approach covering several shortcomings of the models discussed so far, namely the model of Collin-Dufresne and Goldstein (2000).

[44] These authors provide closed form solution for the value of corporate bond and credits spread. Their numerical simulations show that credit spreads are an increasing function of the time period at which the firm value stays below the default boundary.

5. Collin-Dufresne and Goldstein model:

The model of Collin-Dufresne and Goldstein (2000) (denoted hereafter by "CDG") constitutes another notable extension of the structural approach initiated by Merton (1974). It considers two main shortcomings of the models presented above, namely the simple capital structure hypothesis (see Merton shortcoming (*iii*)) and the constant interest rates hypothesis (see Merton shortcoming (*v*)). In addition, the model of Collin-Dufresne and Goldstein (2000) considers the valuation of coupon-paying corporate bonds, which has been scarcely addressed in previous literature[45].

Considering the first contribution of the model, CDG (2000) start from the observation that all previous structural models prevent the corporation from altering its initial capital structure during the life of the bond. In practice, however, firms may have the right to issue new debts, or equities, even before the redemption of their initial debt[46]. The main idea behind the CDG (2000) model was hence to relax this restrictive assumption by allowing the bond valuation framework to take into account the possibility of the firm to modify its capital structure over time. More precisely, based on an empirical evidence provided by Opler and Titman (1997), Collin-Dufresne and Goldstein (2000) note that firms tend generally to adjust their capital structures as a response to changes in the values of their assets; they issue more debt when the value of their assets rises, and reduce their indebtedness when the value of their assets fall below a certain level. As a result, leverage ratios would be stationary in time. Collin-Dufresne and Goldstein (2000) propose hence a valuation framework that captures elegantly this idea by allowing the firm to dynamically, increase, or reduce, its debt as a response to the random movements of its assets. In this setup, CDG (2000) assume, in the same vein as Black-Cox (1976), that default occurs at the first time the firm value (accordingly the leverage ratio) hits some exogenously specified threshold. In contrast to Black-Cox (1976), CDG (2000) assume however that this boundary is driven by randomness, which can be seen as another contribution of the model.

---

[45] The model of Collin-Dufresne and Goldstein (2000) has received only small attention from corporate bond valuation literature compared to the models presented earlier. This can be explained, on the one hand, by the relative recentness of this model, and on the other hand, by its relative complexity.

[46] For instance, firms with sufficient solvency ratios have the legal right to issue additional equal- or higher-, priority debt, as they usually do in practice (see for instance Malitz, 1994). Bondholders may however prevent these actions by the means of early safety covenants. Since the former structural models preclude the firm from altering its capital structure during the life of the bond contract, they can be seen as treating with bonds containing this kind of covenants.

Moreover, as discussed earlier, all the models presented so far assume a flat term structure where the risk-free interest rate (r) is constant and known with certainty at all times. However, in reality, interest rates are known to be time-variant and arguably random. Collin-Dufresne and Goldstein (2000) address this question by introducing stochastic interest rates which evolves according to the Vasicek (1977) term structure model. Using stochastic interest rates in a bond valuation framework was indeed considered by many other structural models of credit risk. These include, on the one hand, Shimko et al. (1993), Longstaff and Schwartz (1995), Brys and de Varenne (1997), who use, similarly to CDG (2000), the Vasicek (1977) term structure model; and on the other hand, Wang (1999), Szatzschneider (2000), Hsu, Saa-Requejo et Santa-Clara (2004), who use the Cox-Ingersoll-Ross (1995) term structure model. Considering random interest rates seem indeed a matter of interest since the firm's activity and its capital structure decisions can be very sensitive to the variations of interest rates. In what follows, we describe the outcomes of the CDG (2000) model in more technical terms.

5.1. Deriving credit spread:

Technically, CDG (2000) start by assuming that the firm value follows a geometric Brownian motion under the risk-neutral measure, in the same vein as Merton (1974), and Black-Cox (1976) (see equation (6)). To make the subsequent calculations more tractable, CDG (2000) take in contrast to these studies the "log" of the firm value process. This implies from equation (6):

$$d\log(V_t) = \left(r_t - \kappa - \frac{\sigma_v^2}{2}\right) dt + \sigma_v \, d\widetilde{\mathbb{W}}_t \tag{21}$$

Second, CDG (2000) assume stochastic interest rates, where the spot rate r_t follows the dynamics proposed by the Vasicek (1977) term structure model, defined as follows:

$$dr_t = a(b - r_t)dt + \sigma_r d\widehat{\mathbb{W}}_t \tag{22}$$

Where a, b and σ_r are deterministic parameters; a is the speed of reversion of interest rates; b is the long term equilibrium value of interest rate; σ_r the volatility of the spot rate, and $\widehat{\mathbb{W}}_t$ a standard Brownian motion under the risk-neutral measure, different from $\widetilde{\mathbb{W}}_t$. In addition, CDG (2000) assume that the two Brownian motions governing the firm value and the spot rate are correlated, with $d\widehat{\mathbb{W}}_t d\widetilde{\mathbb{W}}_t = \rho_1 \, dt$[47].

[47] In this setup the random movements of interest rates affect the random movements of the firm's assets value, which seems plausible from an economic point of view.

Afterwards, CDG (2000) set the standards for the dynamics of the indebtedness of the firm. The firm adjusts the level of its debt according to: the random values of its assets (here $\log(V_t)$), and the random values of interest rates (r_t), in order to maintain a stationary leverage level. Using again the "log" for convenience, CDG (2000) derive the following equation for the dynamic of the debt:

$$d\log(K_t) \ = \lambda \left(\log(V_t) - \upsilon - \phi(r_t - b) - \log(K_t)\right) dt \tag{23}$$

Where $\lambda > 0$ can be interpreted as the speed of mean-reversion of the debt level; $\phi > 0$ as the sensitivity of the debt level to interest rates; and $\upsilon > 0$ an adjustment parameter that can be used by the modeller to alter the long-term leverage level. Equation (23) can be hence interpreted as follows: when $(\log(V_t) - \upsilon - \phi(r_t - b))$ is above the debt level $\log(K_t)$, the firm issues dynamically more debt in order to keep a stationary leverage ratio. Conversely, when $(\log(V_t) - \upsilon - \phi(r_t - b))$ is below $\log(K_t)$ the firm reduces its debt, again to stay within a certain target leverage level. This equation captures also parsimoniously, through the term $\phi(r_t - b)$, the idea that the debt level is a decreasing function of interest rates[48].

After describing the dynamics of the assets and debt values, the main insight of the CDG (2000) model consists of combining these latter to create a dynamic for the firm's leverage. Defining the "log-leverage ratio" as $\log(L_t) = \log(K_t) - \log(V_t)$, and replacing $\log(K_t)$ and $\log(V_t)$ by their dynamics from equations (21) and (23) leads to the following dynamics for the leverage[49]:

$$d\log(L_t) = \ \lambda \left(\overline{L}(r_t) - \log(L_t)\right) dt + \sigma_\upsilon \, d\widetilde{\mathbb{W}}_t \tag{24}$$

Where $\overline{L}(r_t)$ is the risk-neutral target leverage ratio given by:

$$\overline{L}(r_t) = \frac{1}{\lambda}\left(\kappa + \frac{\sigma_\upsilon^2}{2}\right) - \upsilon + \phi b - r_t\left(\frac{1}{\lambda} + \phi\right) \tag{25}$$

In this setup, the firm's leverage ratio becomes the main concern of the model; the random values taken by this ratio define the firm's situation and accordingly its default time. Default is indeed triggered at the first time τ the log-leverage

---

[48] Seen from a different angle, equation (23) can be also interpreted as the (log)-default threshold. Default happens in the CDG (2000) setup at the first time the value hits this exogenously specified threshold. Note that, in contrast to the Black-Cox (1976) setup, this threshold is driven by randomness since it shares the same random variations with the firm's assets (mathematically, $\log(K_t)$ is a written as a function of $\log(V_t)$, and they share the same Brownian motion $\widetilde{\mathbb{W}}_t$).

[49] Recall that the leverage ratio can be written as $L_t = K_t/V_t$, where K_t is the dynamic debt level. Rewriting back using "log" yields to the above $\log(L_t) = \log(K_t) - \log(V_t)$.

ratio reaches zero (or equivalently $\log(V_t)$ reaches $\log(K_t)$). Default is thus a random time and can occur at any time between the bond's issuance and maturity.

Turning to the price of the bond, CDG (2000) assume first that the risky corporate bond pays a known proportion of the face-value if the firm makes default before maturity (i.e. the principal recovery, denoted α). Second, as mentioned previously, CDG (2000) consider the valuation of a coupon-paying bond. They suppose hence that the bond pays a stream of fixed coupons C at times $\{t_i\}$, where $t_1 < t_2 < \cdots < t_n$ and $t_n = T$. Further, CDG (2000) assume that coupons are totally written down if the firm makes default before maturity (i.e. no recovery for coupons). We generalize here the CDG setup by assuming that the bond pays a fixed recovery rate in the case of default, denoted α_c. Based on these assumptions and the pricing formula presented earlier in equation (2), we propose the following reformulation for the price of the risky coupon-paying bond for the model of CDG (2000)[50]:

$$P(t,T) = \sum_{i=1}^{n} \mathbb{E}^{\mathbb{Q}}\left(\underbrace{e^{-\int_t^{t_i} r_s ds}}_{(v)} \; (\underbrace{C\; \mathbf{1}_{\{\tau>t_i\}}}_{(i)} + \underbrace{\alpha_c\; \mathbf{1}_{\{\tau\le t_i\}}}_{(ii)} | \mathcal{F}_t \right)$$

$$+\; \mathbb{E}^{\mathbb{Q}}\left(\underbrace{e^{-\int_t^{T} r_s ds}}_{(vi)} \; (\underbrace{D\; \mathbf{1}_{\{\tau>T\}}}_{(iii)} + \underbrace{\alpha\; \mathbf{1}_{\{\tau\le T\}}}_{(iv)}) | \mathcal{F}_t \right) \tag{26}$$

Where entities (i) and (iii) correspond to the payoff of the bond in the case of no-default (that is, respectively, the coupons C and the principal of the bond D); and entities (ii) and (iv) correspond to the payoff of the bond in the case of default (that is, respectively, the recovery of coupons α_{coup} and the recovery of the face-value α)[51]. All these payoffs are discounted at date t by the stochastic discount factor given by entities in entities (v) and (vi). In order to solve equation (26), we need to compute the density of the first time the log-leverage ratio hits the zero default barrier. This density is in fact not known in closed form; numerical techniques needs hence to be used in order to calculate the relevant bond prices[52]. Assuming, as in CDG (2000), that there is no recovery for

[50] Collin-Dufresne and Goldstein propose another derivation of the price of the corporate bond. We propose this equation for more homogeny with the formulation we proposed so far.

[51] Note that the discount term is taken with integrals in equation (26). That is of course because the risk-free rate is no longer constant as in Merton (1974) and Black-Cox (1976), but follows the dynamics proposed by Vasicek (1977).

[52] Another important insight behind the CDG (2000) paper lays in the numerical technique that they use to calculate the price of the bond. CDG develop indeed a seemingly efficient numerical

coupons (i.e. $\alpha_c = 0$) and that the bond pays 1 EUR at maturity (i.e. $D = 1$), we can however simplify equation (26) as follows:

$$P_{CDG}(t,T) = B_c(t) - C\sum_{i=1}^{n} \mathbb{E}^{\mathbb{Q}}\left(e^{-\int_t^{t_i} r_s ds}\ \mathbf{1}_{\{\tau \le t_i\}}|\mathcal{F}_t\right) \\ - (1-\alpha)\ \mathbb{E}^{\mathbb{Q}}\left(e^{-\int_t^{T} r_s ds}\ \mathbf{1}_{\{\tau \le T\}}|\mathcal{F}_t\right) \quad (27)$$

Where $B_c(t)$ is the price of the equivalent risk-free coupon bond, given by:

$$B_c(t) = \ C\sum_{i=1}^{n} \mathbb{E}^{\mathbb{Q}}\left(e^{-\int_t^{t_i} r_s ds}\ \right) + \mathbb{E}^{\mathbb{Q}}\left(e^{-\int_t^{T} r_s ds}\ \right) \quad (28)$$

Next, the yield to maturity of this bond can be obtained implicitly by matching the price of the bond calculated in equation (27) with the pricing equation provided in equation (2)[53]:

$$P_{CDG}(t,T) = C\sum_{i=1}^{n} e^{-\boldsymbol{Y(t,T)}(t_i-t)} + e^{-\boldsymbol{Y(t,T)}(T-t)} \quad (29)$$

Similarly, the risk-free interest rate $r(t,T)$ can be computed implicitly from the price of the risk-free bond generated from the Vasicek (1977) model and the following equation:

$$B_c(t) = C\sum_{i=1}^{n} e^{-\boldsymbol{r(t,T)}(t_i-t)} + e^{-\boldsymbol{r(t,T)}(T-t)} \quad (30)$$

Finally, using the yields computed from equations (29) and (30), credit spread can be obtained as previously by:

$$S_{CDG}(t,T) = \ Y_{CDG}(t,T) - r_{Vasicek}(t,T) \quad (31)$$

In sum, we note that, in the same vein as Merton (1974) and Black-Cox (1976), credit spread in the CDG (2000) model is a function of the firm's leverage ratio, the risk-free rate, the asset's volatility, the pay-out rate, and the time left until the maturity of the bond. It is however important to recall that CDG (2000) make different assumptions about the firm's leverage ratio and the risk-free rate. The leverage ratio is modelled dynamically and depends on an initial level

technique, based on the equation of Fortet (1943), which they apply to this –first passage time for a two dimensional Markov process– setup.

[53] As mentioned previously, it is not generally possible to derive explicit formulas for the yield to maturity in the case of coupon-paying bonds. Numerical techniques such as the Newton–Raphson method must be employed to approximate the yield which equates bond price derived from the model.

(denoted L_0) and a long-run target level $\overline{L}(r_t)$. For its part, the risk-free rate is assumed to be stochastic and is modelled according to the Vasicek (1977) term structure model. According to CDG (2000), this additional assumption would not change the sign of the relation between interest rates and credit spreads, which remains consistently negative. In addition to these classic structural variables, credit spread in the CDG (2000) model is also found to be a function the exogenously specified recovery level α and the coupon payments C. In what follows, we test numerically the main implications of the model of Collin-Dufresne and Goldstein (2000) on the term structure of credit spreads.

5.2. Numerical analysis:

We test next, numerically, the credit spreads generated from the CDG (2000) stationary leverage model. As previously indicated, the model of CDG (2000) does not provide closed form solutions for the bond prices or credit spreads. Monte-Carlo methods need hence to be used in order to calculate the relevant prices and yield spreads. As in a typical Monte-Carlo iterations, the results would depend on the numerical scheme used and its efficiency, along with the number of Monte-Carlo simulations made. The results of the computations will inevitably keep a certain part of randomness, which is amplified here by the relative complexity of the model (two-factor Markov framework)[54]. This makes it rather hard to compare the different parameter impact on the term structure of credit spreads as we have done previously. For this reason, as well as the space limit, we will concentrate here on the effect of the main feature of the CDG (2000) model, namely the possibility for the firm to maintain a stationary leverage ratio. As regards the remaining factors, we note that the relation between the recovery level α and the coupon payments C must be theoretically negative on credit spreads, since these latter increase generally the value of the bond.

First, in order to assess the specificities of the stationary leverage framework proposed by CDG (2000), it seems appropriate to compare the term structure of credit spreads generated from the model of CDG (2000) to the term structures generated from the models of Merton (1974) and Black-Cox (1976) specified earlier. To ensure that the results are comparable, we converge as much as possible the parameters of the CDG (2000) model with the benchmark parameters used earlier for Merton and Black-Cox. We consider hence for the interest rate process $r_0 = 0{,}06; a = 0{,}06, b = 0{,}1$ and $\sigma_r = 0{,}015$; for the leverage process, we set an initial leverage ratio $L_0 = 40\%$ and a target leverage ratio of 44%

[54] The values obtained from Monte-Carlo methods are in fact approximations of the true values of the computed parameters. Being obtained from a limited number of simulations, the computed prices and credit spreads are hence exposed to the sampling error. Confidence intervals are used in practice to address this problem.

(with $\lambda = 0{,}18$; $\upsilon = 0{,}75$ and $\phi = 2{,}8$)[55]. For simplicity, we take $C = 0$, and similarly to CDG (2000), we set $\rho_1 = -0{,}2$ (i.e. negative correlation between the firm value process and interest rate process), $\alpha = 0{,}45$ and $\alpha_c = 0$. Finally, for the remaining parameters we take as previously $\sigma_v = 0{,}2$ and $\kappa = 0{,}03$.[56] Results of this simulation are presented in Figure I.8.

Figure I.8 - The term structure of credit spreads

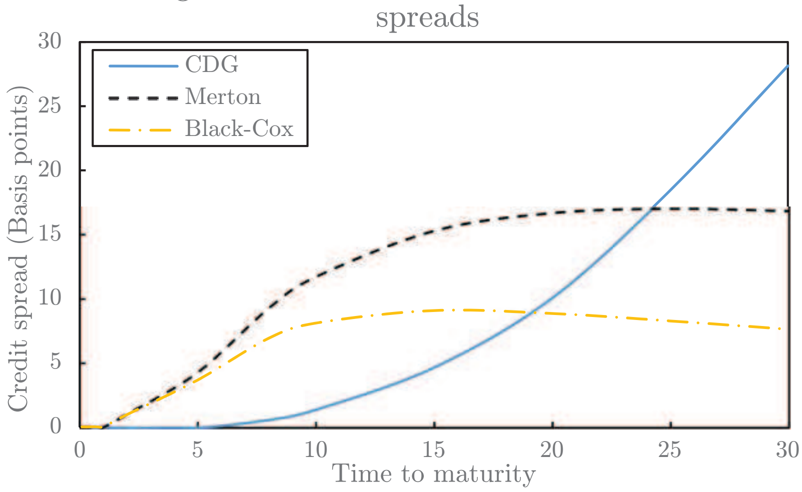


Figure I.8 brings some interesting insights about the impact of the option to maintain a stationary leverage ratio on the term structure of credit spreads. First, with regard to short term credit spreads, Figure I.8 shows that the model of CDG (2000) generates, in the same vein as the previous structural models, very low credit spreads for short maturities. Again, this is mainly due to the diffusion property of the Brownian motion, which makes it hard for firms with relatively low initial leverage ratios to make default at short maturities. In addition, in the CDG (2000) setup, the firm has the possibility to adjust the outstanding of its debt according to the value of its assets (hence adjust the default barrier), which makes default less probable in the short run and generates even lower credit spreads.

Considering the spreads for longer maturities, as discussed previously, the models of Merton (1974) and Black-Cox (1976) preclude the firm from altering its capital structure before the maturity of the bond. Since the firm value is modelled by a geometric Brownian motion (which increases exponentially over time), maintaining a constant debt level makes the leverage ratio fall gradually over time. This leads to low credit spreads at very long maturities (over 30 years)

[55] To find so, replace these parameters in equation (25). These will yield to a log target leverage ratio $\overline{L} \approx -0{,}8$. Next, the target leverage ratio is found by taking $\exp(-0{,}8) \approx 44\%$.

[56] Recall that the benchmark parameters used for the models of Black-Cox (1976) and Merton (1974) are $L = 40\%, \sigma_v = 0.2, r = 0.06$ and $\kappa = 0.03$. For the model of Black-Cox, we take in Figure I.8. a barrier level with $K = 35$ and $\gamma = 0{,}06$.

for firms of low initial leverage, and to downward sloping term-structures for firms with high initial leverage.

Figure I.8 shows however that allowing the firm to adjust its debt according to the values of its assets, as proposed by CDG (2000), generates, consistently, an upward sloping term structure of credit spreads (i.e. higher spreads at long maturities). Indeed, in the CDG setup, the leverage level follows a diffusion process which makes it, in the same vein as the firm value, an increasing function of time; this yields, accordingly, to higher probabilities of default for longer maturities and therefore to an upward sloping yield curve. As a matter of fact, this upward sloping yield curve is more in line with the normal shapes of the yield curves observed empirically. It is well known that, in normal situations, yields rise as maturity lengthens due to the higher uncertainty that conveys the future. Similarly, in this more realistic framework of stationary leverage ratios, there is more uncertainty about the firm's activity in the long run. Further, Figure I.9 brings more insight to these results[57]:

Figure I.9 - Impact of leverage on credit spreads in the CDG model

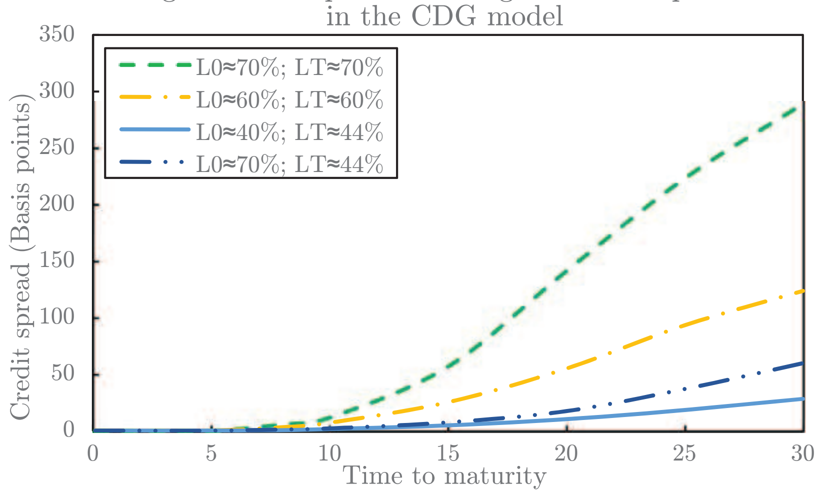


Figure I.9 shows interestingly that, as opposed to the models of Merton (1974) and Black-Cox (1976), the term structure of credit spreads generated from the CDG (2000) model is upward sloping, even for firms with high initial leverage. Once again, allowing for target leverage ratios avoids indeed the situation where the firm's leverage decrease systematically over time as proposed by the former structural models. Hence, under reasonable scenarios credit spreads should be always higher for longer maturities.

[57] To calculate these term structures, we keep all the parameters specified earlier unchanged and we calculate credit spreads for different levels of leverage ratios. We do so for the initial leverage ratios of $L_0 = 40\%;\ 60\%;\ 70\%$ and, respectively, the target leverage ratios of $L \approx 44\%; 60\%; 70\%$

Furthermore, Figure I.9 shows that a firm with an initial leverage ratio of 70% and a target leverage level of 44% has lower credit spreads than a firm with stationary leverage ratio of 60% in the CDG (2000) model. This result is in fact inconsistent with the results of the models of Merton and Black-cox, where firms with higher initial leverage ratios have always higher credit spreads. The intuition behind this observation is as follows: in the setup where the firm does not have the possibility to adjust its leverage (i.e. the models of Merton (1974) and Black-Cox (1976)), default probabilities and credit spreads depend exclusively on the initial leverage ratio of the firm. This yields logically higher credit spreads for firms of higher leverage (since they are closer to the default boundary). In the CDG (2000) setup, however, credit spreads depend not only on the initial leverage, but also on the target leverage level of the firm. Credit spreads become hence less sensitive to the initial leverage level, and we can observe naturally lower spreads for firms with higher initial leverage if their target leverage levels are relatively low. That being said, as can be seen in Figure I.9, in the situation where the leverage ratios are stationary (i.e. the same initial and target levels), the model of CDG (2000) generates consistently higher spreads for firms of higher leverage.

In summary, all the observations made in the previous numerical analyses highlight the importance of the option for the firm to alter its initial capital structure on credit spreads and their term structure.

5.3. Discussion:

In their paper of (2000), Collin-Dufresne and Goldstein propose an interesting bond valuation framework where the future values of the firm's leverage and stochastic interest rates have an impact on the bond's value and credit spreads. All the observations made in this section highlight the important role that plays leverage on the levels and the term structures of the credit spreads that the model generates. Keeping the leverage level constant (e.g. the models of Merton, 1974 and Black-Cox, 1976) or allowing the firm to modify its leverage level over time as proposed by Collin-Dufresne and Goldstein (2000) are found numerically to have significant differences on the levels of credit spreads and their structure by term. Accordingly, a particular attention must be given while modeling to the assumption about the debt of the firm (constant vs. variable), since this may considerably affect the results of the model.

In spite of all its innovations, some criticism can still be addressed to the framework of CDG (2000). First, the model assumes that debt is issued (reduced) dynamically over time, which means that the firm has the possibility to issue (reduce) debt at any time without constraints. In practice, however, the decision to increase or reduce debt may not depend of the firm's will. For instance, due to regulatory constraints or to supply and demand shocks, a firm can be deprived (at least temporarily) from issuing new debt (considering this assumption constitutes one of the main ideas that our model proposes in chapter IV). Additionally, in order to reduce the outstanding of its debt, the firm needs generally to redeem a portion of its initial debt, which may be infeasible due to liquidity problems or to strategic constraints. Second, the model of Collin-Dufresne shares, still, some of the shortcomings of the former structural models. In particular, the perfect market assumption (Merton's shortcoming (i)), the continuous time assumption (Merton's shortcoming (ii)), and the observed low credit spreads for short maturities (Merton's shortcoming (vi)) are still present. Finally, it is important to note that the increased complexity of the CDG (2000) model (two factor Markov framework with no closed form formulas) brings to mind that some trade-offs need to be made between the closeness to reality of the model and its ease of computation. In what follows we present another important innovation in the structural approach proposed by Zhou (2001).

6. Zhou model:

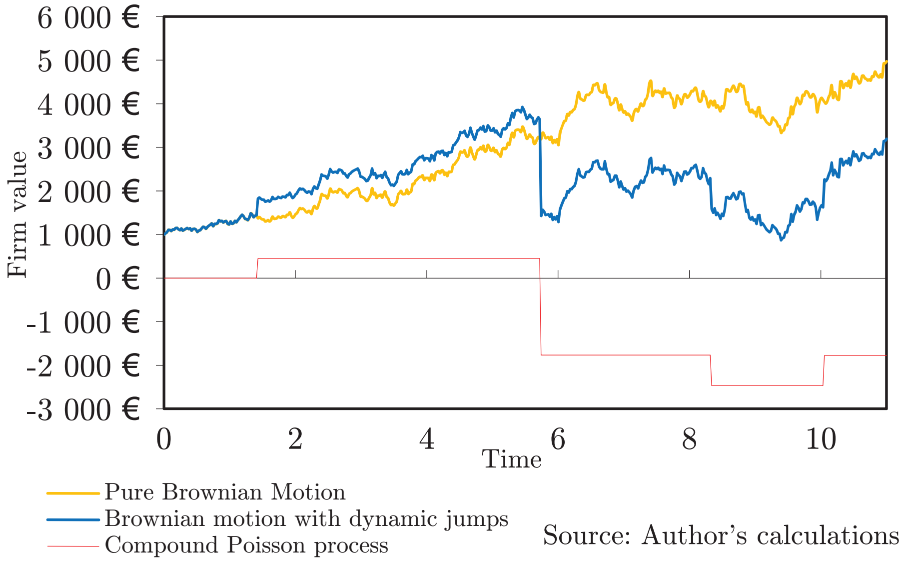
The structural models described so far make the assumption that the firm value follows a geometric Brownian motion. As discussed earlier, under this diffusion type stochastic process, a firm with reasonable leverage ratios has low chances of hitting the default boundary in the short run, which results systematically in near-zero credit spreads for these maturities. However, these near-zero credit spreads are found to be inconsistent with the empirical observations; in practice, credit spreads maintain generally positive levels in the short run, which can be explained by the existence of a permanent default risk even for firms of good standing[58]. In order to address this issue, Zhou (2001) considered modelling the firm value by the means of a jump-diffusion stochastic process. This process consists indeed of a mixture between a Brownian motion and, a jump-type, compound Poisson process; it replicates the diffusion path of a geometric Brownian motion, but unlike this latter, it allows for random, upward, or downward, peaks on the firm value driven by the Poisson process[59].

[58] It is however important to note that during the pre-subprime-crisis period, some firms profited temporarily from confidence excess of market participants to display negative credit spreads over benchmark government rates. We bring more evidence about the levels of credit spreads in our descriptive analysis provided in Chapter II.

[59] Note that Zhou (2001) wasn't the first study to consider jump-diffusion processes in a default risk or corporate bond pricing setup. For instance, Mason and Battachacharya (1981) considered this issue by the means of a pure jump process, where the jump amplitude follows a binomial distribution. Zhou (2001) considers however log-normal jump sizes.

Further, Figure I.10 gives a better idea on the difference between the paths of the firm value under the pure diffusion Brownian motion and the so-called jump-diffusion process[60]:

Figure I.10 - Comparison of firm value paths with and without Jumps



Source: Author's calculations

As can be seen in this figure, compared to the geometric Brownian motion case where the firm value follows a continuous diffusion with only small random movements, the jump-diffusion process allows for discontinuities on the firm value, which can drop or climb, at random times, by random amounts (i.e. respectively, the jump time and the jump size)[61]. By assuming that the firm value follows a jump-diffusion process, the modeller expects hence to account for higher default probabilities and larger credit spreads even in the short run. The firm value has indeed in this case higher chances for crossing the default at short maturities due to a sudden downward jump.

Moreover, the introduction of jumps on the firm value process as proposed by Zhou (2001) seems very attractive from a theoretical point of view. The jumps can be indeed assimilated to some real world events such as economic shocks or crisis, the arrival of a new important information about the firm to the market

[60] The chosen parameters for this sample simulation are: for the firm value, a drift of 0.1, and a volatility of 0.2; for the jump process, a jump intensity (the rate at which jump occurs) $\lambda = 0{,}5$ and a jump volatility $\sigma_j = 0.3$. More details about the jump parameters will be given in following sub-section.

[61] The sudden variations in the path firm value (i.e. the jumps) happen indeed according to the values taken by the compound Poisson process (see the red line in Figure I.10). The firm value jumps at the same random times at which this compound Poisson process jumps, and takes the same jump sizes of this latter. As such, the jump diffusion process is known as a marked Poisson process.

(e.g. an unexpected substantial accounting information or legal proceedings against the firm), or any other unpredictable event that may affect the firm value. These events happen in fact quite often in reality, and as will be discussed later in Chapters II and III, they are found to have considerable impact on the levels and movements of credit spreads. They need hence to be considered in a reasonable corporate bond valuation framework.

In what follows, we describe in more technical terms the main implications of the jump diffusion setup proposed by Zhou (2001) on the valuation of corporate bonds and credit spreads.

6.1. Deriving credit spreads

Technically, Zhou (2001) assumes first that the firm value follows a jump-diffusion process under the risk-neutral measure, which has the following dynamics:

$$dV_t = (r_t - \lambda\vartheta)V_t dt + \sigma_v V_t d\widetilde{\mathbb{W}}_t + (j_t - 1)V_t dN_t \tag{32}$$

Where:

- ϑ, σ_v and λ are positive constants;
- r_t is the risk-free rate which follows the dynamics proposed by Vasicek (1977) (see equation (22));
- $\widetilde{\mathbb{W}}_t$ is a Brownian motion under the risk neutral measure correlated to the interest rate process, with a correlation coefficient equal to ρ_1;
- N_t is a Poisson process which counts the random number of firm value jumps until time "t". This number of jumps is affected by the exogenous intensity parameter λ, which specifies the average rate at which jumps occurs.
- $j_t > 0$ is the random jump size, and $(j_t - 1)$ is the increase in the firm value due to the jump, which has the expected value $\vartheta = \mathbb{E}(j_t - 1)$. This jump size can be indeed set to follow any arbitrary probability distribution; Zhou (2001) make however the assumption that the jump size follows a log-normal distribution where $J_t = \ln(j_t) \sim N(\mu_j, \sigma_j^2)$[62]. Under this assumption, the expected value of the –increase in the firm value due to the jump– becomes equal to : $\vartheta = \mathbb{E}(j_t - 1) = \exp(\mu_j + \sigma_j^2/2) - 1$[63].

[62] Saying that j_t follows a log-normal distribution returns equivalently to saying that the log of j_t follows a normal distribution. We denote here the log of j_t by J_t.

[63] Since the expected value of a log-normal variable (here j_t) is equal to: $\exp(\mu_j + \sigma_j^2/2)$, it is obvious that the expected value of $(j_t - 1)$ is equal to: $\exp(\mu_j + \sigma_j^2/2) - 1$.

Under this dynamics, the firm value is indeed affected by four sources of randomness: the stochastic interest rate r_t, the Brownian motion $\widetilde{\mathbb{W}}_t$, the number of jumps N_t, and the size of the jumps j_t. Zhou (2001) assumes that $\widetilde{\mathbb{W}}_t$ and r_t are correlated; however, he assumes that these latter are mutually independent of N_t and j_t. With all the above specifications, equation (32) can be interpreted as follows: the firm value follows the same normal diffusion path of a geometric Brownian motion with a drift equal to $(r_t - \lambda\vartheta)$ and a constant volatility σ_v[64]. This diffusion path may witness N_t jumps in the interval of length "t"[65]. At each random jump time, the firm value may rise or fall by a random amount j_t[66].

After specifying the dynamics of the firm value, Zhou (2001) proposes the following assumptions about the default time and the recovery in case of default. In the Zhou (2001) setup, the firm makes default at the first time its value hits an exogenously-specified default boundary "$\hat{b}(t)$". Following Black-Cox (1976), he assumes that this default boundary is time dependant and has an exponential form, exactly in the same terms specified previously in equation (16). At default, the ownership of the firm is transferred directly to the bondholders, who receive the remaining value of the firm's assets reduced by a write-down rate "w"[67]. More formally, under the previous specifications the default event is the first time "τ" at which $V_\tau \leq \hat{b}(\tau)$, or equivalently the first time the ratio $V_\tau/\hat{b}(\tau) \leq 1$. If default occurs before maturity, the bondholders receive, at maturity, a recovery "α" equal to $1 - w(V_\tau/\hat{b}(\tau))$, times the face-value of the debt. This recovery is therefore random since it depends hence on the asset value at time τ which is unknown in advance.

Finally, Zhou (2001) assumes for simplicity that the face-value of the debt D is equal to 1 EUR. Under the previous assumptions, the price of the risky zero-coupon bond at a certain date "t" is given by the following expectations:

---

[64] The firm value increases hence with the interest rate and decreases with the intensity and average size of the jumps.

[65] From the model's perspective, the number of jumps is a pseudo-random number, generated from the probability distribution of a Poisson process, which is as follows:

$$P(N_t = k) = \frac{e^{-\lambda t}(\lambda t)^k}{k!}$$

This is indeed nothing but a Poisson distribution with a parameter λt. The generated number of jumps $N_t = k$ is hence affected by the jump intensity parameter λ (which is specified by the modeler) and the length of the time interval "t".

[66] j_t is also a pseudo-random number generated from a log-normal distribution, with parameters μ_j and σ_j^2.

[67] The write-down rate can be seen hence as an inevitable expense in case of default, which lowers the payoff of the bondholders.

$$P_{Zhou}(t,T) = \mathbb{E}^{\mathbb{Q}}\left(\underbrace{e^{-\int_t^T r_s ds}}_{(iii)} \;(\underbrace{\mathbf{1}_{\{\tau>T\}}}_{(i)} + \underbrace{\big(1-w\big(V_\tau/\widehat{b}(\tau)\big)\big)\,\mathbf{1}_{\{\tau\leq T\}}}_{(ii)})|\mathcal{F}_t\right) \tag{33}$$

Where $\mathbf{1}\{\}$ is the indicator function defined as previously, and $\mathbb{Q}$ is the risk-neutral probability measure. Obviously, entity (i) corresponds to the payoff of the bond, at maturity, in the case of no-default (i.e. $\tau > T$), which is the face-value of the debt 1 EUR. Entity (ii) corresponds however to the payoff of the bond, at maturity, in the case of default (i.e. $\tau \leq T$), which is the recovery value $1 - w\big(V_\tau/\widehat{b}(\tau)\big)$. These payoffs are then discounted at date "t" by the stochastic discount factor given in entity (iii).

In order to solve equation (26), one needs to compute the density of the first time at which the firm value hits the default barrier $\widehat{b}(\tau)$. This first-passage-time density is in fact not known in closed for this type of jump-diffusion process. Accordingly, numerical methods needs to be used in order to calculate the relevant bond prices and credit spreads[68].

Next, using the bond prices generated numerically from equation (33), the yield to maturity of the corresponding zero-coupon bond can be computed by:

$$Y_{Zhou}(t,T) = -\frac{1}{T-t}\ln\left(\frac{1}{D}\left(P_{Zhou}(t,T)\right)\right) \tag{34}$$

Finally, using the yields computed from equation (34) and the risk-free rate generated from the Vasicek (1977) term-structure model, credit spread in the Zhou (2001) setup can be obtained as previously by:

$$S_{Zhou}(t,T) = Y_{Zhou}(t,T) - r_{Vasicek}(t,T) \tag{35}$$

From equations (33) to (35), and the assumptions made previously about the process of the firm value, we note that, in line with the models specified earlier, credit spread in the model of Zhou (2001) is a function of:

- The risk-free rate, which is modelled here dynamically;
- The asset's volatility; which is constant;
- The time left until the maturity of the bond, which is function of the date of the valuation "t" and the maturity "T";

[68] Zhou (2001) proposes however a tractable numerical approach to compute this expectation based on two theoretical insights proposed by Bates (1996) and Pennacchi (1999).

- The firm's leverage ratio, which is a function of the random firm value and the constant debt level (the firm hasn't the right to alter its initial capital structure);
- The default barrier, which is exogenous and time-dependent (can be seen as a safety covenant);
- The write-down rate and the recovery amount, which can be generated endogenously from the model[69].

In addition to these variables, the main innovation of the model of Zhou 2001 consists of viewing credit spread as a function of the jumps occurred on the firm value. Specifically, credit spreads would depend on:

- The number of jumps happened on the firm value "N_t", which depends in turn on the average number of jumps per unit of time, or the jump intensity "λ";
- The size of each of jump "j_t", which depends on the mean of the jump size μ_j and the volatility of the jump size σ_j^2.

In what follows, we investigate the main implications of the introduction of jumps on credit spreads and their term structure.

6.2. Numerical analysis:

As previously mentioned, the model of Zhou (2001) does not propose any closed form formulas for the price of the risky bond and credit spreads. Monte-Carlo methods need hence to be used in order to calculate the relevant prices and yield spreads, which might be a delicate issue[70]. In order to present consistent results without getting into the complexity of the numerical procedures, we decide here to reproduce the main numerical results proposed by Zhou (2001). On top of that, we bring more content to the main feature of the model, namely the impact of jumps on credit spreads.

First, Figure I.11 considers the relation between credit spreads and the size of the jumps via the volatility of the jump size "σ_j^2". Keeping all the parameters otherwise equal (in particular $\lambda = 0.05$). Credit spreads are calculated here for $\sigma_j^2 = 0; 0.25$ and 0.5[71]:

---

[69] It is worth noting that Zhou (2001) omits the use of the payout rate compared to the structural models specified earlier.

[70] As discussed earlier, the results of the Monte-Carlo simulations would depend on the numerical scheme used and its efficiency, along with the number of Monte-Carlo simulations made.

[71] The remaining parameters include a jump intensity $\mu_j = 0$; $r = 0{,}05$ (supposed here constant for simplicity) and $V_0/\widehat{b}(0) = 2$ (hence an initial leverage level of about 50%). The parameters

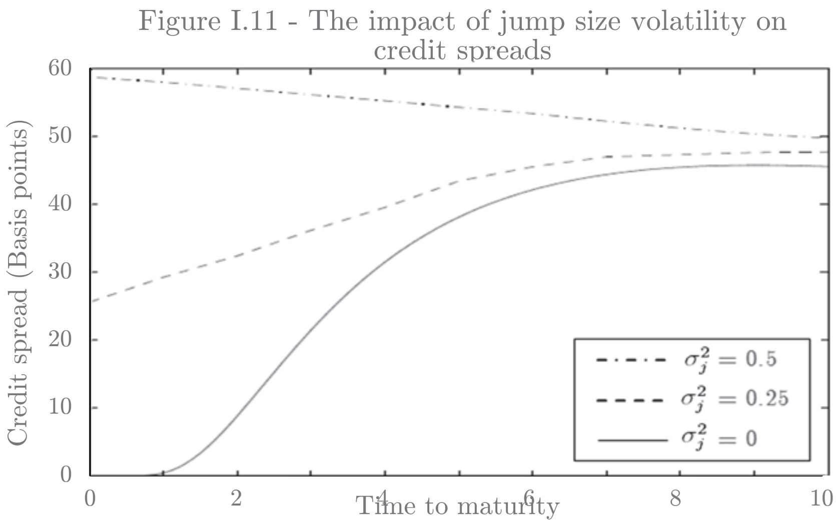


Figure I.11 shows interestingly that an increase in the volatility of the jumps (hence an increase in the dispersion of the levels of the jumps) has a considerable impact on credit spreads. As a matter of fact, for extremely low values of the jump-size volatility (i.e. $\sigma_j^2 = 0$), the model generates a term structure of credit spreads that has a similar shape to the term structures generated by the models of Merton (1974) and Black-Cox (1976). This includes near-zero credit spreads in the short run and an upward-sloping term structure in the medium run. Indeed, for null jump-volatility values, the size of the jumps on the firm value tends also to zero, which means that the specified jump-diffusion process becomes a pure diffusion process. Similarly to the pure diffusion models, the model generates hence low credit spreads in the short term. However, as can be seen in Figure-I.11, for higher jump-volatility values, the model generates, for the first time, high credit spreads for short maturities. For instance, for $\sigma_j^2 = 0.5$, the model produces a credit spread of about 58 basis points (henceforthe "bps") for a bond with a maturity of 1 year. The intuition behind this observation is as follows: under the jump-diffusion dynamics proposed by Zhou (2001), for non-zero jump-volatility values, the firm value has high chances of crossing the default boundary in the short term due to a sudden downward jump in its value. This increases accordingly the probability of default of the firm and produces higher and more realistic credit spreads in the short run. Furthermore, as can be seen in Figure-I.11, these short term spreads are an increasing function of the size of volatility of the jumps. This means that a higher jump-size dispersion makes the firm much more likely to hit the default boundary in the short run.

With regard to the relation between the number of jumps and credit spreads, it is known from the properties of the Poisson process that a higher jump intensity

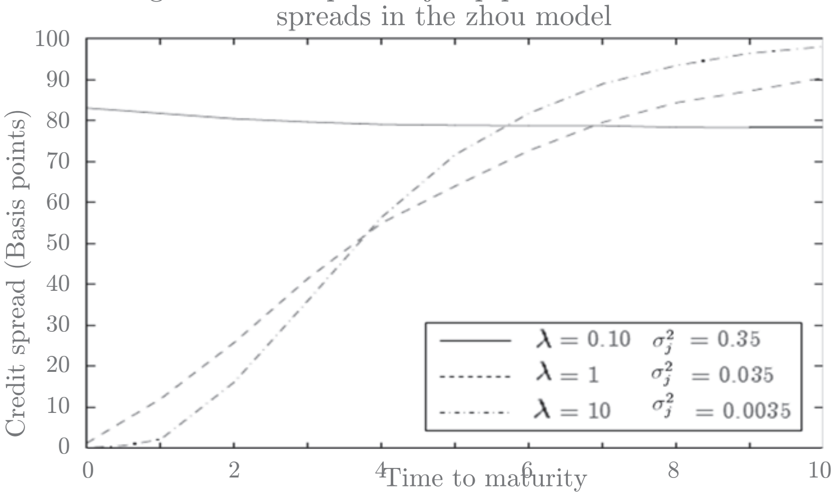
---

used for this numerical analysis are hence, to some extent, comparable to the ones used earlier for the models of Merton (1974), Black-Cox (1976) and CDG (2000).

"λ" (i.e. the average number of jumps per unit of time) is associated with a larger number of jumps. Hence, one can directly see that, for a sufficiently high jump size volatility, a larger number of jumps (i.e. higher "λ") will make the firm value much more likely to hit the default boundary, and makes systematically its credit spreads go up.

Further, as can be noted from the previous lines, the size and the number of jumps cannot be addressed separately from one another. For instance, it is obvious that a large jump size associated to a number of jumps equal to zero won't affect the diffusion path of the firm value nor the credit spreads, while similarly, a large number of zero jumps won't have any effect too. In this concern, Figure I.12 considers the relation between credit spreads and the two main jump parameters: "λ" which governs the number of the jumps and "σ_j^2" which governs the size of the jumps.

Figure I.12 - Impact of jump parameters on credit spreads in the zhou model



Keeping all the parameters otherwise equal, credit spreads are calculated here for, respectively: $(\lambda = 0.10, \sigma_j^2 = 0.35)$; $(\lambda = 1, \sigma_j^2 = 0.035)$; and $(\lambda = 10, \sigma_j^2 = 0.035)$. Figure I.12 shows that a low λ associated to a high σ_j^2 generates generally higher credit spreads in the short run and lower credits spreads in the long run. Conversely, a high λ associated to a small σ_j^2 generates low credit spreads in the short run and higher credit spreads for longer maturities. The intuition behind this observation is as follows. For low values of λ and high values σ_j^2, the number of the jumps on the firm value will not be important. However, if ever there is a jump, its size will be very probably considerable due to the high value of σ_j^2. This makes the firm value likely to cross the default barrier in the short run, even with a single jump, and raises the short term credit spreads. If default doesn't occur in the short run, the firm value will increase over time (due the increasing property of the Brownian motion) and default will be less likely in the long run. As a result, the long term credit spreads reduce gradually[72]. On the other hand, setting a high λ and a small σ_j^2 means that the firm value will experience many jumps, but only with small amplitudes. In this case, credit spreads will maintain low levels in the short run, since these small jumps are not likely to trigger default (see Figure I.12). The effect of these small jumps can be however seen as similar to the effect of the asset's volatility; it causes many small discontinuities on the firm value, and raises only the long term credit spreads.

Of course, it is of interest to add some more economic content to the jumps and their impact on credit spreads. As mentioned earlier, the jumps can be associated to any real world situation which may have a considerable impact on the firm value. Amongst these situations, economic conditions and economic shocks are acknowledged by many studies as factors causing considerable and sudden changes on the firm's situation. One can for instance associate a period of economic turbulence (recession or economic contraction) to a period with a large number of downward jumps on the firm value; these jumps would hence theoretically drive credit spreads up. Similarly, the arrival of a new information to the market (for instance a change in the regulatory environment affecting some particular economic sector) may affect considerably the returns of the firms causing them to jumps and driving hence their credit spreads up. Another case of interest can be the situation where a firm faces an unexpected extreme event (e.g. a natural disaster or a terrorist attack) which can be compared to a single jump, causing immediately default. Hence, the effect of these events on credit spreads should not be neglected.

6.3. Discussion:

The paper of Zhou (2001) proposes an interesting framework for the valuation of corporate bonds where the jump-diffusion path of the firm value and stochastic interest rates affect the bond's credit spreads. This framework relaxes two main shortcomings of the previous structural models, namely the geometric Brownian motion assumption for the firm value (Merton shortcoming (*vi*)) and the continuous time assumption (Merton shortcoming (*ii*)). By doing so, the model of Zhou (2001) takes into account the significant changes that firms may undergo in a small time period (for instance due to economic shocks or crisis) and allows thus, in contrast to the previous structural models, for more realistic short-term credit spreads. Moreover, by using jump processes, the model of Zhou (2001) provides a setup with the advantages of the Reduced-Form models (which are based on jump processes), all while keeping the link with the economic

[72] As demonstrated in the model of CDG (2000), the downward sloping term structure of credit spreads is a direct implication of the static capital structure assumed by many previous structural models.

fundamentals of the firm. As such, it can be seen as a "Structural-Reduced-Form" model, or a reconciliation between the structural and reduced form approaches.

It would be fair also to point out some of the drawbacks of the model of Zhou (2001). For instance, the model does not provide any closed-form formulas for the value of the bond or credit spreads (this makes inevitable the use of numerical techniques, which could be perilous). In addition, Zhou (2001) doesn't allow the firm to alter its initial capital structure over time (Merton shortcoming (*iii*)) and assumes, in the same term as the previous structural models, complete and frictionless markets (Merton shortcoming (*i*)). Moreover, this jump diffusion approach does not provide a clear theoretical explanation for the arrival of jumps, which are supposed to be completely random.

Finally, it is worth noting that the jump-diffusion approach proposed by Zhou (2001) has been extended by many studies in recent years in order to include more sophisticated assumptions about the jump process. For instance, Hilberink and Rogers (2002) propose a corporate bond valuation framework where the jump-diffusion dynamics of the firm value is affected only by downward jumps. Joro and Na (2002) include a second jump component to model the impact of catastrophic events on the firm value and credit spreads. Kou and Wang (2003); Dao and Jeanblanc (2006); Le Courtois and Quittard-Pinnon (2007); Kou and Chen (2009) use a two-sided jump diffusion model, in which the size of the jumps follows a double exponential distribution. Cremers, Driessen, and Maenhout (2007) suppose that the firm value is exposed to three different types of jumps: common jumps, firm-specific jumps and correlated diffusion jump-shocks. They show that their model generates high credit spread levels, close to the ones observed in reality. More recently, Surya and Yamazaki (2012) propose a setup where bankruptcy costs, coupon rates and tax rebate depend on the jump-diffusion asset dynamics[73]. These models include however an increased level of mathematical complexity (they become a subject of research for mathematicians), which may make them lose their appeal for finance practitioners. In addition, it seems to us at this level that some other enhancements are of higher priority from an economic point of view (e.g. relaxing the simple capital structure or the simple bankruptcy mechanism assumption) compared to these sophisticated jump models, which become hard to interpret economically.

[73] The jump-diffusion approach received also much attention recently in modeling the Credit Default Swaps (CDS), another default-risk-dependent instrument. See for instance the studies of Zhang, Zhou and Zhu (2005); Andersen, Bollerslev, and Diebold (2007); Madan et Schoutens (2008) or Jonsson and Schoutens (2009).

7. Other extensions:

In the previous sections we have presented and discussed the outcomes of four of the main structural models of corporate bond valuation, namely the models of Merton (1974), Black-Cox (1976), Collin-Dufresne and Goldstein (2000) and Zhou (2001). This allowed us to show how the credit spreads are generally derived within the structural setup, and accordingly, to discuss the hypotheses and the results of these models. While discussing the shortcomings of these four models, we presented also some of the recent efforts provided by the literature to enhance the former Merton setup, mainly with regard to its shortcomings (ii), (iii), $(iv), (v)$ and (vi).[74] However, we have given only small attention to Merton's shortcoming (i) and (vii) (respectively, the perfect market assumption and the risk-neutral assumption), which are shared by all the models discussed so far. In this section we try hence highlight on some of the recent efforts that has been provided by literature to address these shortcomings. Additionally, we present here another recent strand of structural models which dealing with the impact of economic conditions on the valuation of corporate bonds and credit spreads. Due to the space limit, and to the high level of mathematical sophistication included in these models, we choose to avoid the presentation of different formulations proposed by these models. Instead, we propose to put light on their main innovative hypothesis, the tools they used for modelling as well as the impact of the innovative features of these models on credit spreads. In this sake, we propose to gather these extensions into three main groups of models: (a) a first subsection discusses the extensions of the structural approach that consider the effect of delayed, incomplete or asymmetrical information on the valuation of corporate bonds; (b) a second subsection discusses the outcomes of the models that consider the impact of economic conditions on the structural approach; and (c) a last subsection discusses the structural models that consider the effect of liquidity shocks on the valuation of corporate bonds.

7.1. The impact of incomplete or delayed information:

Most of the structural models discussed so far assume that investors have perfect information about the value of the firm and default barrier (mainly the models that use the geometric Brownian motion assumptions for the dynamics of the firm value)[75]. In such a configuration, default is a predictable event since it is

[74] See subsection 3.3.

[75] The information filtration $\mathcal{F}_t$ adapted to the firm value and the default boundary is supposed to be known by the investor at time "t". The notion of the information filtration has been presented in the foot note 37.

indicated by the distance between the known asset value and the default barrier. As observed earlier, this makes the model generate near-zero credit spreads at short maturities for firms with reasonable leverage ratios (see the short term credit spreads of the model of Merton (1974), Black-Cox (1976) and Collin-Dufresne and Goldstein (2001)). In order to address this perfect information assumption, two main approaches have been advanced by literature: introducing jumps on the process of the firm value (e.g. the model of Zhou, 2001 discussed earlier), or modifying the information filtration available to investors about the value of the firm's assets or the default boundary. This latter approach (denoted by the "incomplete information approach") constitutes an interesting extension of the structural framework which has received much attention from researchers in recent years.

The main idea behind the incomplete information approach consists of assuming that investors have only limited or altered information about the situation of the firm (or the default boundary), which makes the actual distance between the asset value and the default boundary unknown, and thus, default a possible event in the short run. Technically, this is done generally by assuming that investors (which are considered separately) dispose of an information filtration (say $\mathcal{H}_t$) which comprises only a partial or modified information about the situation of the firm. Investors derive hence the value of the firm's assets (or the default boundary) conditionally on this information filtration $\mathcal{H}_t$, rather than conditioning on the global information filtration $\mathcal{F}_t$ as it is done in the previous structural models ($\mathcal{F}_t$ is assumed to be reserved to the management of the firm).

This modified information filtration makes the valuation setup consistent with the real-world situation where investors don't have complete information about the assets of the firm or the default time. In addition to the enhancement of the hypothesis of the model, the main consequence of this incomplete information hypothesis is that the model becomes consistent with credit spreads different from zero for short maturities. This makes default become an unpredictable event in the short run (the available numerical validations of these models show generally that they generate non-null short term credit spreads).

We propose next to review some of the assumptions made by this branch of literature on the information-set available to investors as well as the impact of this information set on credit spreads[76]. In their seminal paper of this approach, Duffie and Lando (2001) assume in agreement with reality that investors receive

[76] The mathematical complexity of the formulations proposed by this approach makes them indeed unsuitable for presentation in the frame of this study.

only periodic and noisy accounting reports about the firm's assets[77]. They find, on the one hand, that the short term credit spreads generated by the model are significantly different from zero, and on the other hand, that credit spreads increase with the accounting noise and the incompleteness of the information that investors have about the firm value. Cetin et al. (2004) and Guo et al. (2006) propose an approach where investors observe only a partial, or lagged, information about the firm's assets. They conclude that this partial or lagged information may affect considerably the credit spreads. Giesecke and Goldberg (2004) assume that investors have incomplete information at the same time on the firm's assets and the default barrier. They show that credit spreads in this context are significantly different from zero in the short-term. Capponi et al. (2009) model the effect of deliberate misreporting done by insiders of the firm. They conclude that credit spreads must increase with the level of accounting distortion faced by investors. More recently, Lindset et al. (2013) propose a model where information about the firm's situation is delayed and asymmetrically distributed between debtholders and equity holders. They find, on the one hand, that credit spreads increase with information asymmetry, and on the other hand, that asymmetric information has more important impact on credit spreads than delayed information.

In summary, the incomplete information approach constitutes a recent theoretical effort to address the perfect information assumption endured by the previous structural models. It sheds light on the impact that might have delayed, noisy or asymmetric information on the valuation of corporate bonds, and accordingly on credit spreads. By doing so, the models considering this approach become consistent with the same informational assumptions proposed by the reduced form approach. As a result, they generate higher short-term credit spreads[78]. Similarly to the jump-diffusion approach, these models could be seen as a mixture between the structural and the reduced form modelling approaches. In spite of these appealing features, the incomplete information approach presents the disadvantage of including an increased mathematical sophistication which makes it quite inaccessible for most economists and finance practitioners. Finally, based on the theoretical evidence provided here on the impact of information on credit spreads, we propose in chapter III to investigate empirically the impact of delayed informational content on credit spreads in the context of the crisis.

---

[77] They do so by assuming that the firm value (which follows a geometric Brownian motion) is observed by investors only at discrete times; to each of these discrete observations, an additional noise is added (assumed to be a sequence of a Gaussian random variables).

[78] As mentioned previously, we do not review in this study the pure reduced form models. We discussed, however, the jump-diffusion models and the incomplete information models which can be seen as a combination between the structural and the reduced form setups.

7.2. The impact of economic conditions:

We consider next another recent strand of structural models which considers the impact of the macroeconomic conditions on the valuation of corporate bonds. Economic intuition suggests that macroeconomic conditions and the phase of the economic cycle (expansion vs. contraction) should have an impact on firms' defaults. Indeed, during periods of economic expansion, firms have generally higher production and higher demand on their activity, which is generally coherent with ample cash flows and accordingly lower probabilities of defaults. Conversely, during periods of economic contraction (recession or crisis) firms' activities and performances are generally likely to diminish, which leads them to a higher likelihood of default. Moreover, as noted by Hackbarth, Miao and Morellec (2006): "it is known that during recessions, consumers are likely to cut back on luxuries, and thus firms in the consumer durable goods sector should see their credit risk increase". In order to account for the macroeconomic conditions impact on credit risk and bond yields, structural models proposed the introduction of jumps on the firm value (jumps can be interpreted as exogenous economic shocks or a recession, see Zhou, 2001). On top of that, a recent branch of structural models have proposed to incorporate more explicitly the effect of macroeconomic conditions into the modeling of corporate bonds. One pioneer study in this branch of literature is proposed by Hackbarth et al. (2006). These latter developed a model where the firm's operating cash-flows depend on the realization of both idiosyncratic and aggregate macroeconomic shocks (reflecting the state of the economy). To do so, they assume that the economic cycle phase changes from expansion to recession according to an exogenous probability (the transition probability from one state to another follows a Poisson distribution, such that the economic condition is a two-state Markov chain). In parallel, cash flows, which follow a geometric Brownian motion, are weighted by a scalar factor linked to the phase of the economic cycle: they are higher in periods of expansions and lower in periods of recessions. In this setup the authors show that:

- Default can be triggered either because the idiosyncratic shock has reached the default boundary or because of a change in the value of the aggregate shock;
- The exogenous macroeconomic changes are important drivers of default, which leads to higher default rates during recessions;
- Credit spreads are higher in a recession than in a boom;
- By counting for macroeconomic conditions, the model is capable of generating positive credit spreads in the short term, similarly to the jump-diffusion and incomplete information models;
- Recovery rates should be higher during periods of economic expansion.

In the same direction, Bhamra, Kuehn, and Strebulaev (2009) propose a model that considers the relation between macroeconomic conditions and credit spreads inside a framework that jointly prices corporate bonds and equities. To do so, they embed a structural model of credit risk inside a representative agent consumption-based model[79]. Macroeconomic conditions are then added by the means of a two-state Markov chain, in the same lines as Hackbarth et al. (2006). They show that the credit spreads generated by the model are close to the default risk component observed empirically inside credit spreads[80]. As noted by Bhamra et al. (2009), their paper is only a first step towards the development of a fully-edged consistent framework for pricing corporate equity and debt and the unification of existing asset pricing and corporate finance paradigms.

Furthermore, Chen (2010) builds a structural model that demonstrates how business-cycle variations influence firms' defaults. To do so, he assumes that the economy is affected by two types of shocks: small shocks, provided by a standard Brownian motion, and large shocks, provided by the movements of a finite-state Markov chain which depends on an independent Poisson processes (each jump in the Poisson process corresponds to a change of state for the Markov chain)[81]. Similarly to Hackbarth et al. (2006), Chen (2010) assumes that the firm's cash-flows dynamics follow a Brownian motion. This dynamics is assumed to be linked to the state of the economy: during recessions, they grow only slowly and may become more volatile, contrarily to periods of expansion[82]. In addition, Chen (2010) adds intelligently in his model the investors' behavior, which is impacted by the state of the economy (starting from the assumption that investors will demand higher risk premia on their risky claims during crisis periods). In this configuration, he shows that defaults vary considerably according to the phase of the business-cycle, and that they are more likely during periods of recessions. Accordingly, credit spreads would be higher during recessions.

More recently, Chen, Xu and Yang (2012) build a model which studies the link between systematic risk and debt maturity, as well as the joint impact of these factors on the term structure of credit spreads[83]. Their model predicts that firms with higher systematic risk exposure will have higher default probabilities

---

[79] See for instance Rajnish Mehra1 (2012) for a review of this approach.

[80] Credit spreads are indeed found empirically to contain more than a default risk component. More evidence for this fact will be provided in Chapters II and III.

[81] Later in the paper, Chen (2010) calibrates the model with nine states for the Markov chain corresponding to different economic conditions. This allows the model to capture richer dynamics of the business cycle as compared to the two states setup proposed by Hackbarth, et al. (2006).

[82] He applies the option pricing technique proposed by Jobert and Rogers (2006) to provide closed form solutions for the prices of the bonds.

[83] They use in the same vein as Hackbarth et al. (2006 and Bhamra et al. (2009) a two-state, continuous-time Markov chain for economic conditions, which affects the firm's cash flows.

and credit spreads. In addition, they show that maturity structure for firms with high systematic risk exposure will be relatively stable over the business cycle. In contrast, firms with low systemic risk exposure have significantly shorter debt maturity in bad times[84]. The paper of Chen et al. (2012) shows that the links between systematic risk and debt maturity are important for understanding the effects of debt maturity on the term structure of credit spreads[85].

In summary, the models presented in this section present an interesting attempt to introduce explicitly the impact of economic conditions within the structural modeling framework. They show, mainly, that firms' defaults, credit spreads and recovery rates should move in line with economic conditions and the economic-cycle phase (recessions are generally associated with higher defaults and credit spreads, and lower recovery rates in contrast to expansions). Based on this theoretical evidence, we bring in chapters II and III a real world evidence on the impact of economic conditions on the spreads during the recent economic and financial turmoil.

7.3. The impact of liquidity:

The structural models presented so far assume perfect markets where bonds are traded continuously without any cost or liquidity premia (Merton shortcoming (i)). However, in reality, bond markets are known to have relatively high transactions costs and low trading volumes. One would then expect investors to propose lower prices for their illiquid securities in order to clear their bond positions[86]. As such, liquidity risk must be an important component of bond prices and credit spreads, which should not be underestimated. In order to capture this idea, a recent branch of structural models proposed to account for the impact of liquidity risk on the valuation of corporate bonds. One pioneering study in this branch of literature is the one proposed by Ericsson and Renault (2006)[87]. These latter propose indeed a corporate bond valuation model that captures, simultaneously, liquidity and credit risk, within a Merton-like contingent claim setup. To do so, they consider a valuation framework in the same spirit as François and Morellac (2004), where default takes place only if the firm's asset

[84] Systemic risk exposure is measured by the asset Beta coefficient.

[85] Other important studies in this strand of literature include the papers of Chen, Collin-Dufresne and Goldstein (2009) and Gomes & Schmid (2010)

[86] Liquidity is defined as the ability to sell a security immediately at a price close to its value in a perfect markets. An illiquid market is then one in which a sizeable discount may have to be applied in order to sell a security immediately (Ericsson and Renault, 2005)

[87] Prior to Ericsson and Renault (2006), Tychon and Vannetelbosch (1997) proposed a model dealing explicitly with the liquidity of corporate bonds. These latter define however liquidity differently: as liquidity premia in their setup are linked to the heterogeneity of investors' perceptions about the costliness of bankruptcy (Ericsson and Renault, 2006).

value remains a certain time below the default boundary[88]. As regards liquidity, Ericsson and Renault (2006) assume that bond investors are subject to liquidity shocks (which arise randomly according to a Gaussian stochastic process) that force them to clear their bond position at a discount fraction compared to the liquid bond. This fraction is in turn assumed to be random (follows a uniform distribution), and is affected by the number of bids that investors receive (assumed to follow a Poisson distribution). Doing so, they decompose the credit spreads generated by the model into a pure default risk component, a liquidity risk component and a component related to the interaction between liquidity and credit risks. In this setup, Ericsson and Renault (2006) show most importantly that: (*i*) their model is able to generate substantial yield spreads even for short maturities (due to the illiquidity component); (*ii*) the components of bond yield spreads due to illiquidity increases as default becomes more likely; and (*iii*) that the term of credit spreads generated by the model is convex and downward sloping for long maturities.

More recently, Chen, Cui et al. (2014) propose a sophisticated structural model that attempts to capture, in the same time, the effects of macroeconomic conditions, liquidity risk and default risk. Using similar assumptions as Chen et al. (2010) for default and economic conditions, they assume additionally that investors face idiosyncratic undiversifiable liquidity shocks in the secondary market, which drives up the cost of holding the bond (the holding cost is also modelled randomly). Doing so, Chen et al. (2014) decompose, in the same vein as Ericsson and Renault (2006), the credit spreads generated from their model into a default component (which is in turn divided into a ”pure default” component and a ”liquidity-driven-default” component), and a liquidity component (which is in turn divided into a “pure liquidity” component and a “default-driven liquidity” component). Calibrating their model to bond data, the authors show that: (*i*) a higher illiquidity is generally associated with higher credit spreads; (*ii*) the pure default component inside credit spreads accounts only for 13% to 50% of credit spread levels depending on the bond rating category; and (*iii*) that the interaction between liquidity and default risk accounts for 25% to 40% of the observed credit spreads levels over the business cycle.

In summary, the studies discussed in this section constitute another recent extension of the structural approach of corporate bond valuation. They put the light on the fact that, contrarily to what is advanced by the previous structural models, bond prices and credit spreads must contain a liquidity component. This strand of literature remains however relatively sparse. The papers presented above

[88] Other assumptions include a firm value that follows a geometric Brownian motion, and a constant risk-free interest rate.

constitute, to our knowledge, the only references that deal with the issue of liquidity within the structural framework. Based on this theoretical evidence, we propose in chapters II and III to study the impact of liquidity on credit spreads since the beginning of the subprime crisis.

8. Conclusion:

This chapter has attempted to analyse the coherence of the structural approach of corporate bond valuation in order to bring the first elements of answer to the purpose of this thesis: emproving the valuation of corporate bonds.

To do so, our approach consisted of presenting an extensive analysis of this literature from the standpoints of hypothesis and results, with a particular emphasis on the models of Merton (1974), Black-Cox (1976), Collin-Dufresne and Goldstein (2000) and Zhou (2001). With regard to the models' hypothesis, we have shown that the structural approach allows a clear link between the economic fundamentals of the firm and the credit spreads of the valuated bond. The mathematics of the different models translate well the relationship between the capital structure of the firm and default, which allows an intuitive economic interpretation of the causes of default and credit spreads. Additionally, we highlighted that this approach is well established in terms of financial theory (e.g. option theory and capital structure theory), which makes it particularly appealing for economists and finance practitioners. Moreover, the structural approach presents the advantage of great flexibility, since the model can be designed to treat a particular situation of the firm, or a specific feature of the bond contract (e.g. safety covenants in the model of Black-Cox, 1976 or dynamic capital structures in the model of Collin-Dufresne and Goldstein, 2000). Further, we have shown throughout this study that the hypotheses of the structural approach has improved considerably since Merton's (1974) seminal paper. Many efforts have been made in order to include more realistic features and enhance the modelling framework. Interesting recent examples include the models of Ericsson and Renault (2006) or the model of Lindset et al. (2013) which considered, respectively, the impact of liquidity shocks and information asymmetries on the valuation of corporate bonds.

Despite the numerous existing efforts to improve the structural approach, we note that throughout this theoretical analysis that it still suffers of many drawbacks, which emanate mainly from the unrealistic hypothesis that the models use. For instance, most of the existing models build on the efficient-market hypothesis, which has been strongly questioned in recent years (see for instance B. Guerrien, 2011 and N. Bouleau, 2013). In addition, we have remarked that only little efforts have been made so far to put aside the risk-neutral valuation technique (which neglects investors risk aversion), or to include more explicitly the effects of economic conditions or crisis. Likewise, the existing models can be extended to account for more realistic capital structures, more realistic bankruptcy mechanisms, or to deviate from the absolute priority rule. In light of all the possible extensions of the structural approach, it seems that some enhancements are of higher priority than others. Firstly, because they consider economic aspects that are frequently encountered in reality (e.g. the simple capital structure or the simple bankruptcy mechanism assumptions). In a second place because some enhancements are relatively hard to accomplish and would require an increased level of mathematical complexity (e.g. the risk neutral hypothesis).

With regard to the models' results, the numerical analyzes that we have led on the credit spreads of the models of Merton (1974), Black-Cox (1976), Collin-Dufresne and Goldstein (2000) and Zhou (2001) were conclusive in several respects. Above all, we have shown that the models using the geometric Brownian motion assumption for the firm value dynamics imply near-zero default probabilities and credit spreads for short maturities. This makes the results of these models highly questionable since credit spreads are generally found to be different from zero in reality, especially in a crisis context. In this regard, the assumption that the firm value follows a jump-diffusion process, as proposed by Zhou (2001), seems more consistent, since it allows the model to generate high short-term credit spreads. Moreover, we have notice from our numerical analyses that leverage plays an important role in the levels and the term structures of the credit spreads generated by the structural models. This important role stems from the assumptions of the structural models where default is generally signalled by the proximity of the firm value to its debt level. As such, keeping the leverage level constant (e.g. the models of Merton, 1974 and Black-Cox, 1976) or allowing the firm to modify its leverage level over time (e.g. the model of Collin-Dufresne and Goldstein, 2000) is found numerically to have significant effect on the levels of credit spreads and their structure by term. Accordingly, a particular attention must be given while modelling on the assumption about the debt of the firm (constant vs. variable) since this may affect considerably the results of the model. Furthermore, we have noted from our analysis that the credit spreads generated by the different theoretical models have evolved over the years to encompass more than a default risk component. The most recent theoretical studies show that credit spreads include an information asymmetry (or delay) component, a liquidity risk component and a macroeconomic risk component. These evidences remain however relatively sparse and need further investigations from both theoretical and empirical perspectives in order to bring them closer to reality. Finally, we have proposed throughout this study to put light on the factors that affect credit spreads according to the different theoretical models. We have analyzed numerically the sign of their relation with credit spreads, and we have tried to give some insights about how these factors are expected to affect credit spreads according to theory. We summarize our main findings for the theoretical credit spread determinants and the sign of their relation with credit spreads in Table I.1 presented below. In the following chapters, we propose to investigate empirically the interaction between these determinants and credit spreads in the context of the crisis in order bring evidence about the consistency of the theoretical models view.

In sum, this chapter has proposed to analyse theoretically the possible elements of enhancement that can be addressed to the models of corporate bond valuation. A more comprehensive analysis is however necessary in order to account, for instance, for the empirical effects of the crisis on credit spreads. This makes the object of the following chapters.

Table I.1: The main theoretic determinants of credit spreads:

Model	Added credit spread determinant	Theoretic sign
Merton (1974)	L: The firm's leverage ratio;	+
	σ_v: The volatility of the firm's assets;	+
	r: The risk-free rate;	−
	$T-t$: Time left until the maturity of the bond;	+
	κ: The payout rate;	+
Black-Cox (1976)	$\hat{b}(t)$: Bond-specific default boundary, stipulated by the bond covenant;	−
CDG (2000)	$\overline{L}(r_t)$: Target leverage ratios;	+
	r_t: Stochastic interest rates;	−
	α: The recovery level;	−
	C: Coupon payments;	−
Zhou (2001)	w: The write-down rate;	+
	N_t: The number of jumps happened on the firm value assimilated to shocks (depends on the average number of jumps per time unit, or the jump intensity "λ";	+
	j_t: The size of each of jump on the firm value (depends on the mean of the jump size μ_j and the volatility of the jump size σ_j^2);	+

Duffie and Lando (2001)	Noisy accounting reports on the firm's assets;	+
Cetin et al. (2004); Guo et al. (2006)	Partial or lagged information on the firm's assets;	+
Capponi et al. (2009)	Deliberate information misreporting on the firm's situation done by the insiders of the firm;	+
Lindset et al. (2013)	Delayed and asymmetrically information about the firm's situation;	+
Hackbarth, et al. (2006); Bhamra et al. (2009); Chen et al. (2010-2012)	Idiosyncratic and aggregate macroeconomic shocks;	+
Ericsson and Renault (2006); Chen, Cui et al. (2014)	Liquidity shocks.	+

Chapter II

The corporate bond market during the crisis: a descriptive analysis of credit spreads

1. Introduction:

Since July 2007, the global economies in general, and the European economies in particular, have been facing a crisis of an unprecedented gravity. This crisis has resulted in a slowdown in the overall economic activity as well as severe turbulence in the financial markets of most major economies. Similarly, the corporate bond market has witnessed substantial instabilities, as evidenced by the bonds' credit spreads. After keeping narrow levels and low volatilities from 2004 to mid-2007, credit spreads have gone through two periods of high levels and considerable volatilities. First, during the 2007-2010 period (i.e. the subprime crisis), which witnessed unprecedented credit spreads levels, coupled with an exceptional turbulence in most financial markets (stock market crashes, drying of interbank liquidity, etc.), and an important wave of banks' defaults and bailouts (e.g. Lehman Brothers and the Royal Bank of Scotland). Second, during the 2010-2014 period (i.e. the Eurozone crisis), which observed historical credit spreads levels, on top of numerous European governments' defaults (e.g. the Greek and the Portuguese governments), and a significant deterioration in the overall business climate. In view of the theoretical analysis that we proposed in chapter I, this increase in the levels of the spreads during the crisis should be explained mainly by an increase in the default risk of the underlying corporations. But are there any other factors and phenomena that have driven this turbulence and that have not been considered by the theoretical models of corporate bond valuation?

In this chapter we attempt to answer this question in order to draw some conclusions that may be useful in pursuing the objective of this thesis: improving the valuation of corporate bonds. To do so, our approach consists basically of presenting a descriptive analysis of corporate bonds spreads. We use a sample of 71 corporate bonds settled in Euro, as well as a sample of idiosyncratic and market-wide risk proxies, over a ten-years period going from July 2004 to July 2014. We proceed our analysis as follows. First, starting from the observations and the descriptive statistics of our sample, we identify a set of ten stylized facts about the evolution of the spreads and the factors that affect them during the crisis. This allows us to shed light on the different factors that caused the turbulence in the corporate bond market and to bring some economic content to these factors. Second, we conduct a Principal Component Analysis of credit spreads for different sub-periods including the pre-crisis, the subprime crisis and the Eurozone crisis periods. This will allow us to analyze the dynamics of pricing inside credit spreads and to detect an eventual change in the factors that explain them since the beginning of the crisis.

Furthermore, compared to the other empirical studies that can be found in literature, this study proposes some original contributions with regard to: (i) the investigated question; (ii) the methodology; used and (iii) the explored sample. With regard to the investigated question, this study addresses the factors and the dynamics that have emerged during the crisis and that need to be taken into account into the valuation of corporate bonds. As regards the used methodology, this work examines the effect of the crises on credit spreads mainly from a descriptive point of view. This allows us to draw some conclusions that can be hardly emphasized with any other statistical tool. Finally, it examines a sample which covers at the same time the pre-crisis, the subprime crisis and the Eurozone crisis periods. To the best of our knowledge, none of the previous studies on corporate bonds spreads have explored a sample that covers all these three periods.

The remainder of this chapter is organized as follows. Section 2 describes the data used in the analysis of corporate bonds spreads. Section 3 presents the proposed stylized facts of credit spreads during the crisis. Section 4 discusses the results of the proposed principal component analysis of credit spreads levels during the crisis, while section 5 concludes the chapter.

2. Data and descriptive statistics:

2.1. Data:

Data used in this study are collected from ”SIX-Financial Information”, ”Datastream” and the European Central Bank (ECB) databases. Data consist of monthly corporate and government bonds yields used to compute credit spreads, in addition to a set of additional variables used to support our analysis of the spreads. More details about these datasets are presented in what follows.

2.1.1 Credit spreads sample:

Data used in the computation of credit spreads consist of monthly observations on corporate and government bonds yields over a 10 years period, starting from July 1st, 2004 to July 31th, 2014[1]. As for corporate bonds, the initial collected sample included a large set of bonds settled in Euro, with maturities of 10 years or more[2]. This bond sample was then filtered in order to reduce possible noise in it. First, all bonds with equity or derivative features (such as callable and puttable bonds), convertible bonds, bonds with warrants as well as bonds with floating interest rates were excluded[3]. Second, all bonds with lacking yield data and those with seemingly problematic data (for instance bonds with constant yields over a long period of time) were also removed. All these filtrations made, the final sample consisted of yields data for 71 bonds. Out of these 71 bonds, 56 are rated Investment-grade while 15 are rated speculative grade[4]; 49 were issued by financial firms and 22 by non-financial firms[5]. As for the government bond, the German ”Bund” yield is chosen as the reference risk-free rate. This choice is motivated by the low default risk associated with the German government (AAA-rated), the high liquidity of the Bund, as well as the data availability over the sample period. A set of Bunds for all available maturities is then collected. Next, using the same formula that was discussed in chapter I, we computed credit

[1] The use of monthly observations is motivated by the fact that data are either not available, or not liquid enough to be used at the daily or weekly level.

[2] Bonds with maturities of 10 years or more consist of only a small part of total corporate bonds issuance in Europe.

[3] This study does not deal with these features of corporate bonds. We note also that our sample includes coupon-paying and zero coupon bonds. In this study, we assume that the effect of coupons is negligible during the life of the bond since the value of the coupons and their frequency of payment are known with certitude by investors.

[4] See Appendix I for a detailed explanation of Ratings. The average rating of a bond in the period of the study is taken here as its reference rating.

[5] As a matter of fact European corporate bond markets were mainly dominated by financial and investment grade bonds issuance in the beginning of the millenary

spread for all the selected bonds as the difference between the yield of the corporate bond and the yield of the German "Bund" of equivalent maturity and compounding frequency. Formally, the credit spread of a bond "i" at time "t" is computed as follows:

$$S_{i,t} = Y_{i,t} - r_{i,t} \tag{1}$$

Where $Y_{i,t}$ is the yield at date "t" of a corporate bond "i" of maturity "T", and $r_{i,t}$ the yield at date "t" on a Bund of equivalent maturity. Appendix II.1 presents the sample of the corporate bonds used in this study.

2.1.2 Additional variables:

2.1.2.1. Leverage ratios:

We collect next data for the Leverage ratios of the different firms composing our sample. The data are provided by Datastream which calculates leverage ratios as follows:

$$Lev_{it} = \frac{LT\ debt + ST\ debt\ \&\ current\ portion\ of\ LT\ debt \times 100}{Total\ capital + \ ST\ debt\ \&\ current\ portion\ of\ LT\ debtt} \tag{2}$$

With lev_{it} the leverage ratio of the firm "i" in time "t", *LT debt* is the long term debt and *ST debt* is the Short term debt. Leverage is used in this chapter as a proxy of the default risk of the firms. Data for leverage ratios is unfortunately available only on the quarterly or the annual level.

2.1.2.2. EUROSTOXX 50 index:

We use next the EUROSTOXX 50 index as a proxy for the firms' performances and the overall macroeconomic conditions. Data for the EUROSTOXX 50 index are collected from Datastream on the daily frequency. Starting from this daily data, we calculate the daily log-returns and then we average them on the monthly frequency.

2.1.2.3. VSTOXX index:

We use the VSTOXX volatility index as a measure of the overall macroeconomic uncertainty as perceived by market participants. Data for the VSTOXX index are collected from Datastream which compute it in such a way that it reflects the market expectations of near-term up to long-term volatilities.

2.1.2.4. EURIBOR and OIS:

We collect additionally data for the EURIBOR and OIS rates from Datastream, which are used to compute the EURIBOR-OIS spread. The

EURIBOR-OIS spread is used as a proxy for market wide liquidity. The difference between these two rates is supposed to catalyze the presence of tensions in the interbank market due to supply and demand shocks.

2.1.2.5. LTROs:

We collect finally monthly data for the Long Term Refinancment Operations (LTROs) from the ECB database. LTROs are long term debts (three years) accorded by the European Central Bank to Banks. They are used here as a proxy of the action of authorities and the central banks during the crisis.

2.2. Descriptive statistics:

We propose first to describe the main statistical properties of our sample of credit spreads. Appendices II.2 and II.3 present, respectively, graphics and descriptive statistics of the whole sample of credit spreads used in this study. To best complete these descriptive statistics, we performed a stationarity and normality tests of the credit spreads. The Augmented Dickey-Fuller (ADF) and the Phillips-Perron tests are used to examine the stationarity of the different corporate bonds spreads, while the Shapiro-Wilk and the Jarque-Bera tests are used to test their normality. Results of these tests are reported, respectively, in Appendices II.4 and II.5. Starting from all these statistics the following observations can be made about the sample of the study:

- The lowest credit spread in the sample is of -252bps, recorded by Lloyds-HBOS bond in July 2004.
- The highest credit spread is of 1701bps, recorded by the bond of Banca Popolare in December 2011.
- The average credit spread of the sample is of 157bps.
- The standard deviation of the credit spread sample ranged over the period of the study between 0.261 and 3,937, with an overall average standard deviation of 1.336.
- All the explored credit spreads present a positive, and different from zero skewness. The distributions of credit spreads are hence mostly asymmetrical with a long tail to the right.
- Credit spreads present a mitigated results with regard to kurtosis: 37 firms have negative kurtosis in the period of the study, 15 firms have a kurtosis that is comprised between 0 and 1, and 19 have a kurtosis superior to 1[6].

[6] We use Pearson's Kurtosis criteria. All the above results can be found in Appendix II.3

- Leading the Augmented Dickey-Fuller (ADF) and Phillips-Perron stationarity tests on the 71 credit spreads show that all credit spreads present a unit root, and hence are not stationary (Appendix II.4). This result implies that any regression analysis of the data in its current state would be biased, and justifies our use of descriptive techniques to investigate credit spreads in levels. Moreover, all credit spreads are found to be integrated of order 1, with a confidence interval of 95%[7].
- Using the Shapiro-Wilk and Jarque-Bera normality tests, we find that 68 credit spreads out of 71 reject the null hypothesis that ”the variable from where is issued the sample follows a normal distribution”, with a confidence interval of 95% (Appendix II.6). Bonds that did not reject the null hypothesis are: CIC 1, Commerzbank 2 and Credit du Nord[8].

After describing the main statistical properties of our corporate bond sample, we provide in what follows some stylized facts about the evolution of credit spreads during the crisis.

3. Stylized facts of credit spreads during the crisis:

Using the samples of credit spreads and risk proxies discussed above, we propose next a set of ten stylized facts about the evolution of the spreads during the crisis. As mentioned earlier, the aim of these stylized facts is to identify the factors and dynamics that emerged during the crisis and that have not been considered by the theoretical models of corporate bond valuation. We take, as a starting-point, the observations that we make about the evolution of our sample of credit spreads (mainly the average credit spread), as well as its specification for different rating categories, maturity groups, sectors of activity and firms' sizes. We compare this evolution to the different developments in the economic and market conditions, as proposed by the risk proxies and the different available information available to us about the different developments of the crisis (e.g. the time line of the crisis events proposed by the European Central Bank). In doing so, we support our observations by the view of the theoretical models of corporate bond valuation discussed in chapter I, as well as some insights from the economic theory that apply, according to us, the observations that we make.

The stylized facts that we identify include indeed three main types of observations. First, we note the emergence of new factors that affect apparently credit spreads and that have not been, or have been only sparsely, considered by

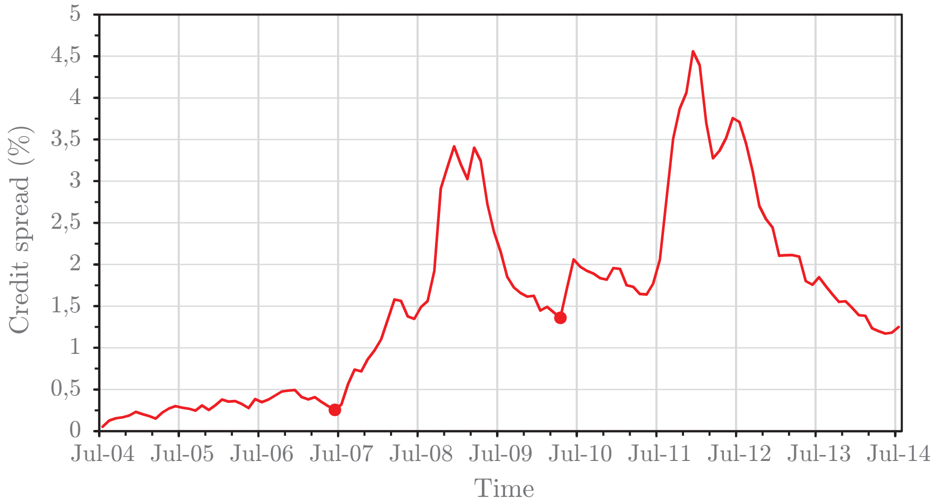
[7] Many previous empirical studies have documented similar non-stationarity results for credit spreads. These include Collin-Dufresne and Goldstein (2001) and Avramov et al. (2007). In chapter III, we use hence changes data to examine credit spreads in a regression analysis.

[8] However, CIC 1 and Credit du Nord spreads are found to be normal only using the Jarque-Bera criteria (see Appendix II.5).

the theoretical models of valuation (e.g. systemic risk, default contagion risk, the effect of government and central banks' actions etc.). Second, we note that the behaviour of some factors that were considered by the theoretical models have changed since the beginning of the crisis (e.g. the effect of leverage and time to maturity). Finally, we note the emergence of some new phenomena that affect the corporate bond market, which are generally acknowledged by the economic theory (e.g. the paradoxes of tranquility and credibility, the phenomena of flight-to-quality and flight-to-liquidity), but are ignored by the valuation theory. More details are presented in what follows.

3.1. Higher credit spreads levels during crisis periods: The paradox of tranquility:

Figure II.1.a - Average credit spread



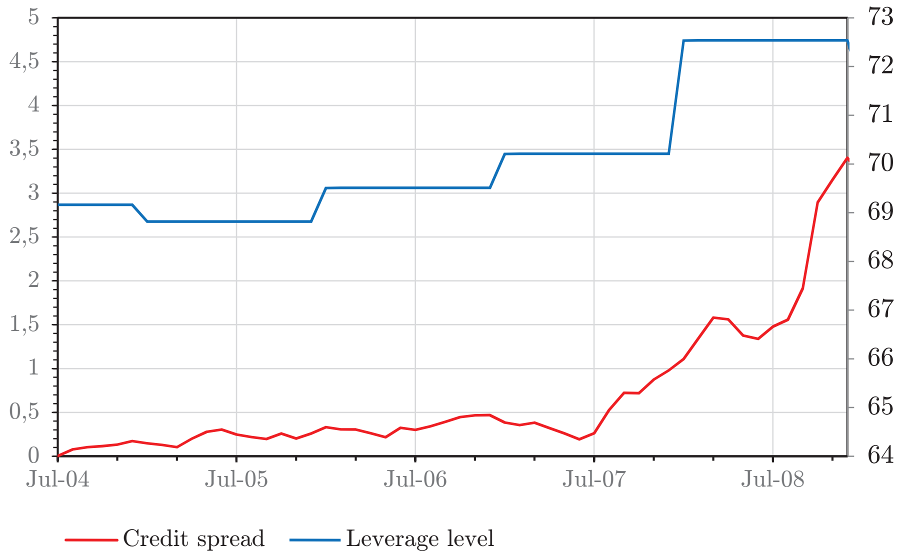
Source: Six Financial, Datastream and author calculation

Figure II.1.a presents the average credit spread for all the bonds composing our sample. As can be seen from this figure (see also Appendix II.2), between July 2004 and June 2007 (i.e. the pre-crisis period), credit spreads of all the firms in our sample maintained relatively low levels, ranging on average between 5 basis points (bps) and 49 bps[9]. The volatility of the spreads kept also globally very low heights, with an average dispersion from the mean of 10 bps. From Appendices II.3 and II.6 we can even see that many bonds displayed negative spreads during this period (for instance, Commerzbank and Fortis), as market participants priced less risks in these bonds than the benchmark European government bond. Following the outbreak of the subprime crisis in July 2007, and up to July 2014 (i.e. the subprime and the Euro crisis periods), the levels of credit spreads soared and maintained relatively high levels (Figure II.1.a). These levels averaged 208

[9] Unless otherwise specified, the used figures are hence in averages.

bps for the period, with two major peaks in December 2008 (341 bps) and December 2011 (455 bps). This situation illustrates indeed very well the paradox of tranquillity proclaimed by Hyman Philip Minsky (1975; 1977)[10]. During the years 1990-2000, market participants profited from a period of tranquil growth, high market liquidities to take higher levels of risks: this included over-indebtedness (i.e. continuous increase in leverage ratios, see Figure II.1.b), speculative attitudes and structures, decrease in risk aversion, and decrease in the price of risk (here in the corporate bond market). To this paradox of tranquillity can be added a paradox of credibility (Borio and Shim, 2007): the increasing credibility of the central banks during the pre-crisis period (mainly in its conduct of the monetary policy) made market participants' confidence in the effectiveness of central banks actions increase. As such they took even higher levels of risk (Artus et al. 2008). These risky behaviours paved the way to the financial vulnerability preluding the crisis. After the onset of the subprime crisis the fragility of the economy emerged and investors risk aversion rose drastically. Thus, the price of risk flew and the levels of credit spreads soared to reach the observed historic levels (Figure II.1.a).

Figure II.1.b - Average credit spread and firms' leverage ratios in the wake of the crisis



Source : Six Financial, Datastream and author calculation

[10] Minsky developed during the seventies an idea, according to which, over-indebtedness crisis find their origins in "tranquil" economic periods, and that economic agents (i.e. firms, households etc.) take generally advantage of economic growth and low interest rates to increase their indebtedness. However, when interest rates increase back again, the levels of indebtedness that seemed sustainable in a low interest rate context become unsustainable and turn to over-indebtedness (Artus et al. 2008).

3.2. Tight connection with economic shocks: the effects of default contagion and systemic risks[11]:

As can be seen from Figure II.1.a and Appendix II.2, starting from July 2007, all the credit spreads in our sample entered a phase of higher levels and more volatile changes. These changes turn out to be closely linked to a sequence of economic shocks associated to the sub-prime crisis (July 2007-April 2010) and the Eurozone crisis (Mai 2010-July 2014)[12]. Since it is relatively hard to know with certitude the exact factor that triggered the variation in credit spreads, we propose here to describe the key shocks that occurred for each main variation in credit spreads. In doing so, we try each time to put light on the factor(s) that seem according to us determinant in the movements of the spreads[13].

More precisely, following the outbreak of the subprime mortgage crisis in the United States (i.e. the bursting of a housing bubble), the spreads of 61 entities in our sample surged immediately, and exceeded in less than a month their highest levels of the July 2004-June 2007 period (56 bps in July 2007 against a maximum of 49 bps between July 2004 and June 2007)[14]. As the financial conditions worsened in the following months (severe tensions in interbank markets worldwide, published results showed increasing losses for banks in 2007, banks distress in the beginning of 2008, see Figures II.2.a, II.2.b, II.2.c), investors risk aversion increased and credit spreads climbed, to reach a high of 158 bps in March 2008 (+126 bps between July 2007 and March 2008). In the few following months, and subsequent to the bankruptcy of Lehman brothers (September 2008) credit spreads skyrocketed (+135 bps in September and October 2008). The effect of this shock resounded up until December 2008, where most of the spreads in our sample reached a peak of 341 bps[15]. The unexpected collapse of Lehman brothers made in fact, markets in general, and the corporate bond market in particular, get into a deep turmoil (runs on systemically important financial institutions; stock market crashes, dysfunction in credit markets, Figure II.2.b): investors' confidence in the resilience of the financial system decreased and the fears of

---

[11] We define systemic risk is the risk of collapse of an entire financial system or entire market. Hence, default contagion risk is a part of the systemic risk but not the only component of it. See for instance D. Hendricks (2009) for a more detailed definition of systemic risk.

[12] By "economic shocks" we denote every unpredictable event that produces a significant change within the economy, which happens inside or outside of it.

[13] The exact determinants of credit spread changes are explored with more details in chapter III.

[14] The spreads in our sample that did not witness an increase in July 2007 are: Confinimmo, Commerzbank 1 and 2, Fortis 4, HBOS 2, Intesa Sanpaolo, Arcelor Fin 2, Italease bca, Gruppo editoriale, Veneto bca.

[15] Two groups of bonds can be distinguished with regard to the levels of spreads they reached in this period: a first group of bonds had a peak in December 2009 (for instance: BPCE and Citigroup) and another group of bonds reached a high in March 2009 (e.g. Lafarge and HBOS)

default contagion to other banks increased (i.e. the effects of default contagion and systemic risks). These, along with the reduced liquidity of the markets (reduction in interbank lending, Figure II.2.c), made credit spreads reach the observed unprecedented levels.

Later, and starting from Mai 2010, credit spreads entered a new phase of turbulence mainly attributed to the outcomes of the European sovereign debt crisis[16]. More specifically, following a succession of events related to the Greek sovereign debt (decrease in Greek bonds notation to speculative grade by Standards and Poor's and the Greek government bailout in Mai 2010, i.e. the effect of bailouts), investors' sensitivity to corporate bonds risks increased once again and credit spreads amplified (see Figure II.1, Appendices II.2; II.3 and II.7)[17]. The effect of this shock was however relatively small and persisted for only two months (+69 bps in Mai and June 2010).

Afterwards, and as a response to the worsening of the Eurozone crisis in the last two quarters of 2011 (Standard & Poor's lowering the Greek debt notation to CCC in June 2011; the new episodes of the Greek bailout[18], the monitoring of the Spanish debt by Moody's, the succession of Eurozone countries austerity plans, high budget deficits and low economic growth) credit spreads climbed sharply (+16%, +35%, and +26% in, respectively, July, August, and September 2011). All these events made investors' worries about the resilience of the Eurozone rise and made, accordingly, bonds risk premiums soar (i.e. the effect of systemic risk, bailouts and economic conditions)[19]. The effect of these shocks and their contagion to other markets continued up until December 2011, where most of the credit spreads in our sample reached historical levels (455 bps on average)[20].

Finally, starting from April 2012, credit spreads observed another period of continuous increase which made them attain the last major peak for the period (a total 14% increase in June 2012). Falls in the major European stock markets in April 2012 (See Figures II.2.a and II.2.b); a decrease in the notation of the Spanish government and some of the major banks in Mai 2012; and a continuous

[16] Henceforth the "Euro crisis period" or the "Eurozone crisis period".

[17] The Greek debt crisis started in fact since the end of 2009 (continuous increase of the Greek debt outstanding and the Greek austerity plans). However, these did not have any significant negative effect on the credit spreads in our sample up to April 2010.

[18] By July 21st 2011, the European leaders announced their agreement on a rescue plan to Greece, and the restructuring of the Greek debt. This increased the worries among market participants about Greece leaving the Eurozone and the weakening of the Eurozone.

[19] This had in turn a deep impact on stock markets; in fact, many stock markets in Europe, United States, Middle East, and Asia witnessed major crashes in the third quarter of 2011. For instance, The EUROSTOXX 50 index reached 2124.31 in September 2011 compared to 2766.60 in June 2011 (see Figure II.2.a).

[20] This made credit spreads total a 112% increase starting from Mai 2011.

uncertainty about the economic and political outlook in Europe were in fact the main characteristics of this period (i.e. the effect of economic and market conditions).

In sum, the previous lines bring evidence to the effects of systemic risk, default contagion risk and bailouts as new factors that affect the levels and movements of credit spreads. Additionally, we note that the situation in the stock markets and in the interbank market (i.e. market liquidity risk) had apparently important effects on the movements of credit spreads during the subprime and the Eurozone crisis periods. This brings support to the view of the structural models which consider firm values and liquidity risks (proxied, respectively, by the stock market return and the Euribor-OIS spread) as determinants of credit spreads. That being said, the order and the extent to which these factors affect spreads are unknown at this level and need further investigations that will be made in chapter III.

Figure II.2.a - Credit spread and stock market index

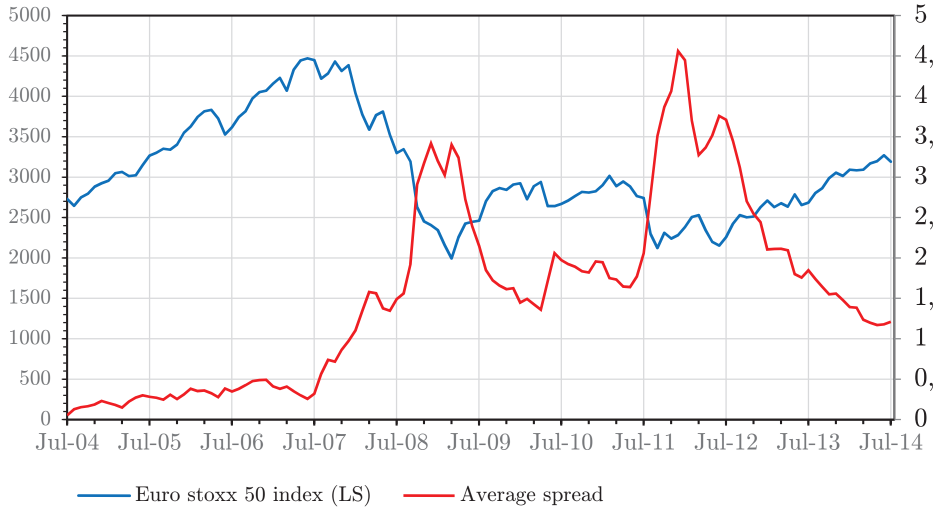


Figure II.2.b - Credit Spread and stock market volatility

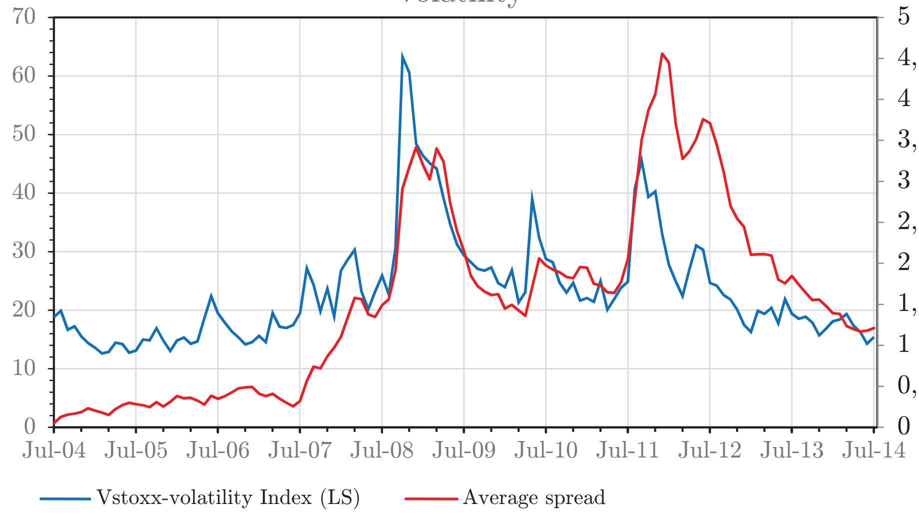
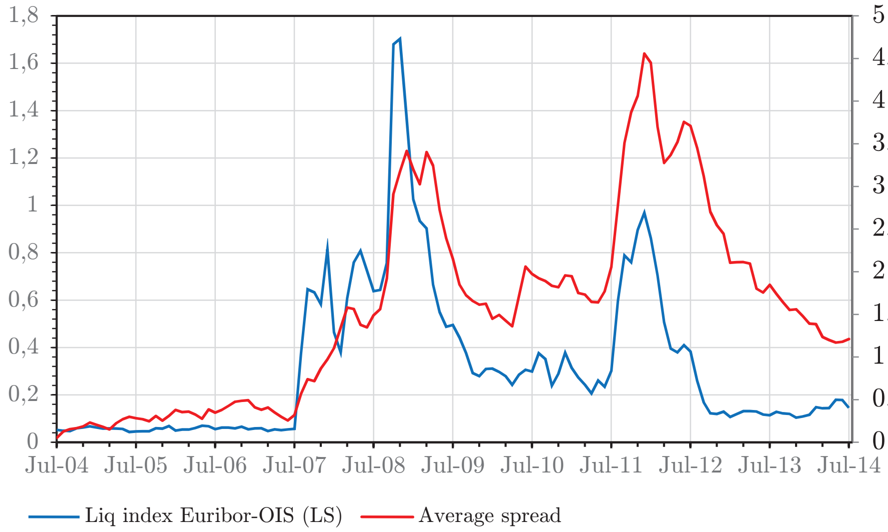
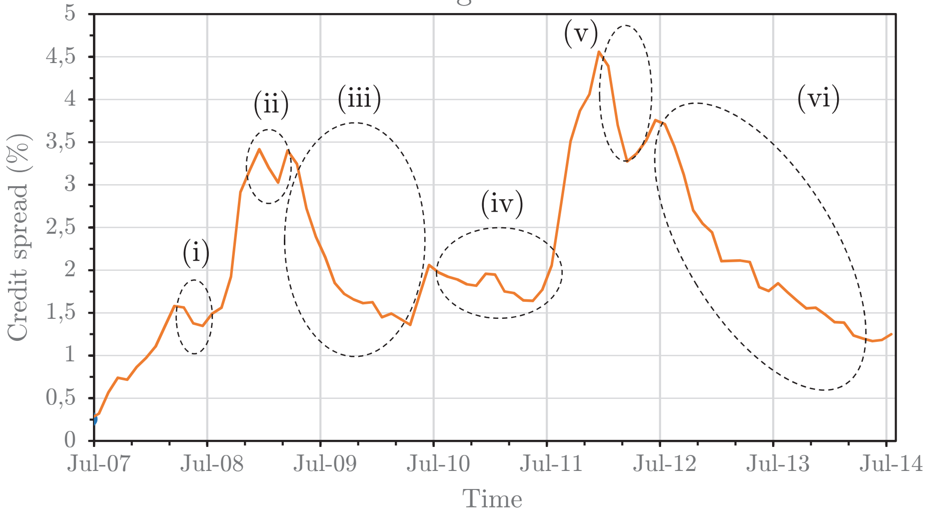


Figure II.2-c - Credit spread and Market illiquidity



3.3. High sensitivity to governments and central banks willingness to help the banking sector:

Figure II.3 - Average credit spread and authorities actions during the crisis



Source : Six Financial, Datastream and author calculation

Since the onset of the subprime crisis in July 2007, governments and the different central banks worldwide (in particular the European Central Bank –ECB–) have undertook many actions in order to enhance the stability of the financial system and restore investors' confidence. These actions turn out to be closely related to the movements of the different credit spreads in our sample. More specifically, following the outbreak of the crisis, and facing the increased instability of the banking sector, the Federal Reserve (FED) acted by providing guarantees and funds to facilitate some of the major mergers and acquisitions (e.g. J.P. Morgan Chase to purchase Bear Stearns in the end of March 2008). On the other side, the ECB proceeded by introducing new refinancing operations addressed to the distressed banking sector (i.e. larger amounts of long term refinancing operations – LTROs – since August 2007 and longer-term refinancing operations introduced in March 2008, see Figure II.3.b). These actions resulted presumably in an improvement of investors' confidence in authorities' support to the banking sector: as such, the levels of credit spreads recorded a slight recovery between April and June 2008 (-23 bps, Figure II.3-(i)). Starting from September 2008, and following the global financial turmoil triggered by the collapse of Lehman Brothers, the ECB responded by initiating the so-called non-standard measures (also referred to as "enhanced credit support")[21]. A slight decrease in credit spreads was observed accordingly in the first two months of 2009 (-39 bps, Figure II.3-(ii)). Later in 2009, the ECB and the G20 governments took another set of important measures in order to improve the stability of the financial system. The main ones were the establishment of the "Financial Stability Board" (FSB) in April 2009 (credit spreads reduced by 4.6% in April 2009) and the reinforcement of the ECB's "enhanced credit support" measures in May 2009 (credit spreads decreased by 16% in May 2009)[22]. Other measures in the few following months included LTROs (see Figure II.3.b), government guarantees on Banks' bonds, capital injections, bailouts and nationalizations of some financial institutions, and asset purchases programs. These measures had also visible effects on credit spreads, which kept tightening by about 6% on average between May 2009 and April 2010 (Figure II.3-(iii)).

Similarly, after the outbreak of the Eurozone crisis the Eurozone countries and the ECB responded by another set of measures to support the banking sector. Mainly, the "European Financial Stability Facility" and the "European Stability Mechanism" were established, respectively, in June 2010 and March 2011[23]. Credit spreads recovered accordingly by about -2.33% per month between July 2010 and April 2011, except in December 2010 (see Figure II.3-(iv)). Later in December 2011, the ECB announced a number of measures to support bank lending and

---

[21] These include Fixed-rate full allotment, the extension of the maturity of liquidity provision, the extension of collateral eligibility, currency swap agreements and Covered bond purchase program. See: The ECB's non-standard monetary policy measures – ECB working paper series (2013).

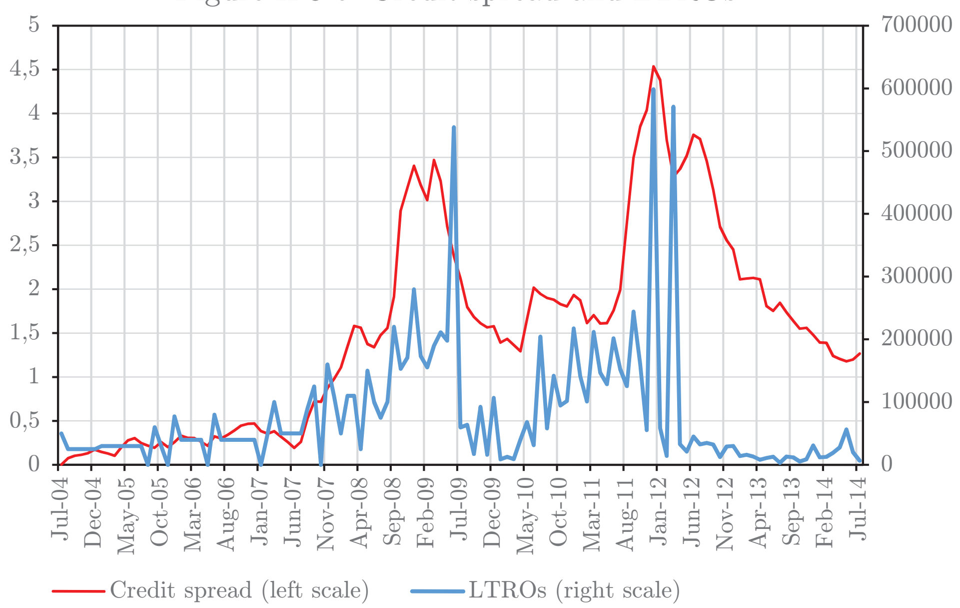
[22] The G20 leaders meeting in London (April 2009) agreed to establish a new "Financial Stability Board" which collaborates with the IMF to provide early warning of macroeconomic and financial risks and recommend actions to be taken. Source ECB.

[23] A permanent EUR 500 billion fund agreed by European finance ministers to serve as a lender of last resort for struggling Eurozone economies.

money market activity (through "Main Refinancing Operations" –MROs– and LTROs)[24]. This made credit spreads decrease by about 30% starting from January 2012 up to the end of March 2012 (Figure II.3-(v)). Finally, after another episode of economic turbulence in the second quarter of 2012, the European Council agreed on the creation of a new European banking supervisory mechanism in June 2012. This had rapidly visible effects on credit spreads which decreased considerably starting from July 2012 (Figure II.3-(vi)).

Finally, it seems important to note that the close connection between the movements of the spreads and the authority's actions can be partly explained by the dominance of the financial firms' bonds in our sample. All the observed evidences on the connection between authority's actions and the value of risk (catalyzed by credit spreads) bring indeed support to the financial instability hypothesis proposed by Minsky (1975; 1977; 1982). Minsky argued that the financial system swings inevitably between robustness and fragility and that these swings are unavoidable, unless regulators and central banks put in place actions to stabilize the system. When considering credit spreads, the instability of the financial system, in addition to the action of governments and central banks, need consequently to be taken into account.

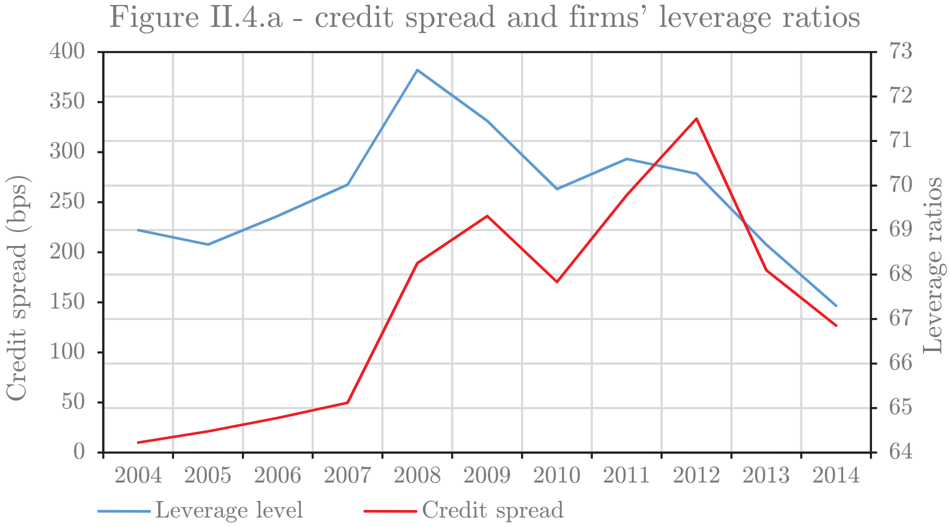
Figure II.3.b. Credit spread and LTROs



Source: ECB, Six-Financial and author calculations

24 "MROs" constitute the one-week liquidity providing operations in euro.

3.4. Decreasing sensitivity to leverage ratios during stress periods:



Annual credit spreads and leverage ratios. Source : Six-Financial, Datastream and author calculation.

Figure II.4.a presents the evolution of the average annual credit spreads and the average annual leverage ratios of all the firms composing our sample[25]. From this figure we can see that, in agreement with the structural models evidence reported in chapter I, an increase in the leverage ratios is generally associated with an increase in the credit spreads of the underlying firms. This is however not the case for the years 2009 and 2012, where decreases in leverage ratios were associated with increases in credit spreads[26]. Facing higher uncertainty about macroeconomic conditions and authorities' willingness to help the banking sector during these periods, investors' focus turned apparently more increasingly toward these factors at the expense of firm-specific leverage ratios. This decrease in the sensitivity of credit spreads to the changes in leverage ratios is particularly noteworthy, since leverage ratios constitute theoretically one of the most important determinants of credit spreads (see chapter I). Further, Figure II.4.a brings another important evidence with regard to the relation between the levels of credit spreads and leverage ratios. Specifically, during the tranquil growth period that proceeded the crisis, the different firms composing our sample maintained generally high leverage levels that ranged between 68% and 72% (i.e. the paradox of tranquility); meanwhile, credit spreads kept low levels that ranged between 5 bps and 49 bps. Following the onset of the crisis, the levels of leverage ratios showed a considerable decrease (mainly due to the deleveraging of the

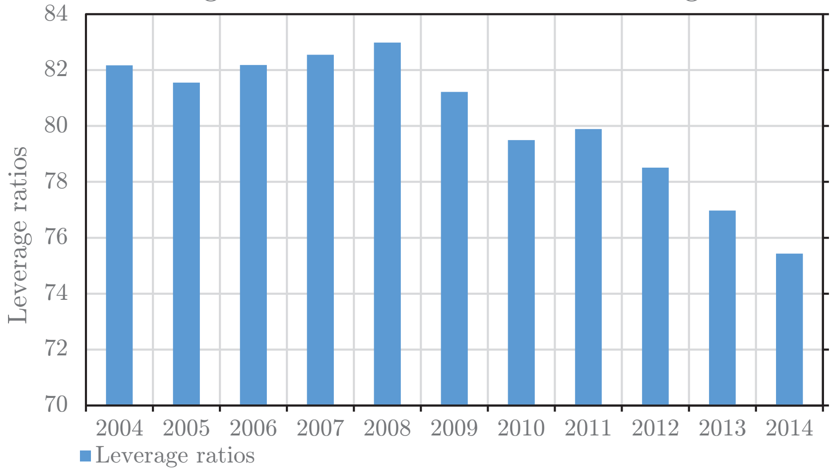
---

[25] Credit spreads are converted to the annual frequency because leverage ratios are available only on the annual or quarterly level. This allows us to have a clearer vision on the joint evolution of leverage and credit spreads.

[26] The decreases and increases are, of course, over previous year's levels.

banking sector since late 2008 to meet the evolving regulatory capital requirements of Basel II and Basel III, see Figure II.4.b). In the same time, the levels of credit spreads increased toward levels that are higher on average than the levels recorded in the pre-crisis period (29 bps on average up between June 2004 and June 2007 and 208 bps on average between July 2007 and July 2014). This increase in the levels of credit spreads, despite the decrease in leverage ratios, brings another evidence to a decrease in the importance of leverage ratios as determinants of credit spreads since the beginning of the crisis.

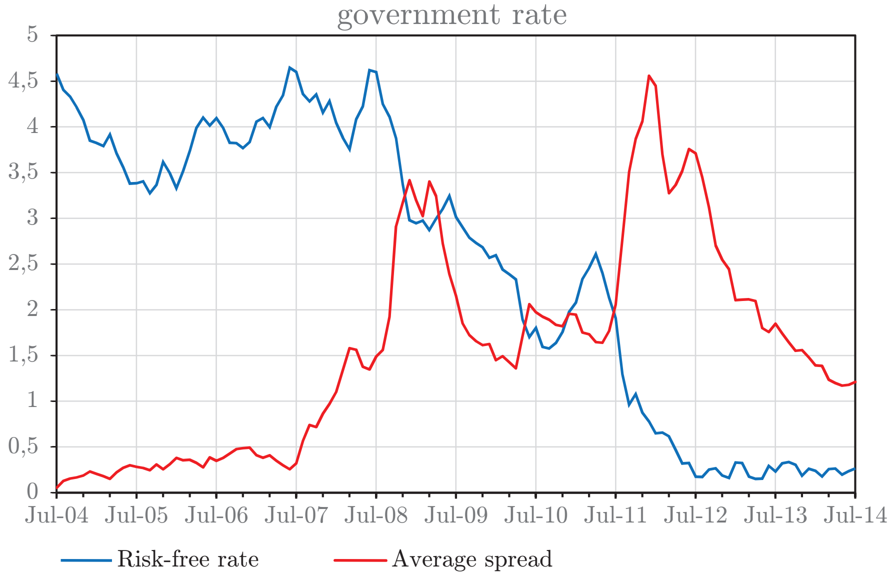
Figure II.4.b - Financial firms leverage ratios



Source : Six-Financial, Datastream and author calculation

3.5. The effect of the phenomena of ”flight-to-quality” and ”flight-to-liquidity”:

Figure II.5 - Credit spreads and the 10 years government rate

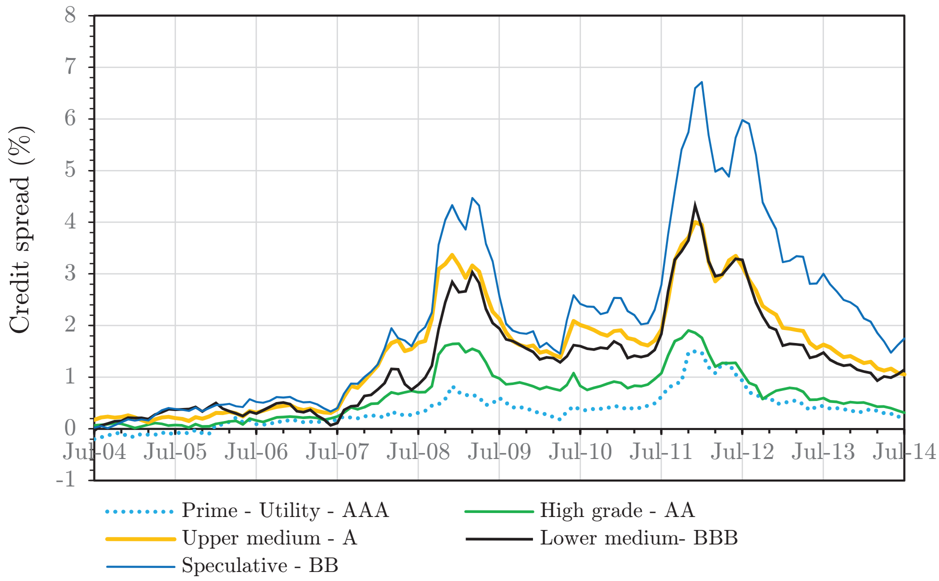


The chosen benchmark government bond is the German Bund. The selcted maturity for comparison is 04/07/2015. Source : Six-Financial, Datastream.

Figure II.5 presents the relationship between the average credit spread and the proxy of the risk-free rate: the 10 years benchmark government bond rate. From this figure, we can see clearly the incidence of sudden falls in the government rate since the beginning of the crisis that were consistently associated with increases in credit spreads (see for instance the last two quarters of 2008 and the third quarter of 2011). These sudden falls suggest indeed the occurrence of the phenomena of ”flight to quality” or ”flight to liquidity” to the expense of the benchmark government bond. Facing higher uncertainty about economic conditions and the increasing instability of underlying corporations since the beginning of the crisis, investors sought apparently refuge in the less risky and more liquid treasury bonds. This led to an increase in the prices of these bonds and accordingly to the observed reductions in their yields, which have resulted in the observed increases in credit spreads. These phenomena were thus important contributing factors to the observed upsurges in credit spreads since the onset of the crisis. Furthermore, as argued by Longstaff (2004), Caballero et al. (2007) or Beber et al. (2008), the phenomena of flight-to-quality or flight-to-liquidity constitute classic behaviours for investors in bond markets, which are caused by the occurrence of unusual and unexpected events. They were for instance observed in the wake of the 1998 Russian default or in the 9/11 attack in 2001. However, as noted by Beber et al. (2008) and Ericsson and Renault (2006), disentangling a flight-to-quality from a flight-to-liquidity is rather difficult because these two phenomena are usually correlated.

3.6. A change in the structure of the factors that affect credit spreads since the beginning of the crisis:

Figure II.6 - Credit Spreads by Rating



Source: SIX-Financial and author calculation

Default risk is known to be evaluated by rating agencies in addition to the valuation models presented chapter I). These agencies publish periodically ratings of corporate bond issuers based on their credit worthiness and likelihood of default. Assuming, that these ratings are correct, and that default risk is the main component of credit spreads (as proclaimed by most of the structural models), one would then expect to see consistently higher credit spreads for bonds of lower ratings. Figure II.6 shows that this logic is respected for the AAA, AA and BB rating categories in our sample: we note indeed that speculative grade bonds (i.e. BB-rated) contain consistently much higher risk premiums (e.g. 659 bps in December 2012) than the average investment grade bonds[27]. In turn, the AAA and AA rating categories are found to have the lowest levels of credit spreads between all the rating categories (respectively, 150 and 186 bps in December 2012). However, as can be seen from Figure II.6, the credit rating logic is not respected for the A and BBB rating categories (respectively, Upper-medium and Lower- medium ratings). In fact, the A-rated bonds are found to have higher credit spreads than the BBB-rated bonds in 91 out of the 121 analyzed months. If the BBB-rated bonds are steadily associated with higher default risk, this means that the A-rated bonds in our sample contain higher levels of additional risks which make them display these higher credit spreads (arguably liquidity, market and systemic risks). Moreover, knowing that 78 of the 91 months where the A-rated bonds had higher spreads were recorded since the beginning of the crisis, one can see this as an evidence of a change in the structure of the factors that affect credit spreads levels since the beginning of the crisis[28]. This observation needs however further investigations, which will be provided in the principal component analysis that we will discuss in subsequent sections.

3.7. Higher financial bonds spreads since the beginning of the crisis: The financial instability hypothesis:

Figure II.7.a presents the average credit spreads for the financial and non-financial bonds in our bond sample[29][30]:

---

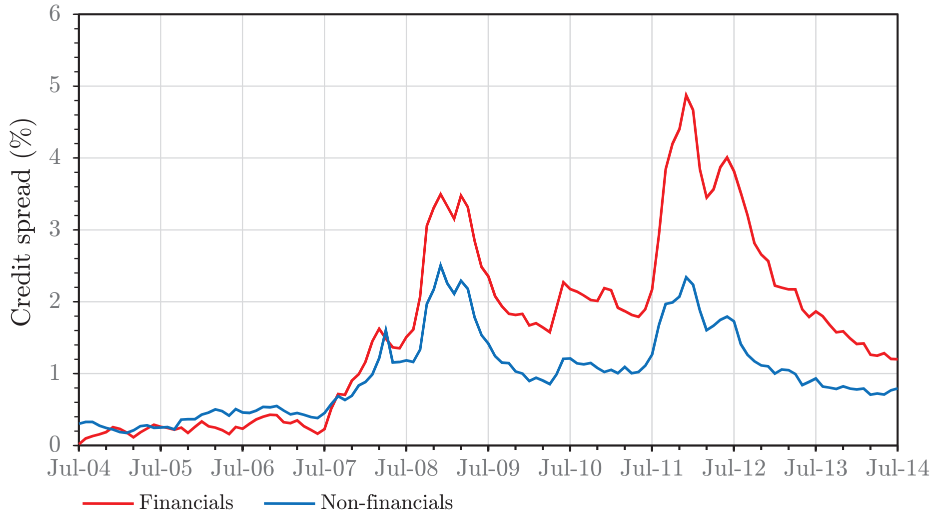
[27] In order to analyze the structure of credit spreads by rating, we divided our sample into four groups of bonds according to their average rating for the period. Doing so, we placed, respectively, 4, 35, 17, and 15 bonds in the "AA", "A", "BBB", and "BB" rating groups. Due to the absence of bonds with "AAA" rating in our sample, we calculated credit spreads for 4 more bonds from the Utility sector with an "AAA" rating (recall that our definition of corporate bonds does not include purely public firms). More details about these bonds are provided in Appendix II.1).

[28] This will be considered with more details in the empirical analysis proposed in chapter III.

[29] The Non-financial bonds sample include bonds from the industrial, services, telecommunication and energy sectors. See Appendix II.1 for more details.

[30] Due to the high levels of speculative grade bonds spreads, data include here Investment grade bonds only. This is supposed to give us a more homogenous view on the difference between

Figure II.7.a - Credit spreads by sector



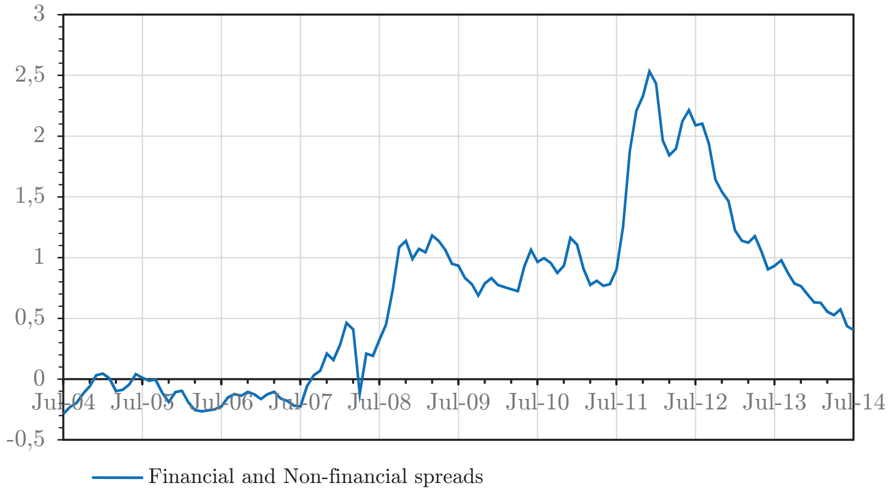
Credit spreads by sector, Investment grade bonds only. Source: SIX-Financial and author calculation

From this figure we can see clearly the occurrence of a shift towards higher spread levels for the financial sector since the beginning of the crisis. More specifically, during the pre-crisis period (i.e. between July 2004 and June 2007) credit spreads of financial firms maintained low levels which ranged between 1 and 42 bps (24 bps on average), while in the same period the spreads of non-financial firms ranged between 17 and 54 bps (36 bps on average)[31]. Facing a period of continuous expansion (supported by high risk taking and speculative behaviours), the banking sector were visibly considered by investors as safer than the other sectors during the pre-crisis period; as such, they demanded lower risk premiums on financial bonds and the credit spreads of these bonds maintained low levels. Following this, the structure of credit spreads levels shifted permanently toward higher levels for the financial sector (Figure II.7.a). The spreads of these latter ranged indeed between 69 and 479 bps (223 bps on average) from September 2007 to July 2014; meanwhile, the spreads of non-financial bonds ranged between 63 and 250 bps (125 bps on average). This observation illustrates once again the emergence of the instability of the financial sector since the beginning of the crisis, caused by the high levels of risk taking and the vulnerability that it has accumulated in the pre-crisis period (i.e. the financial instability hypothesis claimed by Minsky). Facing this increased instability, the price of risk on financial bonds surged and the gap between the spreads of financial and non-financial bonds widened (e.g. 245 bps in December 2011, Figure II.7.b).

financial and non-financial bonds spreads. In doing so, we placed, respectively, 38 and 18 bonds in the financial and non-financial bonds groups.

[31] Non-financial firms had higher spreads in 31 out of the 36 months analyzed in the pre-crisis period.

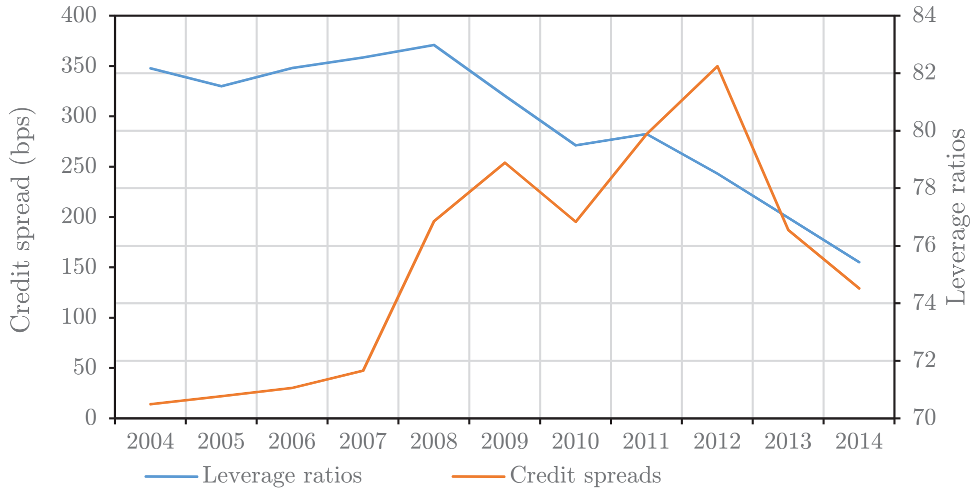
Figure II.7.b - Credit spread gap between financial and non-financial bonds



Credit spreads by type, credit spread of financial bonds minus non-financial bonds spreads. Investment grade only. Source: SIX-Financial and author calculation

Furthermore, the increase in the spreads of financial bonds since the beginning of the crisis seems, remarkably, to go against the view of the structural models. As argued in chapter I, a decrease (increase) in firms' leverage ratios must be associated with a decrease (increase) in their riskiness and thus with a decrease (increase) in credit spreads. Knowing the continuous deleveraging of the financial sector since the beginning of the crisis to meet the regulatory constraints (see Figure II.7.c), this means that lower leverage levels were consistently associated with higher credit spreads for the financial sector. This observation brings indeed another evidence to a decrease in the sensitivity of credit spreads to leverage ratios since beginning of the crisis.

Figure II.7.c - Financial firms credit spreads and leverage ratios

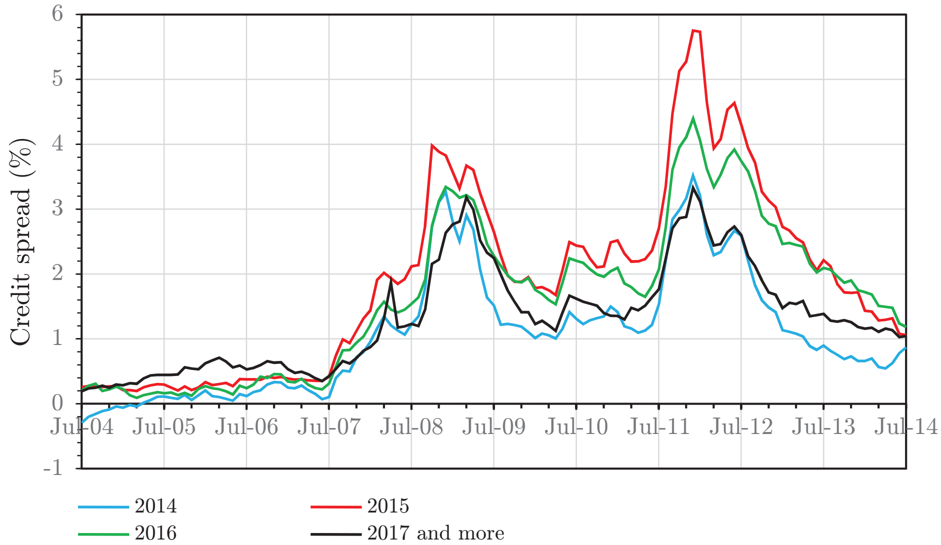


Annual credit spreads and leverage ratios for the fiancial sector. Source : Six-Financial, Datastream and author calculation

Finally, as far as July 2014, the gap between financial and non-financial firms spreads tightened back to 40bp, suggesting a recovery in investors' confidence in the financial sector (Figure II.7.b). This gap is though still far from the negative values observed in the pre-crisis period, which suggests a permanent change in the pricing of risk inside the spreads since the beginning of the crisis. This evidence needs though further empirical investigations that will be presented in subsequent sections.

3.8. A change in the relation between credit spreads and time to maturity since the beginning of the crisis:

Figure II.6 - Credit spreads by Maturity



Credit spreads by maturity, Investment grade only. Source: SIX-Financial and author calculation

Figure II.8 considers the relation between credit spreads and four groups of maturities for the bonds in our sample: bonds maturing in "2014"; "2015"; "2016" and bonds maturing in "2017 and more"[32]. Starting from this figure, we can see the occurrence of a change in the relation between credit spreads and time to maturity since the beginning of the crisis. More specifically, during the pre-crisis period (i.e. from July 2004 to June 2007), we note that the "2017 and more" maturities group (i.e. the longest maturities) had continuously the highest credit spreads (30 bps on average), while the "2014" maturities group (i.e. the shortest maturities) maintained the lowest levels of credit spreads (8 bps on average). In line with the structural models view discussed in chapter I, investors seemed to

[32] Doing so, we placed respectively 18, 11, 14, and 13 in the "2014", "2015", "2016" and "2017 and more" maturities groups. This last group include 2, 8, 2, and 1 bonds maturing, respectively, in 2017, 2018, 2019, and 2022. Note that, as previously, we used here only Investment grade bonds in order to have a more homogenous view on spreads.

price higher risk premiums for bonds with longer maturities during this period[33]. Logically, longer times to maturity were consistently associated with higher uncertainty about economic conditions and firms' defaults; they were thus compensated by higher credit spreads. Following the onset of the subprime crisis, the relation is found to undergo considerable changes. More precisely, Figure II.8 shows that the spreads of the "2017 and more" maturities group witnessed significant reduction since the beginning of the crisis compared to the other maturities group. After keeping the highest levels in pre-crisis period, the spreads of this group became one of the lowest since the onset of the crisis (i.e. the lowest level in 17 months and the second lowest level in 68 months since July 2007). This observation suggests indeed a change in investors risk pricing with regard to maturities since the beginning of the crisis. Facing higher uncertainty about the economic conditions in the short run, investors perceived, arguably, longer maturities as a synonym of a better economic conditions and lower uncertainty; they reduced hence their risk premiums for these bonds, which made their credit spreads decrease. More support to this idea can be indeed given when we see that the "2017 and more" maturities group had the lowest spreads in the periods where the Subprime and Eurozone crisis reached their worst; i.e. in the last two quarters of 2008 and 2011 (Figure II.8). With regard to the remaining maturities groups, Figure II.8 shows that the order of these maturities changed and became more mitigated since July 2007. This can be in fact seen as a proof of a decrease in the importance of the risk premiums associated with time to maturity inside these bonds to the expense of other risk factors since the beginning of the crisis. In sum, these findings bring evidence to a change in the relation between credit spreads and time to maturity since the outbreak of the crisis; the clearest manifestation of this change is a reduction in the risk premiums priced inside bonds of longer maturities.

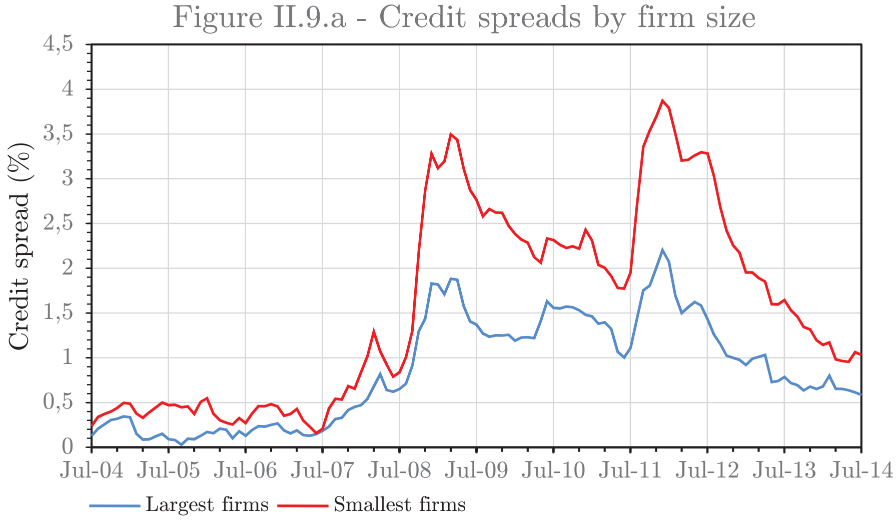
3.9. An increase in the gap between the spreads of the largest and the smallest firms since the beginning of the crisis:

Figure II.9.a and II.9.a present, respectively, the average credit spread for the largest and smallest firms in our sample (based on their market capitalization), and the gap between the spreads of these two groups of firms[34].

---

[33] See for instance the term structures of credit spreads of that we presented in chapter I for the models of Merton (1974) and Collin-Dufresne and Goldstein (2000).

[34] Figure II.9.a presents the average credit spread for the five largest firms in our sample against the five the smallest firms These firms are chosen according to their average market capitalizations for the period and include, on the one hand, BNP, Bank of Scotland, EDF, GDF, and Unicredit for the largest firms sub-sample, and on the other hand, Acea, Confinimmo, Elia-System, Fortis and Credit du Nord, for the smallest firms sub-sample.



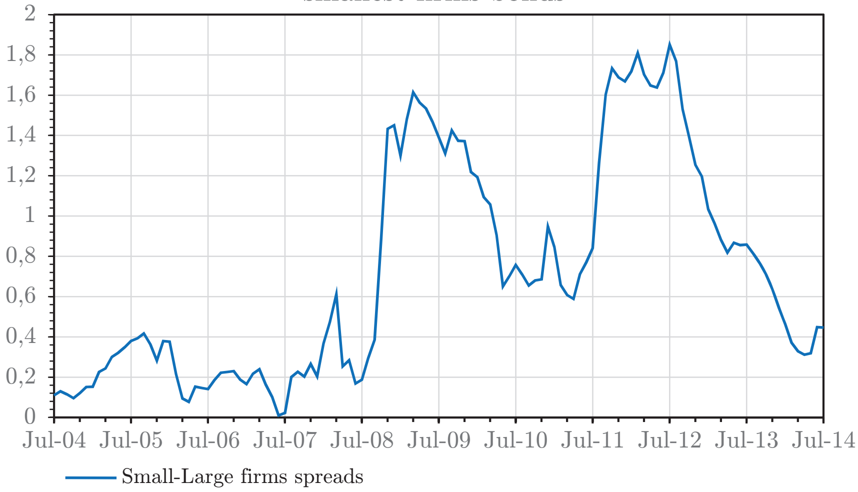
Credit spreads by firm size, Investment grade only. Source: SIX-Financial and author calculation

These figures show clearly the incidence of an increase in the gap between the spreads of the smallest firms and the largest firms since the beginning of the crisis. More specifically, Figure II.9.a shows first that the spreads of the smaller firms maintain consistently higher levels of credit spreads in the pre-crisis and the crisis periods. In agreement with the structural models view discussed in chapter I, firms with higher firm values (here proxied by market capitalization) have lower levels of credit spreads (higher firm values are theoretically associated with lower credit spreads since they drive the firm away from the default boundary). Further, we note remarkably that the gap between the spreads of the smallest and largest bonds increased since the beginning of the crisis (Figure II.9.b)[35]. Ranging on average between 1 and 41 bps before July 2007, this gap widened afterwards, and reached highs of 161 bps in March 2009, and 185 bps in July 2012. This observation can be also interpreted as consistent with the phenomena of "flight to quality": facing an increasing uncertainty about the situation of the smallest firms since the beginning of the crisis, investors turned arguably more increasingly toward "better quality" investments such as firms of higher capitalizations. As such, the demand for these bonds and their prices increased which made their credit spreads fall gradually (conversely, the prices of lower capitalizations decreased and their spreads increased)[36]. Furthermore, Figure II.9.b shows that the gap reached its high during the Eurozone crisis period; everything else being equal, this can be interpreted as an intensification of the phenomenon of flight to

[35] This gap is calculated by subtracting average credit spreads of the smallest minus the average spreads of the largest firms. All things equal, a higher gap means, either lower spreads for larger firms, or higher spreads for smallest firms.
[36] For the case of large banks, the lower spreads can be also due to the implicit authorities' guarantees (see for e.g OECD, 2012 "Implicit Guarantees for Bank Debt: Where Do We Stand").

quality during this period (arguably due to lower risk premiums in the spreads of the largest firms).[37]

Figure II.9.b - Credit spread gap between largest and smallest firms bonds



Avera credit spreads difference between smallest and largest firms sample. Source: SIX-Financial, Datastream and author calculation

3.10. Increase in the volatility of the spreads of the bailed-out firms after the bailouts:

Figure II.10 presents the credit spreads of five firms in our sample that were bailed out during the crisis period[38]. From this figure we note importantly that, following the bailout, the spreads of the bailed-out firms decrease temporarily, but soar to unprecedented levels in the first episode of economic turbulence following the bailout. More specifically, Figure II.10 shows that the spreads of four of the five bond decreased by about 10% on average during the month where they were bailed out[39]. This is indeed in accordane with the theoretical and economic intuition that suggests that receiving a financial help (for instance a bailout or capital augmentation) is supposed to increase the firm's value, drive it away from the default boundary and hence decrease its credit spread. Further, Figure II.10 shows that these reductions in the spreads were only temporary (the spreads of Citigroup and RBS recorded in fact only one month of decrease after their bailout, while the spreads of Commerzbank and HBOS-Lloyds recorded,

[37] In Chapter III we investigate credit spread determinants for different groups of firm sizes.

[38] These include HBOS, Citigroup, Royal bank of Scotland (RBS), Bancaja, and Commerzbank. The red line in each of the sub figure indicate the date of the bailout. Note that the dates of: (i) the beginning of negotiation of the bailout; (ii) the agreement of the bailout; and (iii) the effective fulfillment of the bailout are sometimes hard to distinguish or to find. We use here the first available information about the realization of the bailout as the effective date of the bailout.

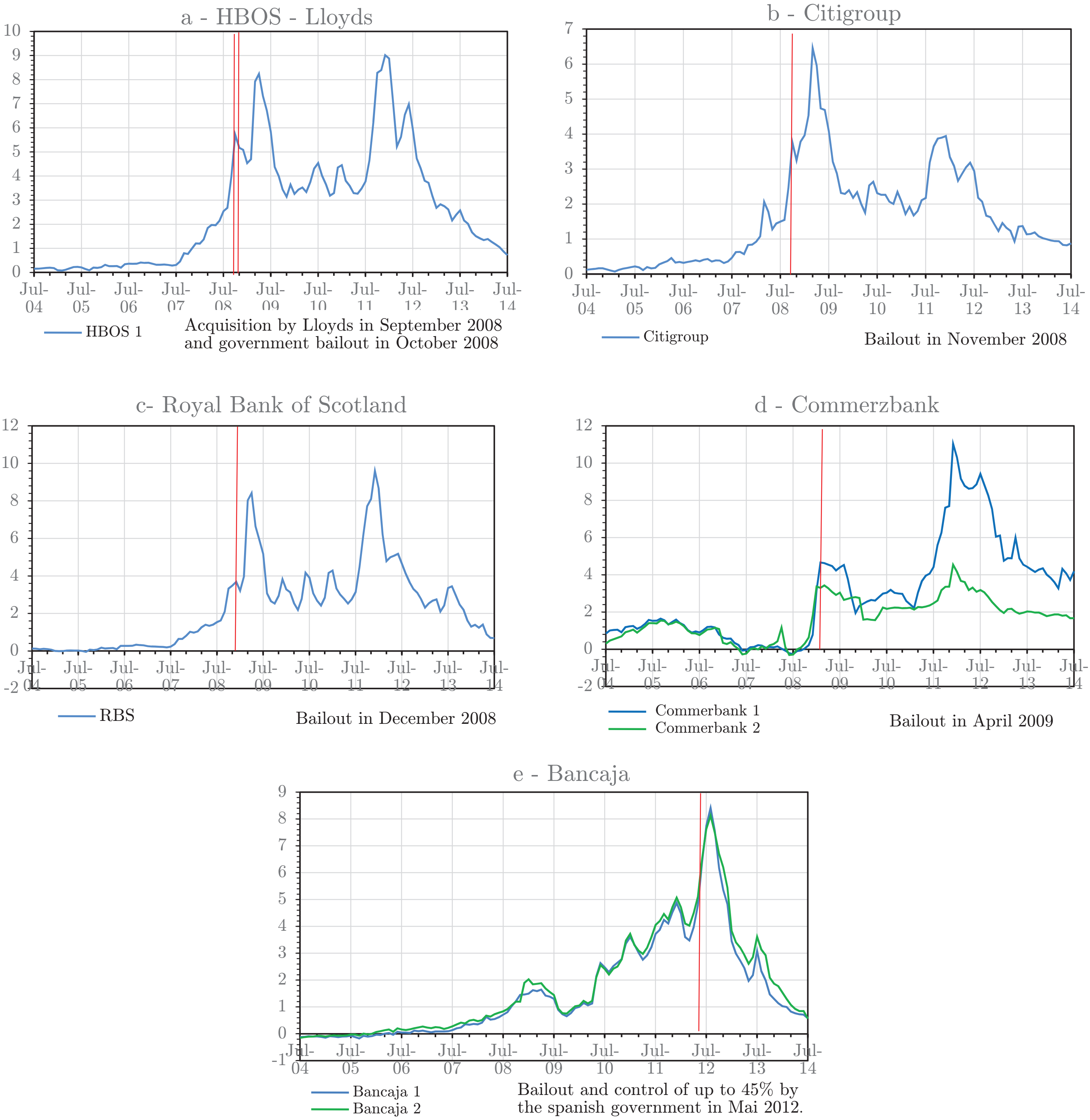
[39] These are HBOS-Lloyds, Citigroup, RBS and Commerzbank. This effect was however less clear for the spreads of Bancaja, which continued increasing in the months following the bailout

respectively, 2 and 3 months of decrease). Following these brief decreases, credit spreads of these entities showed an increasing sensitivity to the episodes of economic turbulence, and soared to unprecedented levels in the first main economic shock following their bailout. In particular, we note that the spreads of HBOS-Lloyds, Citigroup, and RBS reached highs of, respectively, 792 bps, 645 bps, and 803 bps in the turbulence episode of March 2009; the spreads of Commerzbank1 peaked to a level of 1103 bps in the market turbulence of December 2011; while the spreads of Bancaja reached 840 bps in the Eurozone crisis episode of August 2012[40]. These increases in the spreads bring evidence to an increase in markets participants' worries about the robustness of the bailed out firms. These worries can be justified due to their previous setbacks, and arguably, due to a higher incertitude about the authorities' willingness to rescue them once again in the case of default. In sum this observation is consistent with an increase in the volatility of the spreads of the bailed-out firms after the bailouts. This observation is indeed appealing since it considers some of the movement in credit spreads that are not predicted by theory. These results need however further investigations in order to better understand the reality of the effect of the bailouts on the spreads.

In summary, the stylized facts identified in this section allow us to put light on several factors and dynamics that have not been considered by the theoretical models of corporate bond valuation. First, we note the emergence of new factors such as systemic risk (e.g. the threat of the breakup of the Eurozone), default contagion risk (e.g. the fear of contagion following the bankruptcy of Lehman Brothers), bailouts, and the actions undertaken by the Central banks and governments, which had apparently an important impact on the movements and the levels reached by the credit spreads during the crisis. Second, we find that the co-movements between credit spreads and some of the main credit spread determinants according to the theoretical valuation literature (e.g. leverage ratios and time to maturity) have changed considerably since the beginning of the crisis. Third, we note that some well documented phenomena in the economic and financial literature (e.g. the paradoxes of tranquility and credibility, the phenomena of flight-to-quality and flight-to-liquidity) were important drivers of the observed developments in the corporate bond market. Finally, we find a primary evidence on a change in the factors that affect credit spreads since the beginning of the crisis. This evidence needs however further empirical investigations, which will be provided in what follows by a principal component analysis of credit spreads.

[40] We note however that the spreads of Commerzbank 1 and 2 present a mitigated evidence in this regard: the spreads of Commerzbank 1 rose to 1103 bps in December 2011, while those of Commerzbank 2 reached only to 416 bps in the same month.

Figure II.10 - Credit spreads of the bailed-out firms



4. Principal component analysis of credit spreads:

The stylized facts proposed in the previous section bring a primary evidence of a change in the dynamics of credit spreads and the factors that affect them since the beginning of the crisis. To complete this evidence, we propose next to lead a Principal Component Analysis (PCA) of the 71 bonds spreads in our sample. We start this section by bringing more details about the motivation behind the use of this approach and the methodology of the analysis, before reporting the results of the PCA.

4.1. Motivation and methodology:

The aim of this study is to examine of the impact of the crisis on credit spreads in order to draw conclusions for the valuation of corporate bonds. To do so, we propose in this section to explore the principal components of credit spreads levels and to check if these components have changed since the beginning of the crisis. The chosen analytical tool for this aim is the Principal Component Analysis (PCA). PCA is a standard and quite simple statistical tool frequently used in diverse scientific fields. It consists broadly of searching for patterns of movement common to several series in a data set, and then expressing the data in such a way as to highlight its similarities and differences (Smith, 2002). This is done by transforming mathematically the data set to a coordinate system composed by a number of new components; the first component captures the greatest variance of the data set, the second component the second greatest variance, and so on[41]. The features of this technique, as well as its suitability for our credit spreads sample, fits hence to the aim of this study[42]. Another motivation for the use of the principal component analysis streams from the fact that credit spreads' time-series are non-stationary (see Appendix II.4); thus, any regression analysis of credit spread in levels would be biased. Finally, the use of the principal component can be also motived by the large number of studies that used this technique in the analysis of credit spreads. These include, Collin-Dufresne et al. (2001),

[41] This is done by the means of an orthogonal linear transformation of the plugged variables while optimizing a certain algebraic criterion (Jolliffe 2002).

[42] In order to use PCA, four main assumptions need to be made: First, linearity of the variables. Second, mean and variance statistics explain entirely a probability distribution (which is not the case for all probability distributions). Third, the principal components with the largest variances represent the most important structure, while those with lower variances represent noise (which may be sometimes miss-leading). Fourth, the principal components are orthogonal (this assumption is simplification that allows to use linear algebra decomposition techniques). Source: Shlens (2009) A Tutorial on Principal Component Analysis.

Avramov et al. (2007) and Di Cesare et al. (2010)[43]. This brings support to the suitability of this technique for the analysis of credit spreads.

This analysis is organized as follows: we start first by exploring the principal components of credit spreads for the full sample period (i.e. from July 1st, 2004 to July 31th, 2014); this enables us to have an idea on the number of the main determinants of credit spreads levels in the long run regardless the economic conditions for the period. Following this, we explore the changes that components of credit spreads have experienced since the beginning of the crisis. This is done by assessing the variation of the principal components between the, pre-crisis, subprime crisis and Eurozone crisis periods[44]. The following lines present the main results of these principal component analysis.

4.2. Results:

PCA uses the Pearson's correlation matrix to transform the initial data set into a set of new components, or factors, classified by descending order of importance. It attributes a factor to each dimension of the data, and an "Eigenvalue" to each factor. The main information from the data can be then illustrated using "Scree plots of Eigen values" and "correlation circles"[45]. In what follows, we use these illustrations, in addition to the Pearson's correlation matrix, to present the main results from the PCA. We start by discussing the results of the PCA for the full sample analysis before presenting the results of PCA for the three sub-periods analysis.

4.2.1 Full sample analysis:

4.2.1.1. Correlation Matrix:

Appendix II.9 presents an extensive view on the correlation matrix of the credit spreads analyzed between July 2004 and July 2014[46]. The following observations can be made starting from this correlation matrix:

[43] PCA was however used in these studies, either to analyze credit spreads changes, or to investigate regressions residuals after an analysis of credit spreads determinants. An evidence for the use of PCA for levels data exists however for the analysis CDS spreads, which is done by Ericsson et al. (2005). Note finally that PCAs on changes data and regression residuals will be performed in chapter III.

[44] We do so by implementing three Principal Component Analysis on three sub-samples corresponding to each of these periods.

[45] The "Scree plot of Eigen values" is graphical representation of the Eigenvalues of all the factors along with their cumulative inertia.

[46] Due to the size of the matrix (8591 values) we present only an extract of it (Appendix. II.9)

- The correlations between the credit spreads of the different entities are generally high and positive; they revolve around 74% on average. Hence, an increase in the credit spreads of a firm is generally associated with an increase in the spreads of the other firms.

- Using "Bartlett's sphericity test", we find only two firms present non-significant correlations at the 5% level; these are CIBA, and Telstra (two non-financial firms respectively from Switzerland and Australia). Otherwise, the levels of the credit spreads are largely found to be significantly correlated. This brings support to the observations made about the tight connections that exist between the movements of the different spreads.

- Correlations between the credit spreads of the firms from the financial sector are found to be the highest between the analyzed credit spreads; they range around 78% on average.

- Entities that have the lowest correlations with other entities' credit spreads are respectively, CIBA, Telstra, Cofiroute, Airbus, Volkswagen, Arcelor and Wendel. All these, except Wendel, are non-financial firms[47].

- Non-financial firms' spreads present generally low correlations with other non-financial firms' spreads, their correlations revolve around 69% on average. However, the two lowest correlations in the sample are observed, respectively, between the spreads of Telstra-Commerzbank and CIBA-BNP.

4.2.1.2. Principal components:

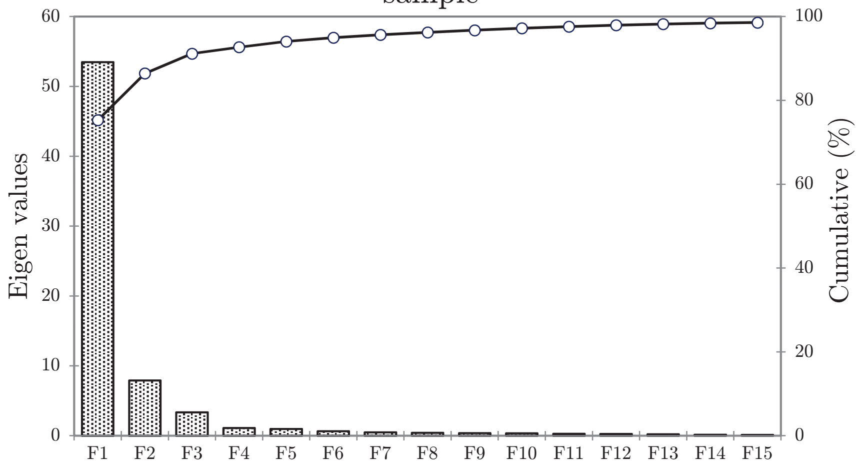
Table II.1 – Eigen values and percentage Inertia:

	F1	F2	F3	F4	F5
Eigen value	53,465	7,912	3,348	1,108	0,954
Inertia (%)	75,303	11,144	4,716	1,560	1,344
Cumulative (%)	75,303	86,446	91,162	92,722	94,066

Table II.1 and Figure II.11.a present the results of the PCA for the full sample analysis. "Eigen values" represent the quality of the projection of the 71 initial spreads on the new factors, while the "percentage inertia" highlight how much each factor represent from the initial variability.

[47] We find so by counting the number of correlations under 40% that each firm has with the others. Similar results are found when calculating the average correlations between each firm and the others.

Figure II.11.a. Scree plot of Eigen values - Total sample



Interestingly, we find that the first principal component of credit spreads levels has a substantial Eigen value (53.4), and captures up to 75.3% of credit spreads' variability. Following the structural models evidence discussed in chapter I, we can interpret this first principal component as representative of the default risk component in credit spreads[48]. Moreover, Table II.1 shows that the second principal factor represents up to 11.14% of the total variability of credit spreads. If default risk is the first principal component credit spreads levels, it is arguably not the only important component; another component represents a significant portion of credit spread[49]. Furthermore, Table II.1 shows that the following three factors capture, respectively, 4.71%, 1.56% and 1.34% of credit spread variance. These three factors need not hence to be neglected, compared to the following components which present very poor projection (less than 1% inertia starting from the sixth factor, see Figure II.11.a). All together, the first five principal components are found to explain up to 94.06% of credit spread variability; according to this PCA, five factors are hence sufficient to capture the most important portion of the information laying behind credit spread levels.

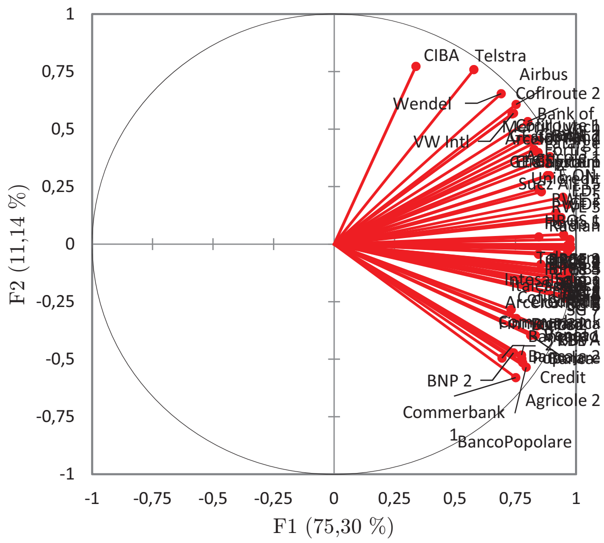
Furthermore, since the Eigen values of the two principal components correspond to a high percentage of the initial variability of the credit spreads (86.45%), we can use the "correlation circle" of the first two factors to have a

[48] One of the major drawbacks of PCA is that it doesn't allow to deduce directly the nature of the components.

[49] Using CDS spreads levels data, Ericsson et al. (2005) find the first and second principal components explain, respectively, 58.7% and 20.3% of CDS spread bids.

better idea on the correlation between credit spreads and these two factors (Figure II.11.b)[50]:

Figure II.11.b - Total sample analysis



Numerous observations can be made starting from this correlation circle. First, in agreement with the results of the correlation matrix, we note that credit spreads are strongly and positively correlated over the ten years period[51]. Second, credit spreads of the different firms are found to be close to the edge of the correlation circle; all the spreads are hence largely dominated by these same two principle components (the lowest correspondence is again attributed to CIBA). Finally, with regard to the correlation between credit spreads and the two principal components, we note that all credit spreads are positively correlated to the first principal component, while 43 credit spreads over 71 are negatively correlated with the second principal component[52]. This brings support to the idea that the first principal component is default risk, since it is known to be positively related

[50] The correlation circle shows a projection of the initial variables onto the factors space and can be interpreted as follows: when two variables are far from the center, then, if they are: close to each other, they are significantly positively correlated (correlation "r" is close to 1); if they are orthogonal, they are not correlated ("r" close to 0); if they are on the opposite side of the center, then they are significantly negatively correlated ("r" close to -1). However, when the variables are close to the center of the circle, it means that some more information is carried on the other axes, and that any interpretation might be hazardous.

[51] The firms that have the lowest correlations are found to be orthogonal to each other in the circle. These include the couples: Telstra and Commerzbank; CIBA and BNP; Wendel and Banca Popolare (See Figure II.11.b).

[52] Similar proportion of negative correlations is also found for the third principal component, 35 and 33 respectively for the fourth and fifth components.

with the levels of credit spreads. The nature of the second component (which is mainly negatively correlated to spread) is however unclear at this level.

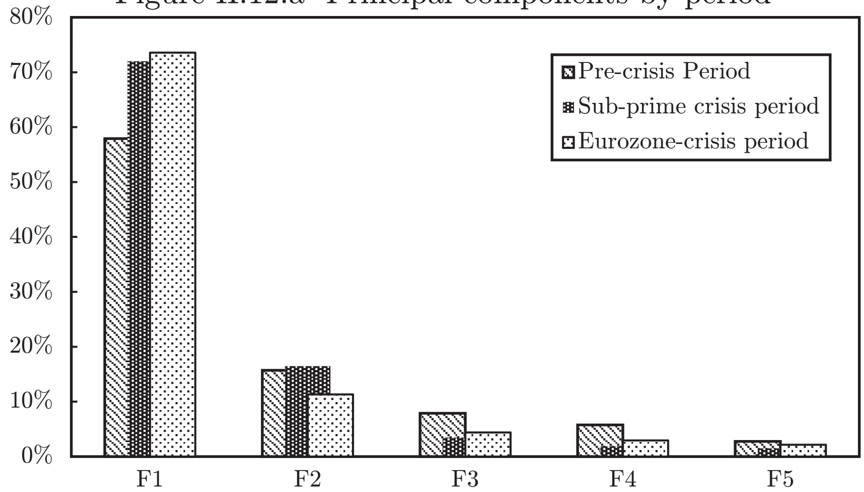
In summary, leading PCA on credit spreads levels for a period encompassing tranquil economic growth and crisis sub-periods shows that the spreads are mostly dominated by the same components. Five principal components are found to be able to explain a substantial portion of the credit spreads variance. While the nature of the first principal component can be logically attributed to credit risk, the nature of the remaining components is rather hard to define at this level. These can be attributed, for instance to macroeconomic or market conditions, to liquidity risk or to information asymmetries[53]. In what follows, we compare these results to the results of the PCA for the three crisis sub-periods.

4.2.2 Sub-periods analysis:

Table II.2 - Eigen values and percentage Inertia by period:

		F1	F2	F3	F4	F5
Pre-crisis Period	Eigen value	41,119	11,162	5,586	4,077	1,952
	Inertia (%)	57,914	15,721	7,868	5,743	2,75
	Cumulative (%)	57,914	73,635	81,503	87,246	89,995
Sub-prime crisis period	Eigen value	51,129	11,691	2,448	1,323	1,054
	Inertia (%)	72,012	16,466	3,448	1,863	1,485
	Cumulative (%)	72,012	88,479	91,926	93,789	95,274
Eurozone-crisis period	Eigen value	52,235	8,039	3,104	2,083	1,515
	Inertia (%)	73,571	11,322	4,372	2,934	2,134
	Cumulative (%)	73,571	84,893	89,265	92,199	94,333

Figure II.12.a- Principal components by period



[53] The nature of these components will be explored with more details in chapter III.

Table II.2 and Figure II.12.a present a comparative overview of the results of the PCAs conducted on the following three periods' sub-samples: (*i*) between July 2004 and June 2007 (i.e. the pre-crisis period); (*ii*) between July 2007 and April 2010 (i.e. the subprime crisis period); and (*iii*) between Mai 2010 and July 2014 (i.e. the Eurozone crisis period)[54]. These PCAs bring some interesting highlights on the impact of the crisis on the credit spreads. First, we note that the first principal component corresponds to an almost similar portion of credit spreads' inertia in the subprime crisis and Eurozone crisis (respectively 72.01% and 73.57%). Compared to the pre-crisis period where it represented only 57.91% of inertia, this result can be interpreted as synonym of an increase in the impact of this component on yield spreads since the beginning of the crisis. If this first principal component is to be attributed to default risk, this means that the default risk took a larger proportion in the levels of credit spreads level since the onset of the crisis. This seems plausible from the structural models point of view since, for instance, a higher level of shocks on the firms' values (the crisis) increases the levels of credit spreads (see the model of Zhou, 2001 analysed in chapter I). Second, with regard to the second principal component, we find contrarily that it represents an almost similar portion credit spreads' variance in the pre-crisis and the subprime crisis periods (respectively 15.72% and 16.46%). The proportion of this second component decreased indeed in the Eurozone crisis period (11.32%), which highlights a change in its impact on credit spreads only starting from Mai 2010. Considering the three following components, we note that, similarly to the first principal component, their percentage inertia witnessed a substantial change since the onset of the subprime crisis. Table II.2 shows that the percentage-inertias of these factors kept closer proportions in the two crisis periods compared to the pre-crisis period (e.g. the third component represented 7.86% inertia in the pre-crisis period 3.44% in the subprime crisis period and 4.37% in the Eurozone crisis period). Finally, we note that the five principal components are capable of capturing a large, and almost similar, proportion of credit spreads variance in the subprime crisis and the Eurozone crisis (respectively 95.27% and 94.33%). Compared to the pre-crisis period where they explain only 89.99% brings evidence of a change in dynamics of risk pricing inside the corporate bond market since the beginning of the crisis. These observations bring a first evidence to the occurrence of a change in the importance of the factors that affect credit spreads since the onset of the crisis. More support to this evidence can be provided by the analysis of the correlation circles of the spreads in the three considered sub-periods:

[54] We do so by dividing our initial sample into three sub-sample corresponding to each of these periods, before running a PCA on each of these sub-samples.

Figure II.12.b - Pre-crisis

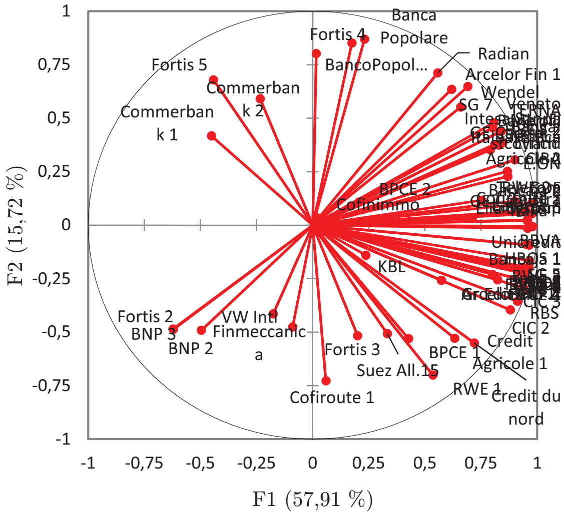


Figure II.12.c - Subprime crisis

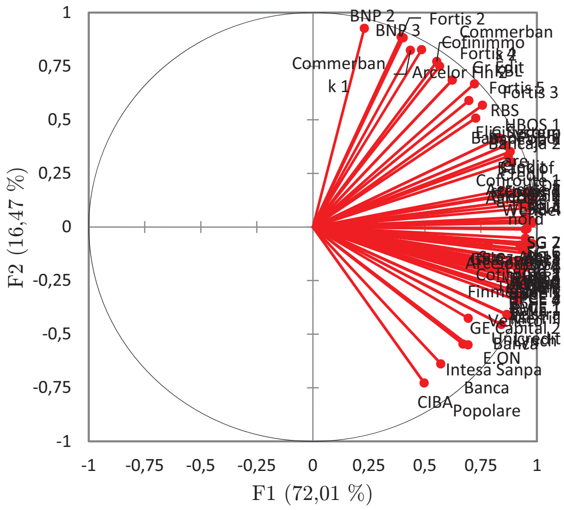
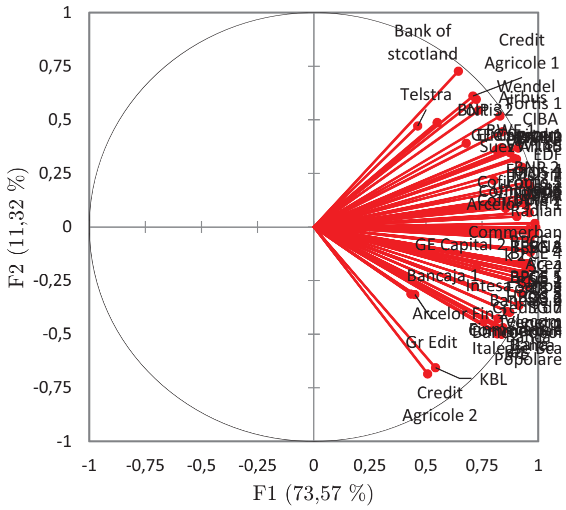


Figure II.12.d - Eurozone crisis



Figures II.12- b; -c; and -d present the correlation circles after PCA for each of the three sub-periods analysis. Analysing these correlation circles brings some more insights to the impact of the crisis on the credit spreads. Considering the correlation between the initial variables, Figure II.12.b shows that credit spreads were quite dispersed onto the factorial map in the pre-crisis period. Correlations between bonds' yields were relatively small in this periods, and the spreads of some firms presented even negative correlations[55]. Following the onset of the crisis, Figures II.12.c and II.12.d show interestingly that tshe correlation between credit

[55] The spreads of seven firms presented generally negative correlations with the spreads of other firms during this period. These are mainly: BNP, BPCE, Commerzbank, Cofiroute, Fortis, Finmeccanica and Volkswagen.

spreads rose substantially (especially during the Eurozone crisis period), and that the signs of the correlations became exclusively positive[56]. This result is appealing in two main regards. First, it highlights an increase in the correlation between the yields of the different firms in the subprime crisis period, and an even higher correlation in the Eurozone crisis period. Similar empirical findings about an increase in the correlation between financial assets have been indeed documented by N. Frank (2009), S. Junior (2011) and I. Moldovan (2012) in the subprime crisis[57]. Second, the increase in the correlations suggests that the factors that drive credit spreads levels became increasingly common to all firms since the beginning of the crisis. This result highlights, interestingly, an increase in the impact of the aggregate factors, such as macroeconomic or market wide risks, on the yields of the corporate bonds since the beginning of the crisis.

We propose next to specify the previous results by analyzing, on the one hand, the correlation between credit spreads and the principal components, and on the other hand, the squared cosine of the credit spreads and the five principal components. As regards the correlations, we note that many firms had low or negative correlations with the first principal component in the pre-crisis period[58]. Comparing this to the following two periods where spreads are found to be strongly, and exclusively positively correlated with the first principal component, suggests an increase in the importance of this component since the beginning of the crisis. Again, if this first component is to be attributed to default risk, this means that market participants priced higher levels of credit risk inside credit spreads since the beginning of the crisis. Considering next the correlation between credit spreads and the following four components, we find quite mitigated evidence about the sign of the correlation in the three sub-periods. Remarkably, we note that the second principal component presented 38 negative against 33 positive correlations with the spreads in the pre-crisis period; 40 negative against 31 positive correlations in the subprime crisis period; and 37 negative against 34 positive correlations in the Eurozone crisis period. This result suggests that the observations made in the full sample analysis about a negative correlation between the second component and the spreads is not stable over time.

Considering the squared cosine of the credit spreads and the five principal components, Table II.3 summarizes the number of credit spreads with the greatest squared cosine for each factor, in each of the studied sub-periods:

---

[56] This can be noted from the closeness of the lines in the correlation circles.

[57] However, these latter concentrate mainly on the stock market.

[58] These firms are the same seven firms mentioned above. These firms had hence different risk structure compared to the other firms in the pre-crisis period.

Table II.3 - Number of spreads with the greatest squared cosine by factor

Period	F1	F2	F3	F4	F5
Pre-crisis period	52	8	7	3	1
Subprime crisis period	60	11	0	0	0
Eurozone-crisis period	65	4	1	1	0

Table II.3 shows interestingly that the first factor was generally the most dominant component of credit spreads across periods. Indeed, 52 spreads had the first factor as their first principal component during the pre-crisis period; 60 spreads in the subprime crisis period; and 65 in the Eurozone crisis period. The observed increase in the importance of this factors reveals additionally an increase in the worries of market-participants about this factor since the beginning of the crisis (arguably, an increase in the worries about firms' defaults). Furthermore, Table II.3 shows that the spreads were more dispersed on the five principal components in the pre-crisis period as compared to the two subsequent crisis periods. For instance, with regard to the last three principal components, we note that 7 bonds had the third factor as their principal component in the pre-crisis period; 3 bonds had the fourth factor as a principal component; and 1 bond had the fifth component as a principal component. Following the outbreak of the crisis, the importance of these three factors decreased substantially as the spreads became mainly concentrated on the two first components in the subprime and the Eurozone crisis periods. This result brings an additional evidence to the occurrence of a change in the importance of the factors that affect credit spreads since the beginning of the crisis. We interpret this result as consistent with a time varying sensitivity of credit spreads to the factors that affect them.

In summary, the different principal component analysis performed in this section bring some interesting insights about the structure of the factors that affect credit spreads' levels as well as their behaviour during the crisis. Our main results are as follows. First, we find that five principal components are able to capture up to 94.06% of credit spreads levels between July 2004 and July 2014. Second, we note that the same five principal factors explain a larger proportion of credit spreads levels since the beginning of the crisis, suggesting in increase in the importance of these factors since July 2007. Third we find evidence for an important increase in market participants' worries about the first principal component since the onset of the crisis, which manifested through an increase in the sensitivity of the different spreads to this factor. Finally, we document an increase in the correlations between spreads since the outbreak of the subprime crisis, which increased even more after the beginning of the Eurozone crisis. This suggests that the factors that affect credit spreads levels become increasingly common. All in all, these findings are consistent with a change in the pricing of risk and a change the sensitivity of credit spreads to the different credit spread determinants since the outbreak of the subprime crisis.

5. Conclusion:

This chapter has attempted to investigate the factors and the dynamics that emerged in the corporate bond market during the crisis, in order to draw some useful conclusions for the valuation of corporate bonds. Our approach was twofold. First, we identified a set ten stylized facts about the evolution of credit spreads and the factors that affect them during the crisis. Second, we conducted a Principal Component Analysis of credit spreads levels for different sub-periods including the pre-crisis, the subprime crisis and the Eurozone crisis periods.

As regard the stylized facts, our analysis allowed us to highlight on three main groups of results. First, we noted the emergence of numerous factors that have not been, or have only sparsely, been considered by the theoretical models of corporate bond valuation, and that have a considerable impact on credit spreads. These include: (*i*) default contagion risk (e.g. the collapse of a bank or the default of a country is generally found to be associated with an increase in the credit spreads of the different corporations); (*ii*) the risk of collapse of an entire economic or financial system (e.g. the threat of the breakup of the Eurozone is found to have a considerable positive impact on the spreads); (*iii*) bailouts and the rescue politics (e.g. the bailout of some major financial institutions and governments is found to be linked to a temporary reduction in their spreads, followed by an increase in the volatility of these latter); (*iv*) the actions undertaken by the central banks and the different governments to stabilize the financial system (e.g. the creation of the Financial Stability Board, the creation of the European Financial Stability Facility, the agreement of the Long Term-, and Main-, Refinancing Operations had presumably considerable effect on the reduction of the spreads).

Second, we found remarkably that the co-movements between the credit spreads and some of the main credit spread determinants according to the theoretical valuation literature (e.g. leverage ratios and time to maturity) have considerably changed since the beginning of the crisis. We noted mainly that: (*i*) the sensitivity of the spreads to the firm specific leverage ratios decreased substantially during the crisis (probably in favour of the market wide risk factors); and (*ii*) that the relation between credit spreads and time to maturity changed since the onset of the crisis. This latter result was evidenced by a decrease in the credit spreads of long-maturity bonds, and suggests, interestingly, that longer maturities became consistent with lower risk premiums since the beginning of the crisis.

Third, we noted that some well documented phenomena in the economic and financial literature can help in explaining the observed levels and movements of the spreads during the crisis. These include: (*i*) the paradoxes of tranquillity and credibility (respectively, Minsky, 1975, 1977; Borio and Shim, 2007), which help understanding the low credit spreads that prevailed in the pre-crisis period and the upsurge of these latter since the beginning of the crisis. (*ii*) The phenomena of flight-to-quality and flight-to-liquidity, which explain the observed sudden increases in the yields of corporate bonds and the sudden decreases in the yields of government bonds yields during the crisis, as well as the higher credit spreads that were observed for the firms of smaller sizes since the onset of the crisis. (*iii*) The financial instability hypothesis (Minsky, 1975; 1977; 1982), which puts light on the increased fragility of the financial sector since the beginning of the crisis and the need for the authorities' actions to stabilize this latter.

As regards the principal component analysis of credit spreads levels, our results were conclusive in many regards. First, we noted that the same five principal components of credit spreads explain a larger proportion of these latter since the beginning of the crisis. This suggests an increase in the sensitivity of credit spreads to these factors since July 2007. Second, we found evidence for a substantial increase in the sensitivity of the spreads to the first principal component since the onset of the crisis. If the principal component of credit spreads is to be attributed to default risk, as claimed by the structural models, our evidence is consistent with higher levels of default risk inside credit spreads since the beginning of the economic and financial turmoil. Finally, we documented an increase in the correlations between the spreads of the different corporations during the subprime crisis, which increased even more during the Eurozone crisis. This result implies that the factors that affect credit spreads levels became increasingly common in these periods. Interestingly, all these results are found to persist since July 2007, suggesting a permanent change in the pricing of risk inside the corporate bond market.

Overall, this chapter brings a preliminary evidence on the effect of the crisis on the credit spreads and their determinants. Our evidence is consistent with a change in the structure of the factors that affect credit spreads, as well as a change in the sensitivity of the spreads to some of their determinants since the onset of the crisis. We conclude that the structural models should be enhanced in such a way as to account for the different stylized facts on the effect of the crisis, in addition to all the possibilities of enhancements discussed in the first chapter.

Finally, the conclusions we made in this chapter about the effect of the crisis on the spreads and their determinants were mainly based on a descriptive approach. This evidence requires hence to be completed by a further statistical investigation. This makes the object of the following chapter.

Chapter III

The determinants of credit spread changes during the crisis

1. Introduction:

The recent economic and financial turmoil has impacted corporate credit spreads in a way that was not considered by most of the existing valuation models. Chapter II has provided preliminary evidence on this impact by highlighting the emergence of new factors and new dynamics during the recent economic and financial crisis, which go beyond the reach of the structural models. In this chapter we propose to extend this evidence by exploring the effective factors that lie behind credit spread movements and the changes that these factors have undergone between the pre-crisis, the subprime crisis and the Eurozone crisis periods. This would allow us to assess the factors that count most in modeling corporate bonds, as well as the changes these factors may incur in a crisis context.

To do so, our approach consists of analyzing, by the means of statistical regression techniques, the most significant factors in explaining credit spread changes, for a sample of 70 Euro-settled corporate bonds, over the July 2004-July 2014 period. In light of the theoretical and descriptive analyses that we carried, respectively, in chapters I and II, we propose to explore a set of credit spread determinants that revolves around five principal components of the spreads. These are: (*i*) credit risk, (*ii*) liquidity risk, (*iii*) macroeconomic and systemic risks (namely, market-wide risks), (*iv*) information asymmetries as well as (*v*) additional factors such as risk premiums and firm-size factors. A parsimonious set of idiosyncratic and aggregate risk proxies is then chosen in order to reflect accurately these determinants.

We proceed our analysis as follows. First, we examine the sensitivity of credit spreads to the introduction, one by one, of the five proposed credit spread components. While doing this, we specify the changes that this sensitivity has undergone between the pre-crisis, the subprime crisis and the Eurozone crisis periods. This allows us to assess the relative importance of each of the explored components and to emphasize the effect of the crisis on this importance. Second, we investigate the robustness of our results by conducting two main types of tests. The first test examines the robustness of the most significant credit spread determinants that we find by assessing how well they explain Credit Default Swap (CDS) spreads. The second test explores the nature of the remaining variation of the spreads by the means of a principal component analysis of the benchmark regression residuals (i.e. the regression that includes all the statistically significant credit spread determinants). Finally, we propose to consider, in further detail, some of the stylized facts that we identified in the previous chapter by specifying our results for different groups of bond maturities, bond ratings and firm-sizes.

Furthermore, compared to some other empirical studies that can be found in literature, this study proposes several original features. First, this study examines the contribution of the main theoretical credit spread determinants to the explanation of credit spread movements, and specifies the changes that this contribution has undergone between the pre-crisis, the subprime and the Eurozone crisis periods. Second, this work explores the effect of some factors and risk proxies that have not been considered by the previous theoretical or the empirical studies on credit spreads. These include: (*i*) "business climate survey" as a proxy of the situation in the real economy; (*ii*) "LTROs" as a proxy of authorities' actions during the crisis, (*iii*) "investors' confidence index" as a proxy of risk premiums, (*iv*) delayed information factors as proxies of information asymmetries, and (*v*) firm-size factors (i.e. the number of employees and market capitalization) as proxies of the "firm-size effect". Third, this study attempts to underline the factors that drive credit spreads for some of the largest firms in Europe, and the changes that factors have experienced since the beginning of the crisis. This aims to emphasize the presence of a "Too big to fail" effect priced in the spreads of the largest firms. Finally, this study checks, in an innovative manner, the robustness of the most significant credit spread determinant by assessing how well they explain CDS spreads.

The remainder of this chapter is organized as follows. Section 2 discusses the empirical literature related to this study. Section 3 presents the hypothesis that we make on the relationship between credit spreads and the factors that affect them. Section 4 describes the data that we use in the analysis of corporate bonds spreads. Section 5 presents the methodology of the analysis of credit spreads, while section 6 discusses its results. Finally, section 7 concludes the chapter.

2. Related empirical literature:

We propose first to review the empirical literature that relates to our study. This will allow us: (*i*) to give some rationale to the approach that we use in our analysis; (*ii*) to shed light on some of the determinants of credit spreads used by the existing empirical studies, and (*iii*) to place our study in a broader context.

Generally speaking, the empirical literature that deals with credit spreads can be divided into two groups of studies. A first group of studies implements the existing theoretical models to real-world data in order to assess their performance in capturing the credit spreads observed in practice. To do so, these studies generally propose methods to estimate the models' parameters (i.e. the credit spread determinants) from market data, then compare the results of the implemented models to the observed credit spreads, or historical default experience. Studies in this strand of literature include Jones et al. (1984); Lyden and Saraniti (2001); Elton, Gruber and al. (2001); Eom et al. (2002); Driessen (2003); Hull et al. (2004); Tarashev (2008), and Forte (2011)[1]. Overall, a consensus emerged from these studies on the fact that the existing theoretical models generate, when implemented, lower credit spreads than those observed in practice. This under-prediction problem has led this strand of literature to talk about the so-called "credit spread puzzle". Despite its theoretical appeal, this approach is rather unsuitable to the aim of this study. It takes indeed as a starting point the existing theoretical models, which makes it impossible to answer one of the objectives of this study: testing the impact of some factors that were not considered by the previous theoretical models on credit spreads.

A more appropriate approach for the aim of this study is in fact the one that has been used by a second group of empirical studies. Initiated by Collin-Dufresne, Goldstein and Martin (2001), this approach consists of using statistical regressions techniques in order to explore the impact of different factors on credit spreads. The observed credit spreads can be hence regressed on the factors that the structural models proposed (or proxies of them), as well as any other factor that the modeler proposes. This approach allows us hence to test the impact of new

[1] Jones et al. (1984) addressed the results of Merton (1974). Lyden and Saraniti (2001) considered the models of Merton (1974) and Longstaff and Schwartz (1995). Eom et al. (2002) implemented the models of: Merton (1974), Geske (1977), Leland and Toft (1996), Longstaff and Schwartz (1995) as well as Collin-Dufresne and Goldstein (2000). Huang and Huang (2003) and Driessen (2003) calibrated their own models to historical default loss data. Hull et al. (2004) implemented the model of Merton (1974) using options' implied volatilities. Tarashev (2008) attempted to calibrate the models of: Longstaff and Schwartz (1995), Sundaresan and Tychon (1996), Leland and Toft (1996), Collin-Dufresne and Goldstein (2000) together with the Moody's KMV model. Finally, Forte (2011) implemented a modified version of Leland and Toft's (1996) model.

factors on credit spreads, and to explore the changes endured by the theoretical determinants since the beginning of the crisis; thereby, it is more suitable for the aim of this study.

Of course, it is of interest to review some of the main results of this strand of empirical literature. In their seminal paper, Collin-Dufresne, Goldstein and Martin (2001) tested the ability of the variables documented by Merton's (1974) model in explaining the changes in the observed credit spread. They found that leverage, risk-free rate and equity volatility (a proxy of assets' volatility) are statistically significant. Interestingly, Collin-Dufresne et al. (2001) found that their set of credit spread determinants were able to explain only 25% of the observed credit spread changes. Analyzing the regression residuals, they found evidence for a large "systemic component" that is beyond the scope of the structural models. Using a quite similar approach, Perraudin and Taylor (2003) tested the impact of a set bond liquidity proxies (i.e. quote frequency, bond age and issue size) on credit spreads. They found that credit spread include a considerable liquidity component. Similarly, Gatfaoui (2004) decomposed credit spread components into a default risk and a liquidity risk components, and gave proof for a non-negligible liquidity risk component inside credit spreads (that is correlated to the default risk component). In the same vein, Avramov et al. (2007) investigated the determinants of credit spread changes using a parsimonious set of idiosyncratic and aggregate variables (e.g. the slope of the yield curve, Fama and French, 1993 factors, and lagged credit spread)[2]. Their time series analysis were able to explain, respectively, about 68%, 55%, and 36% of the total variation in credit spreads for, low-, middle-, and high-grade bonds. More recently, Chen, Lesmond and Wei (2008) have investigated the influence of liquidity on corporate bond spreads. They have found that liquidity factors explain up to 50% of the cross-sectional variation in credit spread levels.

Furthermore, since Credit Default Swap (CDS) and corporate bonds share generally the same risk structure (both depend on the credit risk of the underlying entity as well as liquidity risk), another recent group of studies has investigated the determinants CDS spreads (instead of corporate bonds spreads) in a similar way to the studies discussed above[3]. It can be hence of interest to discuss the main findings of this group of literature, since they are comparable (at least to a certain extent) to the results of the studies that explore corporate bonds spreads. For instance, Ericsson et al. (2005) investigated the relationship between CDS spreads, and the determinants of credit spreads proposed by the structural models

[2] Following Avramov et al. (2007), we use the slope of the yield curve and lagged credit spread in our empirical investigation.

[3] These studies took advantage of the improved liquidity and maturity of the CDS market since the beginning of the noughties.

(namely, leverage, risk free rate and volatility). They found that these variables explain up to 60% of CDS spread levels, and only 23% of CDS spread changes. Analyzing, the regression residuals in a similar fashion to Collin-Dufresne et al. (2001), they found only weak evidence for a single strong residual factor. Further, Tang and Yan (2007) analyzed the impact of "liquidity level" and "liquidity risk" on the CDS spreads. They found that liquidity constitutes a significant component of CDS spreads, which counts for up to 20% of their. Similar results were documented by Annaert et al. (2009), who analyzed individual CDS liquidity and market wide liquidity premias. They found that liquidity played a dominant role in the steep rise of CDS spreads in the recent financial crisis. In a recent paper, Di Cesare et al. (2010) analyzed the determinants of CDS spread between January 2002 and March 2009 (hence including the subprime crisis period). They found that the structural models' credit risk factors, along with liquidity factors explain about 50% of CDS spread changes. Gatfaoui (2010) investigated the dependence structure between credit risk (i.e. DJCDX spreads) and market risk (i.e. DJCI return) and found it to be time-varying. In a more recent study, Mayordomo et al. (2012) analyzed the difference in reaction between the Bond market, the CDS market and Asset swap (ASP) market, during the crisis. Using up to five-period lagged spreads in all these markets, they found that ASP and bond markets are much more closely related in dynamics than the CDS market is to the previous. The findings of this latter study are however to be taken with caution, due to the low explanatory power of the used model (only 11% of adjusted R^2 on average).

In summary, analyzing the existing empirical literature brings several interesting insights. First, we note that the statistical regression approach is more appropriate to the aim of our study (since we look for the effective determinants of credit spread changes). Second, we note that the literature that considered this approach is quite recent, and that the studies that considered solely the corporate bond market are relatively restrained (possibly due to data limitation). Finally, we note from this literature that the determinants of CDS spreads are comparable, at least to some extent, to the determinants corporate bond spreads. This inspires us to check, in a robustness test, the steadiness of the determinants of the credit spreads that we examine in explaining the spreads of CDSs.

In this study, we extend the strand of empirical literature initiated by Collin-Dufresne, Goldstein and Martin (2001), by using some of the credit spread determinants that were proposed by Avramov et al. (2007), as well as a set of determinants inspired from our theoretical and descriptive analyses proposed, respectively, in chapters I and II. On top of that, we explore the changes that these determinants have undergone between the pre-crisis, subprime crisis and Eurozone crisis. In what follows, we present some hypotheses about the determinants of the spreads that we use in this study.

3. Hypotheses on credit spread determinants:

Based on the analysis that we proposed in chapters I and II, and in view of the empirical literature that we discussed in the previous section, we expect credit spreads to be reflected by five principal components: (*i*) a default risk component, (*ii*) a liquidity risk component, (*iii*) a macroeconomic and systemic risk component, (*iv*) an information asymmetry component, and finally (v) a set of small additional factors such as risk aversion or the effect of the size of the issuing company. As such, we propose in this study to use a set of credit spread determinants that we organize in five groups of variables. The first group includes (*a*) the credit risk factors that we extract from the structural models' analysis (denoted the structural credit risk factors); the second group comprises (*b*) the factors that capture macroeconomic conditions, systemic risk and authorities' actions (denoted market-wide factors); the third group contains (*c*) liquidity risk factors; the fourth group covers (*d*) information asymmetry or information delay factors; and finally, the fifth group encompasses (*e*) the additional risk factors that are not considered in the previous componenents. In what follows, we propose some hypotheses on the expected relationships between these factors and credit spreads. These hypotheses take as a starting point the theoretical and descriptive analyses that we proposed, respectively, in chapters I and II. The proxies that we use for each of these factors will be however discussed later in the data section.

3.1. Hypotheses on the structural credit risk component:

We start by discussing the relationships between the credit risk factors that we propose to examine and credit spreads. These credit risk factors are fully motivated by the structural models that we discussed in chapter I. The proposed relationships were also generally proven by the numerical analysis that we proposed in chapter I. We highlight here these theoretical relationships while recalling some of the observed effect of the crisis on them that we emphasized in chapter II.

3.1.1 Negative relationship between firm value and credit spread:

Even though we did not test directly this relationship in the previous chapter, it seems quite intuitive. An increase in the value of a firm's assets makes it far from the default boundary; therefore, its default risk decreases and, accordingly, its credit spreads are expected to diminish. Following the evidence proposed by the previous empirical literature, equity return is used in this study as a proxy for the value of the firm's assets. Improvements or deteriorations in a firm's health is indeed expected to be reflected by the returns of its equities.

3.1.2 Positive relationship between leverage and credit spread:

According to the numerical analysis that we proposed in chapter I, a positive relationship is expected between leverage and credit spreads. An increase in leverage makes indeed the firm closer to the default threshold and leads to higher default probabilities and thus to higher credit spread. Even though these relationships were observed in chapter II to vary in the crisis (e.g. decrease in the leverage ratios of financial firms since 2009, associated with an increase in their spreads), we expect the theoretical relationship to hold on the long run.

3.1.3 Negative relationship between the risk-free interest rate and credit spread:

As evidenced by the numerical analysis that we proposed in chapter I, a negative relationship is theoretically expected between credit spreads and the risk-free interest rate. Again, an increase in interest rates must be associated with an increase in the firm's value and consequently with a decrease in its default risk. Therefore, an increase in the risk-free rate is expected to make credit spreads go tighter.

3.1.4 Positive relationship between volatility and credit spread:

Similarly, we evidenced in section (3.2) of chapter I that an increase in the assets' volatility of a firm must be associated with an increase in its credit spreads. A higher asset-volatility makes the firm more likely to reach the default boundary, resulting in higher yield spread. Following the evidence proposed by the previous empirical literature, we use in this study equity volatility as a proxy for the assets' volatility. More details about this proxy will be provided in the data subsection.

3.1.5 Positive relationship between credit spread and the payout rate:

Likewise, we showed in section (3.2) of chapter I that an increase in a firms' payout ratio must be associated with an increase in its credit spreads. These payments tend indeed to decrease the firm value, to bring it closer to the default boundary and thus to increase its credit spreads. In this study we use the dividend rate as a proxy of the payout rate.

3.1.6 Positive relationship between time-to-maturity and credit spread:

As evidenced by the term structures of credit spreads presented in chapter I (see for e.g. the term structure of the model of Collin-Dufresne et al, 2000), a positive relationship is expected between the time left to the maturity of the debt and credit spreads. One traditional explanation for this relation is that investors have generally more uncertainty about long maturities than they have about short ones (long maturities involve higher risks of firms' defaults and more uncertainty about the general economic outlook). This relationship needs, however, to be tested in the context of the current crisis, where the short-term economic conditions have been far from certain (i.e. we noted in chapter II a shift in the relationship between the spreads and time-to-maturity since the beginning of the crisis).

3.2. Hypotheses on the market-wide component:

We next turn to the hypothesis about what we call the "market-wide factors". These include the factors that affect the economy and the financial markets as a whole (e.g. economic conditions, systemic risk, authorities' actions), and that does not fit in the default risk or liquidity risk categories. The relationship between these factors and credit spreads are generally inspired from the stylized facts that we identified in chapter II.

3.2.1 Positive relationship between economic slowdown and credit spread:

As seen in chapter II, changes in credit spreads seem to be strongly affected by the macroeconomic conditions. One explanation for this is that investors perceive bad economic conditions as a sign for low firm profitability, and thus as an indicator of higher probabilities of default. In this context, investors will demand a compensation for the additional risk they are taking (i.e. risk premium), which will be reflected in higher credit spreads. As such, a positive relationship is expected to exist between credit spreads and bad economic conditions. In this study, we assume that business climate surveys, the slope of the yield curve as well as interest rates capture much of the variation in economic conditions and risk premiums.

3.2.2 Positive relationship between default contagion risk, systemic risk and credit spreads:

Similarly, we showed in chapter II that the episodes of defaults of some major financial institutions (e.g. Lehman brothers), or the episodes of sovereign defaults (e.g. the Greek and Portuguese governments) had considerable effects on the spreads. These events were generally associated with an increase in the overall credit spreads. As such we assume here that a positive relationship exists between these latter and corporate bonds spreads. These systemic events present however the particularity of being hard to catch in a direct and continuous-time proxy. In this study, we use equity market indexes and aggregate equity volatility as proxies of these systemic events; their effect is indeed assumed to be quickly transmitted to the stock market.

3.2.3 Negative relationship between authorities' actions and credit spreads:

Likewise, we found in chapter II that the actions that were undertaken by the different central banks and governments (e.g. bailouts, the creation of the Financial Stability Board, the creation of the European Financial Stability Facility, the agreement of the Long Term-, and Main-, Refinancing Operations) were generally associated with a decrease in the overall corporate bonds spreads. Similarly to the default events discussed above, the action of authorities present the particularity of being hard to catch in a direct proxy. In this study, we assume that equity indexes as well as LTROs fully capture these actions[4].

3.3. Hypotheses on the liquidity risk component:

3.3.1 Positive relationship between illiquidity and credit spread:

As discussed in chapter I, most structural models assume complete markets where trading takes place continuously. This implies an absence of any liquidity premiums when trading bonds which is a non-realistic assumption[5]. In practice, the corporate bond market is known to have relatively high transactions costs and low trading volumes. One would then expect investors to propose lower prices for their illiquid securities in order to clear their bond positions. Hence the illiquidity of a bond is expected to be associated with higher yields spreads. Moreover, illiquidity risk can be considered on the aggregate level. As shown in chapter II, the tensions in the interbank market can be indeed seen as a proxy of market-wide illiquidity. A decrease in markets' liquidity as in the subprime crisis was generally associated with an increase in the overall corporate bonds' spreads. In this study, we use two measures of liquidity: a bond specific and a market wide liquidity measures (respectively Bid-Ask spread and Euribor-OIS spread) in order to explore the liquidity component of corporate spreads.

3.4. Hypotheses on the delayed information component:

Following the "incomplete information approach" models discussed in chapter I, we assume next that credit spreads contain a delayed information component. In what follows we specify the factors that we propose to include in this delayed component and the hypotheses that we make about its relationship with credit spreads.

---

[4] To our knowledge, none of the previous literature on corporate bonds spread determinants have used LTROs as a credit spread determinant.

[5] However, Amihud and Mendelson (1986) and Easley et al. (2002) argue that liquidity is priced because investors maximize expected returns net of transactions (or liquidity) costs.

3.4.1 The relationship between the delayed information component and credit spread can be either positive or negative:

The incomplete information models (e.g. Duffie and Lando, 2001; Cetin et al, 2004; Guo et al, 2006; Capponi et al. 2009; Lindset et al. 2013) explored generally the effect of information delays, or asymmetries, about the values of the firms' assets or their cash flows. In this study, we propose to extend this view by considering: (*i*) the effect of delayed credit risk factors (proxied by lagged equity returns and lagged interest rates), (*ii*) the effect of delayed market-wide risk factors (proxied by lagged market return); (*iii*) the effect of delayed market illiquidity (proxied by lagged Euribor-OIS spread); and (*iv*) the effect of the overall information asymmetries in the corporate bond market (proxied by lagged credit spreads). Lagged levels of these factors are expected to have an impact on credit spreads, especially if there are market frictions and low speeds of adjustments of market participants to the different existing informational contents. By counting for the lagged values of the different risk factors and credit spreads (denoted, the delayed information component), we expect to capture some of the reaction of credit spreads to previous periods' variations. This can be particularly of great concern during the crisis, where we expect previous periods' turbulences episodes (e.g. defaults, bailouts, decreases in governments credit ratings, see section 3.2 of chapter II) to be still priced in the following periods' credit spreads[6]. In this study, the lagged variables are expected to have a similar sign to those of the original variables with a lower impact on spreads.

3.5. Hypotheses on the additional factors:

We assume next that credit spreads reflect the effect of some additional factors that are not captured by the previous components. These include the effects of the size of the firm and investors' risk aversion proxied by their confidence level.

3.5.1 Negative relationship between firm size and credit spread:

The motivation for exploring firm size as a determinant of credit spreads stems from many different regards. First, to our knowledge, none of the previous literature on corporate bond spreads has addressed the question of the relationship between credit spreads and firm size. The only available evidence on the relationship between default risk and firm size exists for bank loans, and deals with small and medium-sized enterprises (SMEs). For instance, Bhattacharjee et al (2002), Bunn and Redwood (2003), Eklund et al (2001) and Jimenez and Saurina (2004), found that, the smaller the firm, the more it is likely to make

[6] Another motivation for the use of the delayed determinants stems from the empirical study of Mayordomo et el. (2012), who explored delays in credit spreads and stock market returns.

default (since its activity is more uncertain). It seems then quite interesting to test the presence of similar patterns in the corporate bond market. Second, we noted in the descriptive analysis which we proposed in chapter II that larger firms were generally associated with lower credit spreads, and that the gap between the smallest and largest firms has increased since the beginning of the crisis. It seems hence interesting to explore these movements in depth using statistical regressions techniques. Another motivation for exploring firm size as a determinant of credit spreads stems from the recent debate about the "Too big to fail" firms. The last episodes of Lehman Brothers bankruptcy (and its systemic consequences), the rescue of the American International Group (AIG) and the numerous bailout plans in Europe, have indeed raised the concern about the presence of some firms (mainly financial institutions) that are "default-free", even if their situations turn bad. As reported by the previous Federal Reserve chairman Ben Bernanke in the "Causes of the Recent Financial and Economic Crisis" testimony:

"If creditors believe that an institution will not be allowed to fail, they will not demand as much compensation for risks as they otherwise would, thus weakening market discipline; nor will they invest as many resources in monitoring the firm's risk-taking".

By counting for firm size as a determinant of credit spreads in this study, we attempt to investigate, on the one hand, the presence of lower risk premiums in credit spreads associated with large firms, and on the other hand, the presence of an even lower risk premium in the credit spreads of these firms since the beginning rescue politics in the wake of the crisis.

One critical decision when addressing the firm-size question is the choice of the firm-size measure. Traditionally, and according to the European commission recommendation, the number of employees and the annual rate of turnover of balance-sheet are used to define a firm's size[7]. The use of the number of employees might be indeed problematic since it is available only at the annual or the quarterly level. To best capture the firm size effect, we use in this study two complementary proxies: firm-specific number of employees and market value. While a negative relationship is expected between credit spread and market value (a larger firm-size should be associated with lower riskiness), the relationship between credit spreads and the number of employees is rather unclear at this level. A larger number of employees can be indeed associated to a larger firm value and hence to lower credit spreads, or can be associated to a cost for the firm, which decreases its value and increases its credit spreads.

[7] Firm size is defined according to the European Commission Recommendation of 6 May 2003 (2003/361/EC), by taking into account the number of employees and sales volume.

3.5.2 Negative relationship between investors' confidence and credit spread:

As mentioned in chapter I, most of the structural models use risk-neutral valuation techniques. This implies that investors risk aversions, confidence or irrational behaviors are not considered. In this study, we introduce investors' confidence as a measure of investors' behavior and risk appetite in the corporate bond market. Higher values of confidence mean that investors demand lower premiums for relatively high risk investments, and so, they are showing confidence in the economy. Inversely, lower values of confidence mean that investors demand higher risk premiums and that they're not confident in the future prospects of the economy. Therefore we expect credit spreads and investors' confidence to be inversely related. By using this variable, we expect additionally to capture some of the phenomena that we documented in chapter II (i.e. the paradox of tranquility, flight-to-quality and flight-to-liquidity). We use here a bond-related confidence measure that we explain in what follows.

4. Data:

Data used in this study were collected from "Six-Financial Information", "Datastream" and the European Central Bank (ECB) databases. The data set consists of monthly observations on bond yields and all the proposed credit spread determinants for a 10 years period, starting from July 1st, 2004 to July 31st, 2014. This allows us to analyze the dynamics of the spreads during the pre-crisis, the subprime crisis, and the Eurozone crisis periods. The use of monthly observations is motivated by the fact that data are either not available, or not liquid enough to be used at the daily or weekly level.

As regards the corporate bond sample, some modification has been made as compared to the sample that we used in chapter II. This is mainly due to the fact that we need stock market data and accounting information, which is not available for all the firms that we analyzed in chapter II. To do so, we collected a larger set of corporate bond yields obtained from stock prices and accounting information and Datastream. All the bonds that we collected are settled in Euro and have maturities of 10 years or more. This initial sample was then subject to a number of filtrations in order to make it suitable for this study. First, we excluded all Bonds with equity or derivative features (such as callable and puttable bonds as well as convertible bonds). Second, we removed all bonds which lack yield data and those whose data seem to be problematic (for example bonds with constant yields over a long period of time). Finally, since this study requires stock market data and accounting information, we kept only listed entities, and those for which accounting data are available. Having made all these filtrations, the final sample consists of bond yields and firm specific data for 70 entities: 58 investment grade and 12 speculative grade bonds; 53 were issued by financial firms and 17 by non-financial firms[8]. Appendix III.1 presents the final sample of entities that we have used in this study. In what follows, we bring more details about the credit spread sample and each of the proxies that we have used in capturing the five principal components of credit spreads that we discussed earlier.

4.1. Credit spread:

For all the selected bonds, we compute credit spreads as the difference between the corporate bond yield and the German "Bund" yield of equivalent maturity and compounding frequency. This choice is motivated by the low default risk associated to the German government (AAA-rated), the high liquidity of the Bund, as well as the data availability over the sample period. Formally, the credit spread of a bond "i" at time "t" is computed (denoted $S_{i,t}$) is calculated as follows:

$$S_{i,t} = Y_{i,t} - r_{i,t} \tag{1}$$

Where $Y_{i,t}$ is the yield at date "t" of a corporate bond "i" of maturity "T", and $r_{i,t}$ the yield at date "t" on a Bund of equivalent maturity.

4.2. Structural credit risk factors:

4.2.1 Leverage:

Leverage ratio data are provided by Datastream. Datastream calculates leverage ratios as follows:

$$Lev_{it} = \frac{LT\text{-}debt + ST\text{-}debt \ \& \ current\ portion\ of\ LT\text{-}debt \times 100}{Total\ capital + \ ST\text{-}debt \ \& \ current\ portion\ of\ LT\text{-}debtt} \tag{2}$$

With lev_{it} the leverage ratio of the firm "i" in time "t"; *LT-debt* is the Long term debt and *ST-debt* is the Short term debt. One major challenge for the use leverage ratios in this study is that balance sheet data are available only on the quarterly or the annual level. Following the evidence from previous empirical studies (see for example Collin-Dufresne et al, 2001; Zhang, Zhou et al, 2005; or Di Cesare et al, 2010), we precede to linear interpolations of the leverage ratios in order to use them on the monthly level.

[8] The dominance of financial corporate bonds in our sample is explained by the dominance of financial firms' issuance during the beginning of the noughties.

4.2.2 Equity return:

Following the evidence provided by the previous empirical studies, we use equity market information as a proxy of firm values. Equity return is, in addition, expected to capture some of the firms' leverage dynamics that are not captured by the incomplete or delayed balance sheet information that we use for leverage ratios. For each underlying entity, we collect stock market daily quotes and we compute their logarithmic returns. The computed returns are then averaged for each month. The equity return of a firm "i" in time "t" is denoted by ER_{it}.

4.2.3 Historical volatility:

Using firm's stock prices, we calculate the historical volatility of each of the underlying entities stock prices as follows:

$$\sigma_{it} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{k}\sum_{t=1}^{n}(ER_{it} - \overline{ER_i})^2} \tag{3}$$

Where σ_{it} is the historical volatility of a firm "i" at time "t", ER_{it} is the firm's equity return, $\overline{ER_i}$ is a moving average based on the return of the stock over a chosen look-back window "n". We calculate here the historical volatilities for the 24 days and 180 days look-back windows. We test then the level of information that each of these measures bring to our empirical analyses in order to choose the most adequate proxy[9]. Further, the previous empirical studies have also used implied volatilities from option prices as a forward looking measure of volatility. Since only few of the chosen entities have publically traded options, we resort to the use firm-specific implied volatility. We use however changes in the VSTOXX volatility index as a proxy of market-wide implied volatility.

4.2.4 The risk-free rate:

Proxies used by previous studies for the risk-free rate include Swap rates, Eonia 3-month rate, Euribor rate, or the 10-year treasury bonds rates. Clearly, no consensus seem to rise from this literature about the most effective proxy of the risk-free rate, especially in the light of the recent debate about the existence of a real risk-free rate. In this study we propose to test empirically the proxy that brings the best information about credit spreads dynamics during the period of

[9] The choice of the look back window is a critical decision while computing volatility. A long look back window conveys more information about past dynamics of equity prices, while a shorter window allows the volatility measure to capture how fast prices respond to recent information. Both cases seem interesting to test in the crisis context. We chose then to test each of these measures effect on credit spreads in order to keep the best proxy.

the study. We propose to test two candidate proxies for the risk-free rate which are monthly series of the 10 year AAA-rated German Bund and the 3-month Overnight Index Swap (OIS) rate. With regard to the used maturities, the use of the 10-year treasury rates seems more reasonable since it is closer to the average sample maturity. The OIS rates are also attractive since lending over short maturity (namely, the overnight rate) is known to be less risky than lending over long ones. We denote by r_t^j the risk-free rate at time "t" of maturity "j" ($j = 0.25, 10$ years).

4.2.5 The dividend Yield:

As mentioned earlier, the dividend yield is used as a proxy of the payout rate. Dividend yields data are provided by Datastream and expresses the dividend per share as percentage of the share price. Dividend yields are calculated by Datastream on the base of the anticipated annual dividends distributed by the companies and they exclude any special or once-off dividends. We denote the dividend yield by Div_{it}.

4.3. Market-wide factors:

4.3.1 The slope of yield curve:

As previously mentioned, the slope of the yield curve is used in this study as a proxy of the overall economic conditions. Future changes in economic conditions and interest rates are indeed known to be signaled by the slope of the yield curve. An increase in the slope (i.e. steepening of the yield curve) is generally perceived by market participants as a signal for good economic growth prospects that would affect positively firms' cash-flows. On the other hand, a steep slope should induce a tightening of credit spreads (hence the relation between credit spreads and the term-structure slope is then expected to be negative). We use here two candidate proxies for the slope of the yield curve (denoted $slope_t$): the differences between the 5-year over 2-year, and 30-year over 10-year European benchmark treasury rate. Each of these proxies is expected to provide different information about the general economic outlook as foreseen by market participants (medium-term against long-term conditions), which may have different effects on the credit spreads. Since these indices are highly correlated, we use only one index at a time in our regression analysis.

4.3.2 Business climate indicator:

We use the "Business Climate Indicator in Eurozone" (denoted BCI_t) as a complementary proxy about the overall macroeconomic conditions (mainly about the effect of the recent economic and financial turmoil). BCI_t is provided by

Datastream and is calculated, by the "The European commission's Directorate-General for competition and financial affairs", using production trends in recent months, firms' order books, stocks and production expectations. BCI_t is expected to capture some of the variation in the conditions of the real economy that are not captured by the above variable.

4.3.3 Market return:

Monthly returns on the EUROSTOXX 50 and the S&P Europe 350 Indexes are used in this study as candidate proxies for systemic and default contagion risks. Monthly market returns (denoted $Mketret_t$) are computed in a similar way to the firm-specific equity returns discussed earlier.

4.3.4 Market Implied Volatility

We use the VSTOXX volatility index as a forward looking measure of overall macroeconomic and systemic uncertainty as perceived by market participants. The VSTOXX index is indeed computed by Datastream from implied volatilities of a basket of options (using the square root of the implied variance across all options of a given time to expiration); it reflects therefore the market expectations of short-run up to long-run volatilities. Additionally, this proxy is expected to bring some information about the situation of the firms that complete the firm-specific historical volatility, which is rather backward looking. Market Implied Volatility is denoted by $MketVol_t$.

4.3.5 LTROs:

We also collect monthly data for the Long Term Refinancement Operations (denoted $LTROs$) from the ECB database. $LTROs$ are long term debts (three years) accorded by the European Central Bank to Banks. As such, we use them as a proxy for the action of authorities and the central banks during the crisis, especially to help the financial sector which constitutes the major part of the bonds in our sample.

4.4. Liquidity risk factors:

4.4.1 Bid-Ask spread:

Following Amihud and Mendelson (1986), and Acharya and Pedersen (2005), the individual (il)liquidity of a security is commonly measured by its transaction cost, which is proxied by the Bid-Ask spread. The Bid-Ask spread refers to the difference between the highest prices a buyer of a bond is willing to pay, and the lowest price a seller is willing to offer. The larger the spread is, the lower the liquidity of the bond becomes. In this study, we use accordingly the Bid-Ask spread as a proxy of the bond specific illiquidity risk. Data for Bid and Ask quotes are provided by Six-Financial information. For each corporate bond "i" in our sample, we compute the difference between Bid and Ask at time "t". This Bid-Ask spread is denoted by $BidAsk_{it}$.[10]

4.4.2 Market liquidity:

In addition to bond-specific liquidity, we use the EURIBOR-OIS spread as a proxy for the market wide (il)liquidity. The difference between these two rates is supposed to catalyze the presence of tensions in the interbank market due to supply and demand shocks. This yield difference can also be seen as systemic risk component. Market liquidity is denoted by $Mketliq_t$.

4.5. Additional factors:

4.5.1 Number of employees:

Data for the number of employees of each firm are available only at the annual or the quarterly level. We precede hence to a linear interpolation of the available data in order to use them at the monthly level. Groups of firms by size are also created in a second time to best specify the firm-size effect.

4.5.2 Market value:

We use the "consolidated market value" of all the underlying entities as a second proxy for firm size. Datastream calculates market value as the sum of all the listed equity securities of a company. The advantage of using market value is that, as opposed to the number of employees, it allows a time series view of a firm's size. The disadvantage though is that it is expected to be highly correlated with the equity return proxy also used in this study.

4.5.3 Confidence Index:

Following the same methodology as "Barron's financial investment services", we construct a confidence index by dividing the average yield on high-grade bonds by the average yield on intermediate-grade bonds in our sample. The discrepancy between the two yields (i.e. the confidence index) is expected to be indicative of the investors' confidence in corporate bonds during the study's period. Confidence Index is denoted by CIX_t.

[10] Knowing the low liquidity of the bond market, data for Bid-Ask quotes seem quite problematic for some bonds, especially high yield bonds. We used linear interpolation technique to obtain a balanced Bid-Ask quotes data.

Further, since we intend to analyze credit spreads in changes, we calculate changes over the last month's observation for each of the dependent variable (i.e. credit spreads) and the independent variables that we described above[11]. A summary of the credit spread determinants used in this study and the expected signs of their relationship with credit spreads are presented in Table III.1. Descriptive statistics for credit spreads and the used independent variables are reported in Appendix III.2.

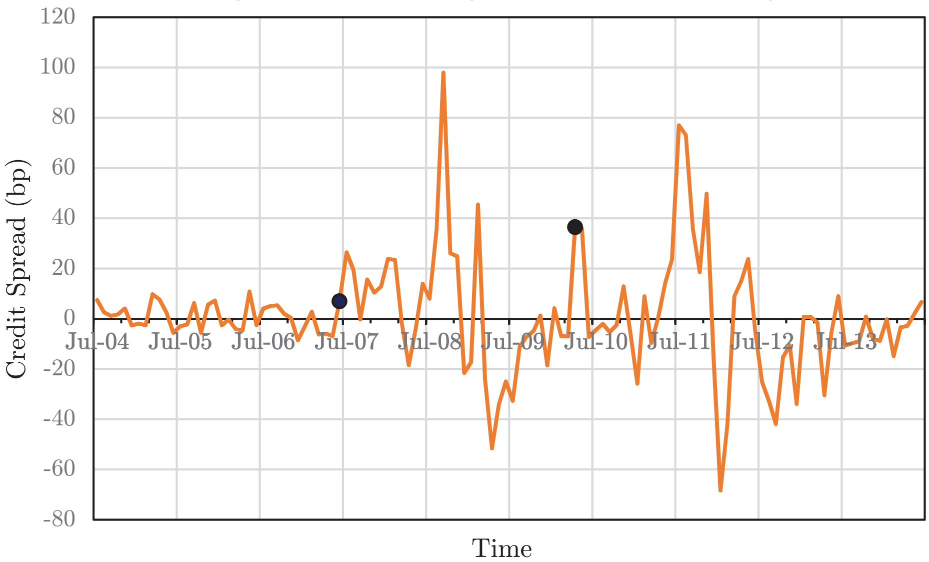
Table III.1. Independent variables and expected signs:

Variables	Description	Sign
ΔLev_{it}	Changes in firm Leverage ratio	+
$\Delta\ r_t^j$	Changes in "j" years risk-free rate	–
ER_{it}	Equity return	–
$\Delta\ \sigma_{it}$	Changes in firm historical volatility	+
ΔDiv_{it}	Changes in dividend yield	+
$\Delta Slope_t$	Changes in the slope of yield curve	–
$Mketret_t$	Market return	–
$\Delta MketVol_t$	Changes in Market volatility	+
ΔBCI_t	Changes in business climate	–
$\Delta LTROs$	Changes in LT Refinancement Operations	–
$\Delta BidAsk_{it}$	Changes in bond specific liquidity proxy	+
$\Delta Mketliq_t$	Changes in Market liquidity	+
$\Delta lagVbles_{it}$	Changes in the lagged variables	+/–
$\Delta NbEmp_{it}$	Changes in the number of employees	+/–
$\Delta Mketvalue_{it}$	Changes in firm specific Market value	–
ΔCIX_t	Changes in Confidence Index	–

[11] Except for equity and market return which are used in terms of return.

Overall, this study's sample consists of 70 entities observed over 120 months, which totals 8400 observations[12]. Figure III.1 displays the average credit spreads changes for the 70 bonds in our sample for the period ranging between July 2004 and July 2014. This Figure seems to confirm the observations that we made in chapter II about three main phases for credit spreads movements. A first phase goes from July 2004 until June 2007, and consists of a period of low credit spreads' volatilities, corresponding to the pre-crisis period. A second phase goes from June 2007 until May 2010, where credit spreads volatility surged due to the out-comings of the subprime crisis, before showing a slow mean-reversion up to April 2010 (we design henceforth this period by the "subprime crisis period"). A third phase goes from May 2010 until July 2014, where credit spreads boosted due to the out-comings of the Eurozone crisis, before showing a slow recovery up to July 2014 (designed henceforth by the "Eurozone crisis" or the "Euro crisis" period). In this empirical study, we propose to analyze the determinants of credit spreads changes for the full sample period (ten years period); in addition, we bring more specification to this result by assessing how these determinants change over the pre-crisis, the subprime crisis and the Eurozone crisis periods.

Figure III.1. Average credit spread changes



Source : Six Financial, Datastream and author calculation

[12] This makes this study's sample one of the largest samples used among the studies that consider Euro settled corporate bonds.

5. Methodology:

The aim of this study is to investigate the determinants of credit spread changes with regard to the recent economic and financial crisis. More specifically, this study attempts to determine what risks are most represented in corporate-bonds spreads, and how the crisis has changed the way these risks are priced in credit spreads.

Changes data are preferred in this study to levels data because they account for the non-stationarity of credit spreads[13]. As shown by Greatrex (2008), analysing credit spreads in levels might lead to biased results.

Considering the estimation method, we use Panel data Ordinary Least Squared (OLS) regressions, robust to heteroskedsticity and autocorrelation. Since data used in this analysis include both time series and cross sectional dimensions, it is possible to use Panel data regressions, which presents the advantage of including more information than pure time series or cross-sectional samples. This is expected to provide more efficient estimations. Moreover, the use of OLS regressions has many motivations. First, previous statistical studies on Credit or CDS spread determinants used mostly OLS regression to explore credit spread determinants. These include, Ericsson et al. (2004), Zhang et al. (2005), Avramov et al. (2007), Di Cesare et al. (2010), Mayordomo et al. (2012), amongst others. Second, since we use first difference data, we expect all unobserved individual fixed effects to be eliminated, which balances in favor of the OLS regression. Finally, in order to confirm the appropriateness of the OLS regression, we run Fisher test on the joint significance of the fixed effects intercepts. Fisher test confirms the non-rejection of the null hypothesis that "all of the fixed effect intercepts are zero", confirming that OLS regression is appropriate for this study[14].

To better answer the aim of the study, we follow a four-steps approach. First, following the same methodology as Avramov et al. (2007), we start by running univariate regressions of credit spread on each of the individual proxies presented above. This allows us to test the significance of the individual variables and to

[13] We have shown in chapter II that credit spreads present generally a Unit root. For confirmation of stationarity of the changes data, we run a unit-root test based on the Augmented Dickey-Fuller test for all the credit spread changes. Results confirm the rejection of the null hypothesis of the presence of unit roots at the 1% significance level for all the spreads.

[14] For robustness, we test later Model 5 with a fixed-effects panel regression. We show later that OLS and Fixed-effects regressions give quite similar results in terms of coefficients and explanatory power.

choose between candidate proxies for the risk free rate, equity volatility window, market return and the slope of the yield curve.

Second, in order to specify the effect of the different credit spread components since the beginning of the crisis, we run five regressions including each time an additional group of determinants. More specifically, we run for each of: (*i*) the whole sample period; (*ii*) the pre-crisis period (between July 2004 and June 2007); (*iii*) the subprime crisis period (between June 2007 and May 2010); and (*iv*) the Eurozone crisis period (between June 2010 and July 2014) the five following regressions models:

- Model 1:

$$\Delta\ spread_{it} = \Delta\ Credit\ risk\ factors_{it} +\ \varepsilon_{it}$$

With $i = 1, \ldots ,70$ firms and $t = 1, \ldots ,120$ periods. The credit risk factors are the variables proposed by the theoretical structural models. These are: the risk-free rate, leverage ratios, equity return, equity volatility and dividend yield. This will allow us to test the reaction of credit spreads to theoretical credit risk variables, and to witness the evolution of credit risk with regard to the crisis.

- Model 2:

$$\Delta\ spread_{it} = \Delta\ Credit\ risk\ factors_{t} + \Delta\ Market\text{-}wide\ factors_{it} +\ \varepsilon_{it}$$

Next, we add to the previous model the market-wide factors which are: the slope of yield curve, market return, market volatility and business climate and LTROs. These factors are assumed to be common to all the underlying corporations and, as mentioned earlier, they are expected to capture changes in economic conditions, systemic and contagion risks as well as the risk premiums lying in credit spreads.

- Model 3:

$$\begin{aligned}\Delta\ spread_{it} = \Delta\ Credit\ risk\ factors_{it} + \Delta\ Market\text{-}wide\ factors_{t}\\ + \Delta\ Liquidity\ factors_{it} +\ \varepsilon_{it}\end{aligned}$$

In the third model we add firm specific and market wide liquidity factors, along with the previous credit spread determinants. Liquidity factors are expected to be significant and test their reaction to crisis, along with the previous credit spread determinants.

- Model 4:

$$
\begin{aligned}
\Delta\ spread_{it} = {} & \Delta\ Credit\ risk\ factors_{it} + \Delta\ Market\text{-}wide\ factors_{t} \\
& + \Delta\ Liquidity\ factors_{it} + \Delta\ Delayed factors_{it} + \ \varepsilon_{it}
\end{aligned}
$$

Afterwards, we test the impact of adding the delayed information component on credit spreads. The delayed factors are: lagged credit spread, lagged market return, lag equity return and the lag of the risk-free rate.

- Model 5:

$$
\begin{aligned}
\Delta\ spread_{it} = {} & \Delta\ Credit\ risk\ factors_{it} + \Delta\ Market\text{-}wide\ factors_{t} \\
& + \Delta\ Liquidity\ factors_{it} + \Delta\ Lagged\ factors_{it} \\
& + \Delta\ Additional\ factors_{it} + \ \varepsilon_{it}
\end{aligned}
$$

Finally, Model 5 constitutes our benchmark setup, and takes into account all the credit spread determinants proposed in this study. The additional factors used in this model are the confidence index and the firm size proxies.

After running these five regression models, we perform, in a third step, three additional checks to assess the robustness of our benchmark setup in Model 5. These include: (a) an examination of the results of the OLS regression method as compared to the results of the fixed effects regression; (b) a check of the robustness of the found credit spreads determinants to the Credit Default Swap (CDS) spread changes; and (c) a Principal Component Analysis of the regression residuals.

Finally, we use the sample of the most significant credit spread determinants, found for Model 5, to lead specification analysis on different firms' sub-samples. These include sub-samples of bond maturities, credit ratings, firm sectors and firm sizes. The results of the estimates are reported in the next section[15].

6. Results:

This section presents the results of the four groups of tests mentioned above. A first subsection presents the results of the univariate regressions for the selected proxies. A second subsection presents the results of the five regression-models specified earlier, while highlighting each time the impact of the crisis on the different components of the spreads. In the third subsection we discuss the robustness of these determinants, before specifying the benchmark regression in a last subsection.

---

[15] All estimations are done using STATA 12

6.1. Results of the univariate regressions:

Table III.2 reports the results of a series of OLS regressions of credit spread changes over the individual credit spread determinants in the period from July 2004 to July 2014. The aim of these regressions is to witness the relative importance of each of the suggested credit spread determinants and to choose between the candidate proxies for the risk free rate, equity volatility, market return and the slope of the yield curve.

Table III.2. Univariate regression results for the whole sample:

Variables	Expected Sign	Univariate Regressions	Adj-R^2
Leverage	+	0.0147* (1.875)	0.1%
Equity Return	-	-0.742*** (-23.79)	6.3%
Historic volatility 180	+	3.747*** (3.942)	0.2%
Historic volatility 24	+	0.369*** (3.027)	0.1%
10yrs treasury rate	-	-0.693*** (-30.24)	9.8%
Dividend yield	+	0.0186*** (8.769)	0.9%
OIS 3mth rate	-	-0.464*** (-21.39)	5.2%
Market return	-	-2.500*** (-35.07)	12.8%
Market return SP 350	-	-2.805*** (-34.71)	12.5%
VSTOXX Index	+	0.0185*** (25.48)	7.2%
Term slope 30y-10y	-	-0.247*** (-5.212)	0.3%
Term slope 5y-2y	-	-0.107*** (-3.128)	0.1%
Business Climate	-	-0.290*** (-20.52)	4.8%
Bid-Ask spread	+	0.00977*** (4.454)	0.2%

Market liquidity	+	0.707***	7.5%
		(26.18)	
lagged spread	+	0.348***	11.6%
		(33.28)	
Lagged equity return	-	-0.643***	4.7%
		(-20.43)	
Lagged Market return	-	-2.006***	8.2%
		(-27.44)	
Lagged 10yrs rate	-	-0.218***	1.0%
		(-9.059)	
lagged Market liquidity	+	0.477***	3.4%
		(17.26)	
Market value	-	-2.19e-05***	5.3%
		(-21.58)	
Number of employees	+	1.43e-06*	0.0%
		(1.743)	
Confidence Index	-	-0.0429***	7.5%
		(-26.17)	
LTROs	-	-7.48e-09	0.0%
		(-0.26)	
Number of observations		8400	

This table shows regression results using Robust pooled OLS regressions. Associated t-statistics are reported in parentheses under the coefficient estimates. *** indicates significance at 1% level, ** at 5% level, and * at 10% level (1% level is indicated with boldfaces).

Results in Table III.2 show that almost all the selected proxies are statistically significant in explaining credit spread changes. More specifically, Table III.2 shows that amongst all the investigated variables, changes in the returns of the Eurostoxx50 index has the most important impact on credit spreads with regard to significance and explanatory power. By itself, it explains up to 12.8% of corporate credit spread changes, with a T-statistic of about (-35.07)[16]. The second variable with the most important impact on credit is found to be the lagged credit spread. It explains by itself 11.6% of credit spread changes. Surprisingly, the theoretical credit risk determinants are not the variables with the most important impact on credit spread changes in terms of explanatory power and significance. The first structural variable with a high impact on credit spread changes is the 10-year government rate (adjusted R-Squared of 9.8%). Doing a similar analysis for the period between 1990 and 2003, Avramov (2007) found that the risk-free

[16] The explanatory power of the variables is assessed by their respective Adjusted R-squared.

rate has the most important impact on credit spread changes in univariate regressions. Other structural models variables used in this regression include leverage, equity return (proxy of firm value), equity volatility (proxy of asset volatility) and dividend yield. These variables are found to be significant with the expected signs but they are clearly far from being the most influential variables on credit spreads in the period from July 2004 to July 2014. Furthermore, Table III.2 shows that the added variables have relatively good explanatory power. For instance, the adjusted R-squared are remarkably of 7.5% and 5.3% for, respectively, the confidence index and the market value. Overall, except (*i*) LTRO which is found to have no statistical significance; (*ii*) the number of employees and leverage which are significant only at the 10% level, all the used determinants are significant at the 1% level. The signs are also remarkably in line with theory and the previously made hypothesis.

As far as the choice of proxies is concerned, since no ambiguity is documented for the significance and the signs of all the candidate proxies, we chose to keep the proxies that explain the largest portion of credit spread variation. Column 4 of Table III.1 reports the adjusted R-squared of all the individual credit spread determinants used in the univariate regressions. Accordingly, the 10-year treasury rate is preferred to the 3-month OIS rate as a proxy of the risk-free rate (their adjusted R-squared are respectively of 9.8% and 5.2%)[17]; the 180 days window is retained for equity volatility at the expense of the 24 days window (adjusted R-squared, respectively, of 0.2% and 0.1%); the 30-10 years slope is kept as it explains 0.3% of credit spread changes (while the 5-2years slope explains only 0.1%), and finally the Eurostoxx 50 market return is preferred to S&P 350 return as the first explains 12.8% of credit spread variation while the second explains 12.5% of the same variation.

All in all, the results of the univariate regressions are encouraging since most of the investigated variables have the ability to explain changes in credit spreads. We investigate in what follows the combined explanatory power of these variables.

6.2. Results of the five regression models

We next consider the results of the five regression models presented earlier. Every regression model allows us to test the joint explanatory power of the proposed credit spread determinants organized in groups of homogenous components. We summarize here some of our main findings about the impact of the crisis on each of these components.

[17] This choice is also supported by the closeness of the ten years maturity to the average maturity of our bond sample.

6.2.1 Structural credit risk factors:

Table III.3. Regression Model 1 – Credit risk component:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0324***	0.00547	0.00165	0.0623***
	(3.506)	(0.647)	(0.0815)	**(3.876)**
Equity Return	-0.604***	-0.0227	-0.633***	-0.985***
	(-19.42)	(-0.700)	**(-11.22)**	**(-15.69)**
Historic volatility	2.657**	-3.462	3.502**	0.319
	(2.300)	(-1.323)	**(2.027)**	(0.134)
10yrs treasury rate	-0.635***	-0.483***	-0.924***	-0.517***
	(-27.85)	**(-21.68)**	**(-16.50)**	**(-14.25)**
Dividend yield	0.00645***	0.0337***	0.00459*	0.00987
	(3.169)	**(3.805)**	**(1.735)**	(1.113)
Constant	-0.00130	0.00802**	-0.00526	-0.0133**
	(-0.379)	**(2.515)**	**(-0.651)**	**(-2.278)**
Observations	8,400	2,450	2,450	3,500
Adj R-squared	0.144	0.171	0.165	0.160

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces).

We consider first the results of the regression model that includes the theoretical credit risk variables[18]. Results in column 1 of Table III.3 show that most of the variables investigated in the full-sample regression contribute to explain changes in credit spreads. The signs of the estimated coefficients agree also with theory and the proposed hypotheses about the structural credit risk component. This finding tends to confirm that the credit spread determinants proposed by the structural models (in particular the model of Merton, 1974) are generally robust in the long run.

Further, Table III.3 shows that the structural variable with the most important and stable impact on credit spread is the 10-year rate (significance level superior to 1% for all periods). The negative coefficient found between the 10-year rate (i.e. proxy of the risk-free rate) and the yield spread, confirms that a decrease in interest rates is generally associated with an increase in default probabilities and so with an increase in credit spreads[19]. This result is consistent with the theoretical evidence provided in chapter I, as well as the findings of many empirical studies done before the crisis, such as Collin-Dufresne et al. (2001), and Avramov et al. (2007). We note though that risk-free rate loses slightly of its impact over the three explored sub-periods (T-statistics of -21.68, -16.50, -14.25 respectively in the pre-crisis, the subprime crisis and the Eurozone crisis periods).

[18] As discussed in chapter I, these variables are common to almost all the structural models.

[19] This result holds for the pre-crisis, the subprime crisis and the Eurozone crisis sub-samples.

This can be interpreted as a sign of investors losing confidence in the monetary policy and the economic perspectives since the beginning of the crisis.

The second theoretical variable with the strongest effect on credit spreads in the full sample regression is the equity return (T-statistic of -19.42). As expected, a negative relation is found between equity return and credit spreads, confirming that low firms' returns are associated with higher probabilities of default and higher credit spreads. Turning to the sub-periods regression, we note that the impact of equity return on credit spreads became much higher since the beginning of the crisis. Similarly to Di Cesare et al. (2010), we interpret this result as consistent with investors in bond market becoming more sensitive to firm-specific factors since the beginning of the crisis[20].

Some support to the increase in the sensitivity of the spreads to firm specific factors since the beginning of the crisis can be given when we look to the impact of leverage on credit spreads. Table III.3 shows that the effect of leverage became much more important since the beginning of the Eurozone crisis (the significance of leverage rose considerably in the last sub-period with a T-statistic of 3.876). The effect of leverage is however found to be less obvious in the first two sub-periods. This is very likely due to the disconnections between leverage levels and credit spreads that we documented in chapter II (an increase in leverage ratios in the pre-crisis period were associated with low credit spreads, while a decrease in leverage ratios during the subprime crisis period were associated with higher credit spreads, i.e. the paradox of tranquility). That being said, column 1 of Table III.3 shows that leverage is statistically significant for the ten years period, with a sign in line with the view of the structural models. This leads us to say that the structural models' view about the relationship between leverage and credit spreads holds in the long run.

Another structural credit risk variable used in Model 1 regression is equity volatility as a proxy of the firm value's volatility. Results in Table III.3 show that equity volatility is significant for the full sample analysis with the expected positive sign. Ceteris paribus, a one percent increase in equity volatility should increase firms' credit spreads by about 2.657 percent. Columns 2, 3 and 4 of Table III.3 show though that this relation is not stable over time. The relation between volatility and credit spread is found to be negative in the pre-crisis period, positive and significant during the subprime crisis and non-significant in the Eurozone crisis period. These results suggest that the relation between credit spread and volatility is nonlinear and cannot be captured by a simple linear OLS regression. In fact, equity volatility is not expected to have a constant and linear effect over

[20] Di Cesare et al. (2010) investigated however CDS spread data.

time since it is not the case for the structural models. The structural models assume generally that the firm-value volatility is constant over time; this allows in reality implicitly for a time varying equity volatility since this latter is dependent on a stochastic firm value. As such, the relation between credit spread and equity volatility is theoretically expected to be non-linear, which makes it hard to capture by the OLS regression. A complex relation between equity volatility and credit spread has also been documented by previous empirical studies done before the crisis; Collin-Dufresne et al. (2001), Zhang et al. (2005), Avramov et al. (2007), amongst others, found the signs and the significance of the volatility to be variant over time. Their findings are then robust to the crisis context.

The last theoretical variable included in Model 1 regression is the dividend yield. As expected, a positive and significant relationship is found with credit spread for the whole sample analysis. This result confirms the structural models view that we tested in chapter I about an increase in credit spreads in the case of an increase in payout ratios. Furthermore, since several companies announced reductions or temporary halts in their dividend payments during the crisis, the high credit spreads observed since the beginning of the crisis are not expected to be directly linked to increases in dividend yields. Columns 3 and 4 of Table III.3 give reasonable insight to this relation as we observe a lower significance for dividend yields in the subprime and the Eurozone crisis periods. This result is consistent with lower sensitivity of credit spreads to dividend yields since the beginning of the crisis.

Overall, the results of Model 1 show that all the explored theoretical determinants behave well in explaining credit spreads especially in the long run. The structural credit risk component explains up to 14.4% of the credit spread variation between July 2004 and July 2014. This result is in fact hardly comparable to the findings of previous empirical studies due to differences in dependent variables (credit spread as opposed to CDS spread), the investigated time periods or the used testing methodology. We note, however, that Collin-Dufresne et al. (2001) found that structural factors can explain about 25% of credit spread changes, Ericsson et al. (2006) found the same variables were capable of explaining 23% CDS spread changes, and Avramov et al. (2007) found credit risk variables are capable of explaining 43% of the time-series credit spread changes. Our results are therefore consistent with these studies in the sense that we find credit risk variables capable of explaining only a small portion of credit spread changes.

As regards the sub-periods regressions, we note that credit risk variables can explain respectively, 17.1%, 16.5%, and 16% of credit spread changes during the pre-crisis, the subprime crisis and the Eurozone crisis periods[21]. This decrease in the joint explanatory power of the structural variables, along with the increase in their t-statistics, bring evidence on the fact that the relation between credit spreads and credit risk variables became less linear since the onset of the crisis. The credit risk factors explain a higher portion of credit spread changes in periods of stable economic outlook where the relation between credit risk and credit spreads is seemingly more linear; during crisis periods the impact of the credit risk factors on credit spreads increases (as witnessed by the increase in t-statistics) but the relation between the two become apparently less linear yielding to the observed lower adjusted R-squared. A longer pre-crisis sample period would have very likely increased increased the significance of the structural variables tested in Model 1 to make them reach the levels documented by the previous studies.

We turn next to the robustness of structural variables to the introduction of new credit spread determinants. Tables III.-4, -5, -6 and -7 present the results of the estimates after the addition of, respectively, the market-wide factors, the liquidity factors, the lagged component and the additional variables[22]. Overall, we find that all the structural variables, except dividend yield, are robust to the introduction of the additional determinants. The dividend yield loses in fact slightly and then completely significance as we introduce, respectively, the aggregate and liquidity components. This result suggests that much of the variability of dividend yields is captured by the macrocosmic and market liquidity components.

Furthermore, Table III.4 shows that the introduction of the market-wide factors (i.e. market return, market volatility, the term-structure slope, the business climate indicator and LTROs) make idiosyncratic equity return lose much of its explanatory power. This result puts forward the presence of collinearities between individual equity return and some of the market factors, which is very likely to be Eurostoxx50 return (the average correlation coefficient between equity return and Eurostoxx50 return is of 0.56). Having done quite similar analysis, Avramov et al. (2007) found, contrariwise, that Market return loses significance in favor of idiosyncratic equity return when the two variables are set together. This result suggests that the market-wide factors have gained power since the beginning of the crisis at the expense of individual structural factors. This needs though further specifications that will be given later. Finally, looking to Table III.7 we notice that equity return loses more of its significance when the additional variables are introduced. Once again, this can be attributed

[21] As proposed by the adjusted R-squared.

[22] These tables are presented for convenience in the following subsections.

to the collinearity between equity return and firms' market value, as the average correlation coefficient between these two variables is of 0.55.

In summary, we find that all the used credit risk variables, except dividend yield, are robust in the long run (hence to the crisis context) and to the introduction of additional determinants. This credit risk component explains however only a small part of credit spreads, which is consistent with a large non-default component. This non-default component is explored in what follows.

6.2.2 Market-wide factors:

Table III.4. Regression Model 2 – Impact of market factors:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0315***	0.00620	0.0131	0.0380**
	(3.517)	(0.737)	(0.671)	(2.422)
Equity Return	-0.199***	-0.00569	-0.143**	-0.392***
	(-5.583)	(-0.173)	**(-2.121)**	**(-5.344)**
Historic volatility	3.523***	-2.226	4.958***	5.049**
	(3.135)	(-0.850)	**(2.959)**	**(2.154)**
10yrs treasury rate	-0.601***	-0.495***	-0.818***	-0.572***
	(-25.21)	**(-21.51)**	**(-14.42)**	**(-13.52)**
Dividend yield	0.00382*	0.0308***	0.00287	0.0117
	(1.936)	**(3.430)**	(1.131)	(1.350)
Market return	-1.276***	-0.450**	-0.436*	-2.323***
	(-10.12)	**(-2.020)**	**(-1.782)**	**(-9.156)**
VSTOXX Index	0.00345***	0.00130	0.00921***	-0.0121***
	(3.316)	(0.463)	**(5.702)**	**(-4.699)**
Term slope 30-10y	-0.492***	-0.350***	-0.0156	-0.755***
	(-10.90)	**(-3.810)**	(-0.180)	**(-10.07)**
Business Climate	-0.0718***	0.0748***	-0.229***	-0.00835
	(-4.739)	**(3.629)**	**(-8.175)**	(-0.284)
LTROs	-8.54e-09	-1.55e-08	-6.63e-08	9.08e-09
	(-0.33)	(-0.70)	(-0.72)	0.24
Constant	0.00278	0.00654	-0.00692	-0.0115**
	(0.836)	(1.488)	(-0.878)	**(-1.990)**
Observations	8,400	2,450	2,450	3,500
Adj R-squared	0.200	0.182	0.239	0.217

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

Table III.4 reports the results of the regression in Model 2. In addition to the structural variables previously explored, we added in this regression the Eurostoxx-50 return, the slope of the yield curve, the VSTOXX implied volatility index, the chosen business climate indicator and LTROs. As mentioned earlier, these variables are expected to capture some of the variation of credit spreads that is due to changes in economic conditions, systemic risks, risk premiums and recovery rates.

Column 1 of Table III.4 shows that all the added variables have a significant impact on credit spreads in the full-sample analysis (up to the 1% level), with the expected coefficient signs. More precisely, we find that market return and the term slope had the most important impact on credit spreads changes between July 2004 and July 2014 (t-statistics respectively of -10.12 and -10.90). As expected, the deterioration of economic conditions since the beginning of the crisis has been reflected by a shallow term slope and hence a negative relation between credit spreads and the slope of the yield curve. Further, we notice that the term slope became a very poor proxy for credit spread changes during the subprime crisis. This gives an indication about the low visibility that market participants had during the crisis about the future economic conditions. Moreover, the high significance of the Eurostoxx50 return is consistent with high sensitivity of credit spreads to systemic and default contagion risk that this proxy is expected to capture. This result brings support to the observations that we made in chapter II about the importance of these risks and their impact on the variations of credit spreads. Additionally, this proxy reveals an increase in the importance of the risk premiums asked by market participants since the beginning of the financial turmoil. Similarly to the term slope, we note a decrease in the significance of market return during the subprime crisis; this shows that this variable became a low proxy for market conditions during this period, which became increasingly unstable.

Moreover, in order to capture more informational content about the deterioration of economic conditions during the crisis, we used the business climate indicator as a proxy of the conditions in the real economy. Results in Table III.4 show that this variable is highly significant in the long run with a particularly high impact during the subprime crisis. This result, combined with the low significance of the market return during the subprime crisis, suggests the presence of collinearities between these two variables, and thus the business climate indicator became a better proxy of the overall economic conditions during the subprime crisis.

Furthermore, we used the VSTOXX index as a forward looking measure about the overall systemic and macroeconomic uncertainty. Non-significant during the pre- crisis period, the implied volatility index became an important determinant of credit spread changes during the subprime crisis, with the expected positive sign. This result highlights the important impact that the economic shocks and systemic events that happened during the crisis had on investors' uncertainty about the future economic conditions. Further, we note from Table III.4 that the relation between credit spread and the VSTOXX index became negative during the Eurozone crisis, even though always highly significant. This result suggests once again the presence of non-linearities between credit spreads and volatility. Nonetheless, the impact of the VSTOXX index is positive and significant on the long run in accord with a positive relation between market turbulence and credit spreads.

Finally, we investigated the impact of LTROs as a proxy of the actions of governments and central banks to stabilize the financial system (such as bailouts or the creation of financial stability boards). We find interestingly that this variable presents generally a negative relation with credit spreads. This tends to confirm the observations that we made in chapter II about a decrease in the overall credit spreads each time the authorities undertook actions to stabilize the system. However, we find unfortunately LTOS to be a poor proxy for these actions as it is non-significant in explaining credit spread changes over the different explored periods[23].

Overall, we interpret the results of Model 2 as consistent with a substantial reaction of the spreads to the market-wide risk factors. The sensitivity of the spreads to these factors is, however, time-varying and changes across the different crisis periods. In each of the analyzed sub-periods, we find indeed that some of the explored factors had more impact on credit spreads. This outlines the complementary nature of the chosen aggregate factors, and highlights the difficulty of capturing in a single proxy the explored market-wide risks in a crisis context.

To complete this view, we look next to the linear fit of the model. By adding these factors we can explain another 5.6% of credit spread changes for the full sample analysis. In particular, the five market-wide variables added only 1.1% of linear fit to the pre-crisis sample, while they added, respectively, 7.4% and 5.7% fit to the subprime crisis and Eurozone crisis sub-samples regression[24]. This result brings out clearly the important changes that the pricing of risk has undergone since the beginning of the crisis. For the same sample of bonds, we show that the aggregate risk factors became up to seven times higher during the subprime crisis, and up to five times higher in the Eurozone crisis period.

Considering finally the robustness of these proxies to the introduction of additional determinants, we note most of all that the VSTOXX volatility index loses too much of its significance as we introduce the lagged component in Model 4. Despite its statistical significance, the business climate index loses also its economic significance when the lagged variables are introduced (as its relation with credit spreads became positive). Market return and the term slope are shown to be independent of the other credit spread determinants and keep almost the

[23] We omit henceforth the use of the "LTRO" variable as it was not significant in none of the explored periods in Model 2 regression.

[24] Adjusted R-squared rose from 16.5% to 23.9% during the subprime crisis and from 16% to 21.7% after it.

same level of economic and statistical significance for all the subsequent models. In what follows we explore the effect of the introduction of the liquidity factors.

6.2.3 Liquidity risk factors:

Table III.5. Regression Model 3 – Impact of liquidity component:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0255***	0.00606	0.00496	0.0223
	(2.882)	(0.746)	(0.257)	(1.458)
Equity Return	-0.180***	-0.00752	-0.128*	-0.330***
	(-5.141)	(-0.237)	**(-1.917)**	**(-4.627)**
Historic volatility	4.141***	-2.148	5.078***	5.389**
	(3.733)	(-0.848)	**(3.062)**	**(2.365)**
10yrs treasury rate	-0.592***	-0.481***	-0.862***	-0.456***
	(-25.14)	**(-21.26)**	**(-15.24)**	**(-10.87)**
Dividend yield	0.00260	0.0263***	0.00235	0.00873
	(1.332)	**(3.028)**	(0.936)	(1.033)
Market return	-1.504***	-0.517**	-0.847***	-1.598***
	(-12.00)	**(-2.401)**	**(-3.396)**	**(-6.349)**
VSTOXX Index	-0.0048***	0.000573	0.00133	-0.0144***
	(-4.123)	(0.212)	(0.678)	**(-5.738)**
Term slope 30-10y	-0.375***	-0.410***	0.0543	-0.503***
	(-8.301)	**(-4.571)**	(0.630)	**(-6.712)**
Business Climate	-0.0520***	0.0771***	-0.185***	-0.0440
	(-3.469)	**(3.796)**	**(-6.503)**	(-1.535)
Bid-Ask spread	0.00738***	0.0488***	0.0123***	0.000596
	(3.808)	**(13.37)**	**(2.617)**	(0.244)
Market liquidity	0.462***	0.255	0.304***	1.154***
	(14.94)	(0.565)	**(6.812)**	**(14.37)**
Constant	0.00250	0.00640	-0.0110	-0.00988*
	(0.761)	**(1.507)**	**(-1.407)**	**(-1.755)**
Observations	8,400	2,450	2,450	3,500
Adj R-squared	0.222	0.238	0.256	0.261

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

In order to assess the importance of the liquidity premiums lying behind credit spread changes, we used in this study two illiquidity proxies: the Bid-Ask spread as a transaction cost measure of bond-specific liquidity and the Euribor-OIS spread as a market-wide illiquidity proxy.

Considering the first measure (i.e. the Bid-Ask spread), results reported in Table III.5 show that there is a significant and positive relationship between credit spreads and Bid-Ask spread for the whole sample period. This result is consistent with the hypothesis that we made previously, and brings support to the previous empirical studies that used the Bid-Ask spread as a liquidity measure. These include, De Jong and Driessen (2005), Acharya and Pedersen (2005) and Chen and Lesmond (2007). Moreover, column 2 of Table III.5 shows that the Bid-Ask spread were highly significant in the pre-crisis period (t-statistic of 13.37). As liquidity drained in the wake of the subprime crisis, the pricing turbulence increased and the transaction cost measure became apparently a poor proxy for bond individual liquidity; as such, it lost much of its significance. The Bid-Ask spread became even totally non-significant in the Eurozone crisis period (see column 4 of Table III.5), suggesting the continuation of the same pattern as for the crisis period (i.e. widening of Bid-Ask spreads). Hence, we can't unfortunately bring evidence for an increase in bond-specific illiquidity since the beginning of the crisis by the means of this transaction cost measure. We rather find evidence for an increase in the pricing turbulence that made this proxy lose much of its significance.

Turning to the Euribor-OIS spread, results in column 1 of Table III.5 show that changes in the market liquidity have the expected positive sign with a much higher significance level than the Bid-Ask spread. With regard to the crisis sub-periods, we notice that market liquidity has opposite dynamics to those documented for the Bid-Ask spread. Changes in the Euribor-OIS spread is found to be non-significant for the pre-crisis period while it becomes a very important determinant of credit spread since the onset of the crisis. This result confirms the observations that we made in chapter II about an increase in the tensions in the interbank market since the beginning of the crisis. These tensions are found to have a more important impact on the spreads in the Eurozone crisis period.

Despite the time-varying significance observed for the used liquidity proxies, the overall evidence is consistent with a positive and important relation between illiquidity and credit spreads, with a higher impact for the market-wide liquidity. The importance of this liquidity component in credit spreads is however found to be relatively small. Adding the above liquidity proxies made the adjusted R-squared go from 18.2% to 23.8% for the pre-crisis sample (i.e. 5.6% change), from 23.9% to 25.6% (i.e. 1.7% change) during the subprime crisis, and from 21.7% to 26.1% (i.e. 4.4% change) after it. According to this evidence, illiquidity premiums had a larger increase during the Eurozone crisis periods, but were not the major determinant of the high credit spreads observed since the beginning of the crisis. Illiquidity is actually shown to have a higher impact on credit spreads in periods of relatively stable economic outlook. Encouragingly, these results are greatly robust to the introduction of additional credit spread determinants as shown in Tables III.-5 and -6.

6.2.4 Lagged component:

Table III.6 presents the results of the regression in Model 4. This model explores the joint explanatory power of all the previous credit spread determinants along with the lags of: credit spreads, equity returns, market return, the risk-free rate, and the Euribor-OIS spread.

Table III.6. Regression Model 4 – Impact of the lagged component:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0201**	0.00538	0.00805	0.0144
	(2.406)	(0.684)	(0.425)	(1.016)
Equity Return	-0.153***	-7.28e-05	-0.0705	-0.227***
	(-4.587)	(-0.00224)	(-1.035)	**(-3.285)**
Historic volatility	5.554***	-0.561	5.567***	5.730***
	(5.260)	(-0.227)	**(3.427)**	**(2.665)**
10yrs treasury rate	-0.529***	-0.474***	-0.835***	-0.370***
	(-22.33)	**(-19.13)**	**(-13.75)**	**(-8.885)**
Dividend yield	0.000868	0.0273***	0.00125	0.00589
	(0.469)	**(3.216)**	(0.507)	(0.747)
Market return	-1.253***	-0.381	-1.210***	-1.618***
	(-9.749)	(-1.357)	**(-4.436)**	**(-6.658)**
VSTOXX Index	0.00162	0.00466	0.000386	-0.00173
	(1.323)	(1.428)	(0.183)	(-0.681)
Term slope 30-10y	-0.384***	-0.379***	-0.0692	-0.348***
	(-8.921)	**(-3.888)**	(-0.765)	**(-4.954)**
Business Climate	0.0294**	0.0803***	-0.101***	-0.00395
	(1.981)	**(4.048)**	**(-2.981)**	(-0.144)
Bid-Ask spread	0.00653***	0.0451***	0.0119***	0.000153
	(3.554)	**(12.72)**	**(2.593)**	(0.0674)
Market liquidity	0.273***	1.059**	0.291***	0.390***
	(8.646)	**(2.225)**	**(6.140)**	**(4.211)**
Lagged spread	0.280***	0.242***	0.198***	0.322***
	(26.44)	**(12.41)**	**(9.976)**	**(19.45)**
Lag Equity return	-0.145***	0.0331	-0.203***	-0.197***
	(-4.404)	(1.023)	**(-3.075)**	**(-2.909)**
Lag Market return	-0.260***	-0.0778	0.386**	-0.481***
	(-2.756)	(-0.523)	**(2.005)**	**(-2.935)**
Lag 10yrs rate	0.0959***	0.0416	-0.000993	0.214***
	(4.118)	(1.452)	(-0.0167)	**(5.984)**
Lag Market liquidity	0.0548**	0.734	-0.00858	0.238***
	(2.006)	(1.281)	(-0.215)	**(2.691)**
Constant	0.00129	0.00251	-0.0154**	0.00182
	(0.409)	**(0.576)**	**(-1.979)**	**(0.335)**
Observations	8,400	2,450	2,450	3,500
Adj R-squared	0.303	0.286	0.292	0.367

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

As mentioned previously, these lagged variables are expected to capture some of the information asymmetry and market frictions lying behind credit spread movements. Results in column 1 of Table III.6 show that all of the added variables have high statistical significance in explaining credit spread changes for the full-sample regression. Interestingly, the "lagged credit spread" has by far the highest significance in explaining credit spread variations (t-statistic of 26.44). Its positive coefficient sign suggests that an increase in previous months' credit spread is associated by market participants to an increase in current months' credit spreads. Turning to the sub-periods analysis, Table III.6 shows that the "lagged credit spread" is the only significant variable among the introduced lagged variables in the pre-crisis period. Hence, prior to June 2007, none of the delayed information from stock markets or interest rates had an impact on credit spreads, as the economic conditions were stable. After June 2007, results in columns 3 of Table III.6 bring evidence to an increase in the sensitivity of credit spreads to the delayed information, particularly from stock markets (both lags of equity and market returns became significant in the subprime crisis period). This sensitivity became even more important in the Eurozone crisis period, as the delayed values of the risk-free rate and the Euribor-OIS spread became also highly significant (hence all the delayed factors became significant in this period). Our interpretation is that the turbulence that markets have experienced since the beginning of the crisis has increased the level of information asymmetry among market participants, and put forward the imperfections of the price adjustment process in the corporate bond market. As such, the previous periods' values of the considered proxy became significant in explaining current values of credit spreads. These findings are found to hold for the subprime crisis, the Eurozone crisis, and the full-sample periods regressions, suggesting a durable change in the pricing mechanisms inside the corporate bond market. This result brings support to the ideas of R. Shiller et al. (1989) and A. Orleans (1999) about the fact that market imperfections and information asymmetries tend to worsen during the periods of instability and crisis (which prevents them from returning quickly to equilibrium). All these observations highlight a major drawback of the structural models, which consider perfect and frictionless pricing mechanisms in the corporate bond market.

Overall, the impact of the delayed information component on credit spread seems very interesting as it adds up to 8.1% of fit to the adjusted R-squared found in model 3. This impact is found to be particularly considerable in the Euro crisis period, where the adjusted R-squared went from 26.1% to 36.7% (i.e. 10.6% increase) due to the introduction of this component. In what follows, we consider the impact of the remaining credit spread determinants.

6.2.5 Additional variables:

Finally, we consider the impact of the introduction of the Confidence Index and the firm-size proxies on credit spread changes.

Table III.7. Regression Model 5 – Impact of the additional variables:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0205**	0.00541	0.00605	0.0130
	(2.457)	(0.687)	(0.321)	(0.922)
Equity Return	-0.0699*	0.00293	0.0761	-0.0453
	(-1.924)	(0.0883)	(0.987)	(-0.573)
Historic volatility	5.333***	-0.548	5.115***	6.415***
	(5.059)	(-0.222)	**(3.153)**	**(2.990)**
10yrs treasury rate	-0.516***	-0.489***	-0.807***	-0.367***
	(-21.66)	**(-18.53)**	**(-13.26)**	**(-8.817)**
Dividend yield	0.00109	0.0274***	0.00229	0.00411
	(0.590)	**(3.196)**	(0.934)	(0.521)
Market return	-1.111***	-0.510*	-1.074***	-1.532***
	(-8.521)	**(-1.735)**	**(-3.932)**	**(-6.277)**
VSTOXX Index	0.00143	0.00364	8.24e-05	-0.00194
	(1.168)	(1.093)	(0.0392)	(-0.764)
Term slope 30-10y	-0.382***	-0.472***	-0.0855	-0.361***
	(-8.870)	**(-4.183)**	**(-0.948)**	**(-5.157)**
Business Climate	0.0614***	0.0807***	-0.0116	0.0128
	(3.651)	**(4.050)**	(-0.277)	(0.410)
Bid-Ask spread	0.00667***	0.0451***	0.0114**	0.000682
	(3.643)	**(12.72)**	**(2.493)**	**(0.301)**
Market liquidity	0.287***	0.949**	0.305***	0.379***
	(9.055)	**(1.967)**	**(6.420)**	**(4.102)**
Lagged spread	0.277***	0.242***	0.190***	0.321***
	(26.17)	**(12.38)**	**(9.616)**	**(19.44)**
Lag Equity return	-0.129***	0.0336	-0.210***	-0.206***
	(-3.914)	(1.034)	**(-3.198)**	**(-3.023)**
Lag Market return	-0.241**	-0.0813	0.510***	-0.444***
	(-2.548)	(-0.545)	**(2.617)**	**(-2.714)**
Lag 10yrs rate	0.0916***	0.0571*	-0.000755	0.206***
	(3.941)	**(1.894)**	(-0.0127)	**(5.748)**
Lag Market liquidity	0.0544**	0.379	0.0189	0.240***
	(1.987)	(0.619)	(0.461)	**(2.703)**
Market value	-5.8e-06***	-2.01e-07	-6.6e-06***	-1.1e-05***
	(-5.482)	(-0.167)	**(-3.681)**	**(-4.449)**
Number of employees	1.8e-06***	1.44e-07	6.06e-07	7.1e-06***
	(2.674)	(0.244)	(0.487)	**(3.729)**
Confidence Index	-0.0075***	0.00326	-0.0169***	-0.00271
	(-3.823)	(1.629)	**(-3.560)**	(-0.710)
Constant	0.00126	0.00241	-0.0156**	0.00290
	(0.401)	(0.552)	**(-2.019)**	(0.537)
Observations	8,400	2,450	2,450	3,500
Adj R-squared	0.307	0.287	0.300	0.373

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

Results in Column 1 of Table III.7 show that, as expected, a negative and significant relationship exists between credit spread and investors' confidence. This relation is found to be particularly high during the subprime crisis period, while no significant impact is signaled for the pre-crisis or the Eurozone crisis periods. As the crisis stepped by, the discrepancy between the yields of the speculative grade bonds and the intermediate grade bonds decreased, showing a decrease in the investors' confidence and an increase in their risk aversion. Thereby, they demanded even higher risk premiums for the same promised cash-flows in the subprime crisis period, as compared to the pre-crisis period where their risk aversion and risk premiums were low. This situation again illustrates very well the paradox of tranquility proclaimed by Hyman Philip Minsky (1975; 1977)[25], and brings an additional explanation to the huge levels and variations of credit spreads witnessed during the crisis. This result sheds light on another major drawback of the structural models, which refrain from considering investors' risk aversions; these latter are found to explain a non-negligible part of credit spread movements, especially during crisis periods.

Further, in order to investigate the presence of a firm-size effect lying behind credit spread changes, we used in this study firms' number of employees and market value as complementary proxies for firms' sizes. These two variables are found to be remarkably significant in the whole sample analysis (see Table III.7). As regards the coefficient signs, an increase in the firms' market value is found to be associated to a decrease in credit spreads (hence in accord with the made hypothesis and the structural models' view), while an increase in the number of employees is found to be associated to an increase in credit spreads (hence an increase in the number of employees is associated to a cost that reduces the firm value and increases its spreads). Further, consistently with the evidence reported for the structural credit risk variables, we find that credit spreads' sensitivity to firm-size variables has increased since the beginning of the crisis (see columns 3 and 4 of Table III.7). Again, this result suggests an exacerbation in the difference between firms since the beginning of the crisis, which made investors become more sensitive to idiosyncratic risk factors like firm-size. This result is encouraging since it brings support to the presence of a size-related premium in credit spreads. It needs, however, further specification that will be provided later[26].

Finally, we note that the linear contribution of these additional variables (confidence index and firm size proxies) is relatively small as the adjusted R-squared rise only from 30.3% to 30.7% in the full-sample regression. In the same lines as previously, we find that credit spreads present a higher sensitivity to the

[25] See chapter II, section 3.1 for more details.

[26] Regression results for groups of firm-size will be presented in the "specification" sub-section.

added variables during the subprime crisis (+0.8 linear fit) and the Eurozone crisis (+0.6 linear fit), as compared to the pre-crisis period (+0.1 linear fit).

Finally, Table III.8 summarizes the results of the five regression models that we explored:

Table III.8. Summary of the five regression models:

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Leverage	0.0324***	0.0315***	0.0255***	0.0201**	0.0205**
	(3.506)	**(3.517)**	**(2.882)**	**(2.406)**	**(2.457)**
Equity Return	-0.604***	-0.199***	-0.180***	-0.153***	-0.0699*
	(-19.42)	**(-5.583)**	**(-5.141)**	**(-4.587)**	**(-1.924)**
Histvol 180	2.657**	3.523***	4.141***	5.554***	5.333***
	(2.300)	**(3.135)**	**(3.733)**	**(5.260)**	**(5.059)**
10yrs rate	-0.635***	-0.601***	-0.592***	-0.529***	-0.516***
	(-27.85)	**(-25.21)**	**(-25.14)**	**(-22.33)**	**(-21.66)**
Dividend yield	0.00645***	0.00382*	0.00260	0.000868	0.00109
	(3.169)	**(1.936)**	(1.332)	(0.469)	(0.590)
Market return		-1.276***	-1.504***	-1.253***	-1.111***
		(-10.12)	**(-12.00)**	**(-9.749)**	**(-8.521)**
VSTOXX Index		0.00345***	-0.0048***	0.00162	0.00143
		(3.316)	**(-4.123)**	(1.323)	(1.168)
T-slope 30-10y		-0.492***	-0.375***	-0.384***	-0.382***
		(-10.90)	**(-8.301)**	**(-8.921)**	**(-8.870)**
Business Climate		-0.0718***	-0.0520***	0.0294**	0.0614***
		(-4.739)	**(-3.469)**	**(1.981)**	**(3.651)**
Bid-Ask spread			0.00738***	0.00653***	0.00667***
			(3.808)	**(3.554)**	**(3.643)**
Market liquidity			0.462***	0.273***	0.287***
			(14.94)	**(8.646)**	**(9.055)**
Lagged spread				0.280***	0.277***
				(26.44)	**(26.17)**
Lag Equity Ret				-0.145***	-0.129***
				(-4.404)	**(-3.914)**
Lag Market Ret				-0.260***	-0.241**
				(-2.756)	**(-2.548)**
Lag 10yrs rate				0.0959***	0.0916***
				(4.118)	**(3.941)**
Lag M-liquidity				0.0548**	0.0544**
				(2.006)	**(1.987)**
Market value					-5.8e-6***
					(-5.482)
Nb of employees					1.84e-6***
					(2.674)
Confidence Index					-0.0075***
					(-3.823)
Constant	-0.00130	0.00278	0.00250	0.00129	0.00126
	(-0.379)	(0.836)	(0.761)	(0.409)	(0.401)
Observations	8,400	8,400	8,400	8,400	8,400
Adj R-squared	0.144	0.200	0.222	0.303	0.307

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

We show that most of the variables used up to Model 5 have a certain impact on credit spread changes for the full-sample analysis. Only LTROs had no statistical significance, while the dividend yields and market volatility lost their statistical significance, respectively, when the liquidity component and the delayed information component were introduced. In parallel, the ”business climate indicator” lost its economic significance when the delayed information component was introduced.

Further, Table III.8.b gives an idea on the importance of the investigated credit spread components in each of the analyzed sub-periods. The importance of each component is established on the basis of its contribution to the adjusted R-squared of each regression model:

Table III.8.b. Credit spread components by period:

Period / Order	Pre-crisis	Subprime crisis	Eurozone crisis
1	Credit risk (17.1%)	Credit risk (16.5%)	Credit risk (16%)
2	Liquidity risk (5.6%)	Market-wide risks (7.4%)	Delayed information (10.6%)
3	Delayed information (4.8%)	Delayed information (3.6%)	Market-wide risks (5.7%)
4	Market-wide risks (1.1%)	Liquidity risk (1.7%)	Liquidity risk (4.4%)
5	Additional factors (0.1%)	Additional factors (0.8%)	Additional factors (0.6%)
Total Adj-R^2	28,70%	30,00%	37,30%

Table III.8.b adds some interesting insights to the conclusions made earlier. First, we note that credit risk always constitutes the most important component of credit spread changes in each of the analyzed sub-periods. This result brings support to the view of structural models, which generally consider credit spreads to be driven by credit risk. Second, Table III.8.b shows that the relative importance of the liquidity risk, market-wide risks and the delayed information components have changed considerably since the onset of the crisis. While liquidity was the second most represented risk in credit spreads in the pre-crisis period, it became only the fourth most important component of credit spreads in the subprime crisis and the Eurozone crisis periods. Macroeconomic and systemic risk factors become presumably the second most important drivers of credit spread changes in the subprime crisis period (i.e. +7.4% for market-wide risks), whereas the delayed information component took a more considerable place in the spreads during the Eurozone crisis period (+10.6%). Interestingly, this result brings evidence to a change in the structure of the risks priced inside corporate bonds' credit spreads since the beginning of the crisis.

All in all, the suggested credit spread determinants are found to explain up to 30.7% of credit spread changes for the period between July 2004 and July 2014. This result is interesting given the large and comprehensive set of variables investigated in this study. It is, however, consistent with the findings of many previous empirical studies that documented a large unexplained portion of credit spread changes. We note for instance that Collin-Dufresne et al. (2001) and Avramov et al. (2007) found their sets of determinants to be able to explain, respectively, 34% and 54% of average time-series credit spread changes, while Mayrordomo et al. (2012) found their set of variables to be able to explain only 14.1% of credit spread changes. Our interpretation for the large unexplained portion of credit spread changes that we document is as follows. First, we believe that the effect of some of the credit spread determinants that we consider is not well-captured by the OLS regression technique. The OLS regression assumes indeed that the used determinants affect credit spreads in a linear fashion. However, as we have shown in the numerical analysis that we proposed in chapter I, the relationship between credit spread and their determinants is generally nonlinear. Second, some of the factors that we have explored are not apparently well proxied (e.g. LTROs the proxy of authorities' actions was not significant). Better proxies would have arguably improved the fit of our model. Finally, we expect a portion of the unexplained variation to be due to one, or more, factor(s) that we do not consider in our set of credit spread determinants. The nature of this (these) factor(s) will be explored, amongst others, in the robustness checks that we propose in what follows.

6.3. Robustness checks:

To further assess the robustness of our results, we conducted three series of robustness checks. These include: (*i*) a check of the robustness of the OLS regression method compared to the results of the fixed-effects regression; (*ii*) a check of the robustness of the found credit spreads determinants to Credit Default Swap (CDS) spread changes; and (*iii*) a Principal Component Analysis (PCA) of credit spreads changes and Model 5 regression residuals. The results of these three tests are discussed in what follows.

6.3.1 OLS vs. Fixed-effects regression:

First, we checked the robustness of the OLS regression by running Model 5 using Fixed-effects Panel regression. Results in Table III.9 show that the coefficients and the t-statistics are extremely close for both regression methods. This tends to confirm the robustness of the OLS regression.

Table III.9. OLS vs Fixed-effects regression: (Model 5)

Variables	OLS Regression	Fixed effects
Leverage	0.0207**	0.0230**
	(2.481)	(2.514)
Equity Return	-0.0709**	-0.0696*
	(-1.983)	(-1.930)
Historic volatility	5.251***	5.257***
	(4.987)	(4.972)
10yrs treasury rate	-0.522***	-0.522***
	(-22.00)	(-21.92)
Market return	-1.181***	-1.181***
	(-12.81)	(-12.76)
Term slope 30-10y	-0.381***	-0.381***
	(-8.919)	(-8.886)
Business Climate	0.0570***	0.0566***
	(3.477)	(3.441)
Bid-Ask spread	0.00674***	0.00674***
	(3.678)	(3.668)
Market-liquidity	0.321***	0.321***
	(12.33)	(12.28)
Lag spread	0.281***	0.279***
	(26.83)	(26.55)
Lag Equity return	-0.127***	-0.126***
	(-3.870)	(-3.814)
Lag Market return	-0.245***	-0.249***
	(-2.845)	(-2.879)
Lag 10yrs rate	0.0959***	0.0950***
	(4.157)	(4.103)
Market value	-5.96e-06***	-5.98e-06***
	(-5.581)	(-5.570)
Number of employees	1.94e-06***	1.94e-06***
	(2.831)	(2.815)
Confidence Index	-0.00714***	-0.00716***
	(-3.639)	(-3.638)
Constant	0.00125	0.00140
	(0.398)	(0.444)
Observations	8,400	8,400
Adj R-squared	0.307	0.307

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

6.3.2 Credit spread vs. CDS spread regressions:

Next, we checked the robustness of our final set of credit spread determinants by examining how well they explain CDS spreads changes[27]. Finding CDS data that have comparable features to the bond sample that we used was not an easy task. As a matter of fact, not all the used bond entities have quoted CDS contracts, in addition to the fact that the maturities of corporate bond and CDS contracts may be hardly comparable. To make this robustness check as consistent as possible, we proceeded as follows. First, we started by searching for CDS contracts quoted for the same entities that we use in our bond sample. Only 27 CDS contracts were available for these firms on Datastream. Next, in order to converge the maturities of the bonds and CDS contracts, we decided to use only the CDS contracts of 10-year maturity (as they are closer to the average maturity of the bond sample)[28]. Finally, we deleted the CDS contracts that have missing data over a long period of time. The final sample consisted of CDS spread data for 20 different entities that we use in this robustness check[29]. In addition to the limitation in the bond sample, this robustness analysis was also limited by the period of availability of the CDS data on Datastream. The CDS data are indeed available only starting from November 2008[30]. Hence, in order to make the results of the CDS regression comparable to the ones of credit spreads, we ran again the Model 5 regression using the exact same 20 bond entities available for the CDS data, and the exact same time period (from November 2008 to July 2014). Results of this robustness test are reported in Tables III.10 and III.11.

The results of this robustness check are interesting in many regards. First, we find that the same determinants are capable of explaining an almost similar portion of the variation of credit spread and CDS spread changes since November 2008 (the adjusted R-squared is of 35.5% for CDS spread and 35.7% for credit spread). Second, the first columns of Tables III.10 and III.11 show that equity return; the 10-year rate; market return; the term-slope; the lagged spread and the lagged 10-year rate have generally significant impact on credit spreads and CDS spreads. This leans in favour of the robustness of these determinants. The most-

---

[27] Credit spreads and CDS spreads are expected to have the same determinants according to the previous empirical studies. Hence we can check the robustness of our set of credit spread determinants by assessing how well they explain CDS spreads changes.

[28] CDS contracts have generally maturities of five or ten years.

[29] These entities are described in Appendix III.4.

[30] Fortunately this data set captures the last quarter of the year 2008 which is key period in the crisis. We omit hence the pre-crisis period for this robustness test.

Table III.10. Regressions for the twenty CDS entities:

Variables	Since November 2008	Since May 2010
Leverage	2.477404	-1.912351
	(0.71)	(-0.74)
Equity return	-85.20***	-44.82***
	(-6.244)	**(-3.729)**
Historic volatility	-2.254	-1.648
	(-0.381)	(-0.302)
10yrs treasury rate	-45.32***	5.642
	(-6.339)	(0.867)
Market return	-210.8***	-325.1***
	(-7.532)	**(-12.31)**
Term slope 30-10y	-92.30***	-45.29***
	(-7.927)	**(-4.127)**
Business Climate	-7.808	-5.141
	(-1.506)	(-1.113)
Market-liquidity	-2.337	43.06***
	(-0.338)	**(3.471)**
Lagged spread	0.268***	0.223***
	(11.46)	**(7.553)**
Lag equity return	9.135	-19.58**
	(0.836)	**(-2.023)**
Lag market return	11.57	-28.69
	(0.454)	(-1.139)
Lag 10yrs rate	18.62***	20.90***
	(2.780)	**(3.851)**
Market value	3.27e-05	0.000584
	(0.0617)	(0.879)
Number of employees	0.00175	-0.00221
	(0.703)	(-1.025)
Confidence Index	1.051	-0.280
	(1.471)	(-0.478)
Constant	-1.448	1.467*
	(-1.504)	(1.788)
Observations	1,600	1,020
Adj R-squared	0.355	0.519

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

remarkable difference between the determinants of the two spreads is indeed documented for their sensitivity to equity market information. While equity return is found to have only small impact on the credit spreads of the chosen twenty entities, it is found to have a highly significant impact on CDS spreads. Conversely, we find that the lagged equity return is significant only for credit spreads. We interpret this result as consistent with different speeds of adjustments between the corporate bond and CDS markets to information from equity markets. The slow speed of adjustment of the corporate bond market (catalysed

Table III.11. Regression for the twenty bonds entities:

Variables	Since November 2008	Since Mai 2010
Leverage	0.0451	0.0455
	(1.566)	(1.250)
Equity return	-0.0779	-0.400***
	(-0.694)	**(-2.593)**
Historic volatility	2.174	1.194
	(0.869)	(0.357)
10yrs treasury rate	-0.469***	-0.249***
	(-7.119)	**(-2.781)**
Market return	-1.269***	-1.552***
	(-5.033)	**(-4.217)**
Term slope 30-10y	-0.472***	-0.331**
	(-4.401)	**(-2.197)**
Business Climate	0.0758	0.0547
	(1.589)	(0.827)
Market-liquidity	0.457***	**0.596*** **
	(7.118)	(3.421)
Lagged spread	0.291***	0.356***
	(12.45)	**(11.95)**
Lag equity return	-0.214**	0.0539
	(-2.162)	(0.410)
Lag market return	-0.344	-1.080***
	(-1.493)	**(-3.394)**
Lag 10yrs rate	0.102*	0.244***
	(1.656)	**(3.227)**
Market value	-1.75e-05***	-7.56e-06
	(-3.790)	(-0.848)
Number of employees	2.85e-06*	1.89e-05***
	(1.770)	**(3.274)**
Confidence Index	-0.00826	-0.00821
	(-1.271)	(-0.999)
Constant	-0.0111	0.0131
	(-1.231)	(1.149)
Observations	1,600	1,000
Adj R-squared	0.359	0.391

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

by the higher impact of the lagged equity return on credit spreads) seems to be in accord with the inefficiencies in the bond market documented earlier. Moreover, Table III.10 shows that the market liquidity proxy (i.e. the Euribor-OIS spread) is significant only for the credit spread regression; this suggests a higher impact of market illiquidity on corporate bonds credit spreads[31]. Considering the confidence index and the number of employees, we cannot, unfortunately,

[31] We omitted the use of Bid-Ask spread in this robustness test due to the non-availability of CDS Bid-Ask data.

conclude about the robustness of these variables from this check since they are not significant for the CDS regressions (possibly due to the sample restrictions). Further, the second column of Tables III.10 and III.11 explores these results by assessing the impact of these same determinants on credit spreads and CDS spreads in the period from May 2010 to July 2014[32]. Interestingly, we find that market liquidity became statistically significant, which confirms the impact of liquidity shocks on CDS spreads, and brings some evidence to the robustness of this proxy. Furthermore, Table III.11 shows that the same determinants explain a higher portion of CDS spreads for this period (51.9% of adjusted R-squared for CDS spreads against 38.3% for credit spreads[33]). Hence, in accord with results found for the bond regressions, the impact of our set of determinants on CDS spreads is also found to be time-varying, with a higher impact in the Eurozone crisis period. The effect of these factors is however found to be much more important in the CDS market, which brings some understandings to the higher Adjusted R-squared reported by the previous empirical studies for the CDS spreads regressions. In summary, despite the potential differences in risk pricing between the Bonds and CDS markets, this robustness test was very conclusive since it shows that the majority of used risk proxies have impact on both CDS and Corporate bonds markets. The evidence is likewise consistent with a large unexplained portion of the spreads in the two markets.

6.3.3 Principal component analysis of credit spreads changes and regression residuals:

To further explore the nature of the unexplained portion of credit spread changes, we finally implement a Principal Component Analysis (PCA) of credit spreads and the regression residuals of Model 5.[34] Following Collin-Dufresne et al. (2001), many empirical studies have used the PCA technique to understand the structure of the remaining variation of credit spreads. Collin-Dufresne et al. (2001) documented that up to 75% of the variation in the residuals of their regression were due to the first principal component, which they attributed to a large systematic component lying behind credit spread changes. Leading three PCAs on different CDS spread residuals sub-samples, Ericsson et al. (2004) reported only weak evidence of a residual common factor. The first principal component explained in their analysis only 30% of the residuals variation. In the same vein,

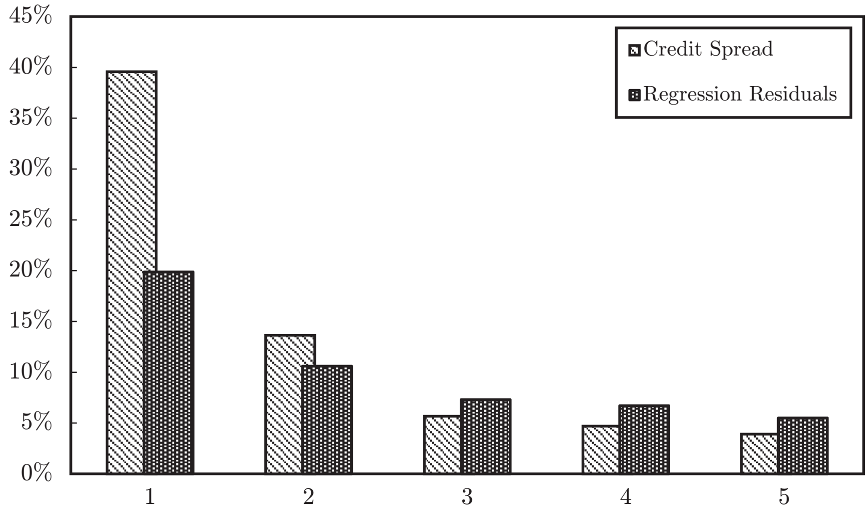
[32] Consistent with the Eurozone crisis period explored earlier.

[33] Recall that for the 70 bonds sample we were able to explain only 37.3% of credit spread variation for the Eurozone crisis period (See column 4 of table 7).

[34] The aim of the Principal Component Analysis performed here is not to establish the number of the driving factors nor their nature, but to assess their relative variation between credit spreads and the regression residuals. This PCA differs also from the one that was done in chapter II, which was performed on levels data.

Avramov et al. (2007) compared the principal components of credit spreads to the principal components of the regression residuals and found that the first principal component counts for 30% of individual credit spreads variation, while it counts for only 5% of the residuals variation. More recently, Di Cesare et al. (2010) investigated the fraction of residuals explained by the principal components for CDS spread data during the subprime crisis. They found that the first component counts for only 40% of the residuals variance during the crisis. Finally, Mayordomo et al. (2012) found that the first principal component explains only 20% of the residuals variation for Bond and CDS spreads. They found that up to ten principal components are needed to explain 54% of the variation of credit spread and CDS spread residuals. In view of this literature, it seems that the study of Collin-Dufresne et al. (2001) was one of the few studies to find evidence for a common latent factor lying behind the unexplained portion of credit spread changes. Here, we contribute to this literature by performing a Principal Component Analysis on both credit spreads changes and the regression residuals of our benchmark setup in Model 5. In addition, we specify our results by performing different PCAs for each of the pre-crisis, the subprime crisis and the Eurozone crisis periods, similarly to what we have done in chapter II. This should allow us to assess how the unexplained portion of credit spread changes has evolved since the beginning of the crisis. The results of these PCAs are reported in Figures: III.2, III.3 and III.4.

Figure III.2. Principal Component Analysis of credit spread changes and regression residuals



First, Figure III.2 summarizes the results of the PCA of credit spreads and the regression residuals for the whole sample period[35]. Focusing on the components of

[35] We recall that our set of credit spread determinants were able to explain only 30.7% of credit spread changes in the full sample analysis.

credit spread changes, we note that the two principal components count respectively, for 39.57% and 13.64% of credit spread variation (the five principal components count all together for 67%, while all the other components are relatively small).[36] Turning to the regression residuals, Figure III.2 shows that the two principal components count only for 19.87% and 10.6% of the variation in credit spread residuals; this confirms the ability of our benchmark setup to capture a considerable part of the factors lying behind credit spread changes. Furthermore, we note that seven principal components are needed in order to explain 60% of the regression residuals. This result suggests that numerous, relatively-small, factors are needed in order to explain the remaining portion of credit spread changes. Our evidence is hence more in agreement with the findings of Avramov et al. (2007) and Mayordomo et al. (2012), rather than those of Collin-Dufresne et al. (2001) who documented the presence of a single common factor that explains most of the latent credit spread variation.

Our interpretation for the remaining portion of credit spread changes is as follows. First, we estimate that some of the latent variation of credit spreads is due to the factors that our proxies fail to capture, or do not capture sufficiently well. These include mainly authorities' actions during the crisis (e.g. the bailouts or the creation of the different financial stability boards) that our LTRO proxy fails to capture. Second, we believe that a non-negligible portion of the unexplained variation of the spread changes must be due to mispricing performed by investors with biased beliefs[37]. This mispricing cannot seemingly be captured by our comprehensive set of credit risk, market-wide risks, liquidity risk, information asymmetries and risk aversion proxies. In the following, we specify the changes that this latent portion of credit spread changes have undergone since the beginning of the crisis.

Figures III.3 and III.4 present, respectively, the proportions of the five principal components of credit spreads changes and Model 5 residuals specified for the pre-crisis, the subprime crisis and the Eurozone crisis periods. These principal components are additionally specified for the pre-crisis, the subprime crisis and the Eurozone crisis periods. First, in agreement with the observations made previously, we note that our model explains generally a larger portion of credit spread changes in the subprime and the Eurozone crises periods (e.g. the

---

[36] The results of the PCA led on credit spread changes differ hence substantially from those found for the PCA led on credit spread levels. We found in chapter II that the first principal component of credit spread levels explains up to 75% of credit spread variance, while the five principal components counted for up to 94% of credit spread variance (see section 4.2.1.2 of chapter II).

[37] Several studies have highlighted the presence of mispricing performed by investors in capital markets (mainly from the stock markets). These include Lakonishok, Shleifer et al. (1994), Sloan (1996), Shiller (2003), Farhi et al. (2004), or more recently Aydogan et al. (2011).

Figure III.3. Principal Components of credit spreads for the three sub-periods analtysis

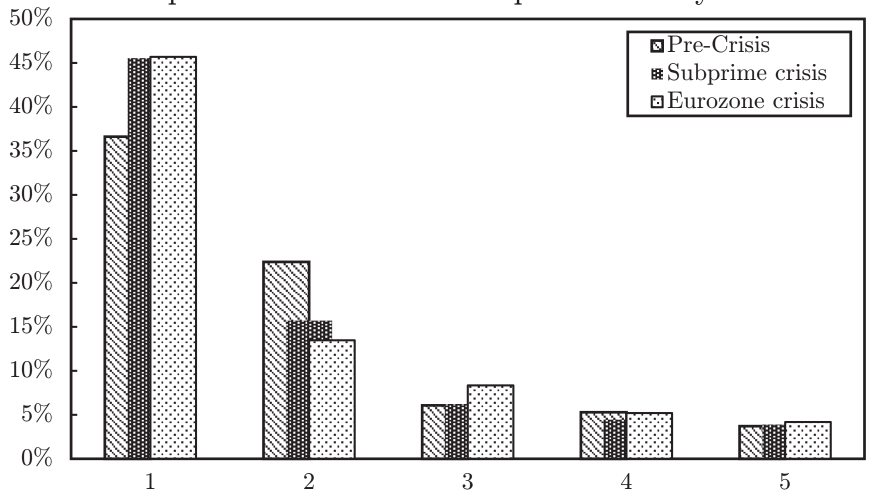
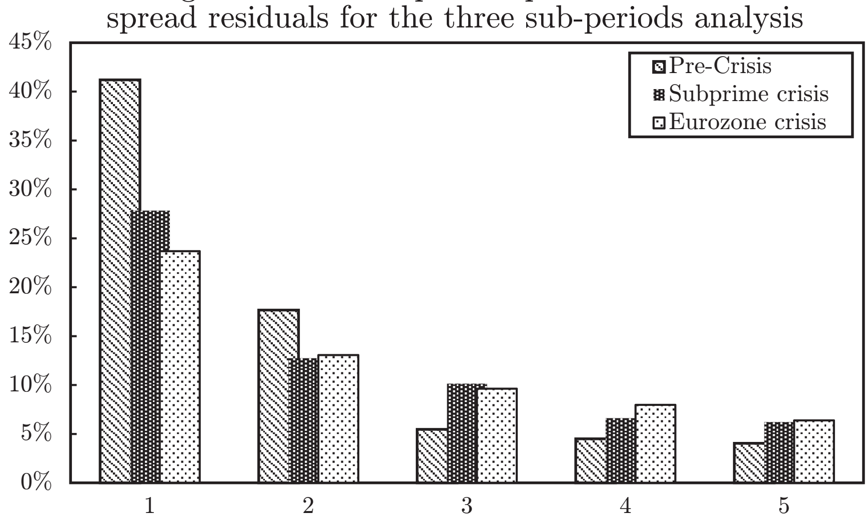


Figure III.4. Principal components of credit spread residuals for the three sub-periods analysis



portion explained by the first principal component decreases from about 45% before regression to 27% and 23% after regression for, respectively, the subprime and the Eurozone crisis periods). Focusing on the regression residuals, we note that four principal components were needed to explain 70% of credit spread residuals in the pre-crisis period, while seven components were need to explain a similar portion in the subprime and the Eurozone crisis periods. This result suggests an increase in the number of factors that affect credit spreads changes since the beginning of the crisis, which remain beyond our set of credit risk, market-wide risks, liquidity risk, information asymmetries and risk aversion proxies.

6.4. Specification analysis:

To further understand the nature of the variation of the spreads, we ran next a series of specifications on our benchmark setup in Model 5. To do so, we split our initial bond sample into sub-groups of bonds defined according to their maturities, ratings and firm-sizes. We then ran the Model 5 regression for each of these groups, in each of the sub-periods specified earlier. The main findings of this specification analysis are discussed in what follows.

6.4.1 Maturity sub-samples:

As shown in chapter I, structural models imply generally that credit spreads increase with the time-to-maturity of the bond. However, in chapter II we noted that the relationship between credit spreads and time-to-maturity has changed since the beginning of the crisis. To better understand this result, we decided to specify our Model 5 regression for different groups of bond maturities. To do so, we divided our bond sample into three different groups of bonds. A first group includes bonds maturing in 2014 (designed by the short maturities sub-sample); a second group includes bonds maturing in 2015 and 2016 (designed by the middle maturities sub-sample); and a third group includes bonds maturing in 2017 and more (designed by the long maturities sub-sample)[38]. Afterwards, we repeated our benchmark regression in model 5 for each of these groups, in each of the pre-crisis, the subprime crisis and the Eurozone crisis periods. Tables III.12, III.13 and III.14 present the regression results for respectively, the short maturities, middle maturities and the long maturities subsamples.

Our main findings for this specification analysis are as follows. First, we note that the explanatory power of the model is higher for bonds with short maturities (the overall adjusted R-squared is of 34.4% for short maturities against 30.7% for long maturities). Making analogy with previous results where the sensitivity of credit spreads increased in periods of higher uncertainty (the adjusted R-squared were higher in crisis periods), we interpret this result as consistent with higher levels of risks priced in bonds of shorter maturities (i.e. a shorter time-to-maturity includes a higher sensitivity of the spreads to the proxied risk factors). Second, we note that the explanatory power of the model increases for both short and middle maturities since the beginning of the crisis. This relation is, however, inversed for long maturities where the explanatory power of the model is higher for the pre-crisis period and decreases for both the subprime crisis and the Eurozone crisis periods. This tends to bring support to the observations that we made in chapter II about a decrease in the levels of risks priced in bonds of longer

[38] These three sub-samples include, respectively, 15, 28 and 27 corporate bonds.

Table III.12. Short maturities sub-sample:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
leverage	0.0119	0.0242**	for-0.0262	0.00259
	(0.724)	**(2.075)**	(-0.490)	(0.129)
Equity Return	0.280***	0.0772	0.642***	-0.0415
	(2.858)	(0.986)	**(3.189)**	(-0.273)
Historic volatility	5.050*	-8.576**	8.665*	-4.645
	(1.857)	**(-2.027)**	**(1.925)**	(-0.772)
10yrs treasury rate	-0.512***	-0.390***	-1.049***	-0.235***
	(-8.977)	**(-10.72)**	**(-6.656)**	**(-2.676)**
Market return	-1.593***	-0.907***	-1.738***	-1.357***
	(-7.018)	**(-4.171)**	**(-3.454)**	**(-3.824)**
Term slope 30-10y	-0.280***	-0.481***	0.0735	-0.192
	(-2.734)	**(-3.238)**	(0.299)	(-1.333)
Business Climate	-0.00322	0.0686**	-0.0542	-0.128**
	(-0.0817)	(2.329)	(-0.536)	(-2.014)
Bid-Ask spread	0.306***	0.0649	0.231***	0.568***
	(6.791)	(0.836)	**(3.181)**	**(5.870)**
Market liquidity	0.526***	0.653	0.553***	0.606***
	(8.288)	(0.983)	**(5.495)**	**(3.588)**
lag spread	0.192***	0.208***	0.0908**	0.284***
	(8.700)	**(4.736)**	**(2.175)**	**(8.528)**
lag equity return	-0.223**	0.157**	-0.445**	-0.0505
	(-2.470)	**(2.140)**	**(-2.417)**	(-0.366)
Lag Market return	-0.223	-0.0647	0.323	-0.490
	(-1.030)	(-0.328)	(0.646)	(-1.560)
Lag 10yrs rate	0.0884	0.00568	0.0393	0.170**
	(1.608)	(0.134)	(0.249)	**(2.289)**
Market value	-1.4e-5***	-2.73e-06*	-1.84e-05***	-1.9e-05***
	(-6.904)	**(-1.917)**	**(-4.387)**	**(-4.536)**
Number of employees	2.68e-06*	2.04e-07	-1.87e-06	1.7e-5***
	(1.684)	(0.326)	(-0.381)	**(3.178)**
Confidence Index	0.00401	0.00762***	-0.00750	0.0222***
	(0.845)	**(2.727)**	(-0.595)	**(2.804)**
Constant	0.00532	0.0111**	-0.0409**	0.0135
	(0.706)	**(1.966)**	**(-1.992)**	(1.172)
Observations	1,800	525	525	750
Adj R-squared	0.344	0.349	0.363	0.444

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

maturities since the beginning of the crisis. Furthermore, we note from the first columns of Tables III.12 and III.14 that liquidity risk factors (i.e. Bid-Ask spread and market liquidity) had a larger impact on the spreads of short-maturities' bonds. Looking to two last columns of tables III.12 and III.14, we note that the spreads of short-maturities bonds have become even more sensitive to liquidity risk factors since the beginning of the crisis, as compared to long-maturities bonds.

Table III.13. Middle maturities sub-sample:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0225	-0.00145	0.00912	-0.00438
	(1.400)	(-0.102)	(0.274)	(-0.144)
Equity Return	-0.144*	-0.194	-0.0824	0.129
	(-1.907)	(-1.144)	(-0.657)	(0.964)
Historic volatility	2.467	-0.659	0.762	5.621**
	(1.574)	(-0.142)	(0.307)	**(2.008)**
10yrs treasury rate	-0.424***	-0.482***	-0.644***	-0.224***
	(-10.99)	**(-12.81)**	**(-7.223)**	**(-3.155)**
Market return	-1.428***	-0.971***	-1.010***	-1.670***
	(-8.862)	**(-4.094)**	**(-3.420)**	**(-5.565)**
Term slope 30-10y	-0.387***	-0.370**	0.147	-0.473***
	(-5.520)	**(-2.428)**	(1.054)	**(-3.919)**
Business Climate	0.142***	0.105***	-0.0147	0.154***
	(5.280)	**(3.458)**	(-0.254)	**(2.912)**
Bid-Ask spread	0.0512*	-0.204**	0.0519	0.0502
	(1.940)	**(-2.565)**	(1.353)	(0.946)
Market liquidity	0.273***	0.460	0.261***	0.537***
	(6.421)	(0.672)	**(4.595)**	**(3.896)**
lag spread	0.321***	0.0683**	0.251***	0.349***
	(19.68)	**(2.057)**	**(8.138)**	**(14.07)**
lag equity return	-0.244***	0.0952	-0.271***	-0.284***
	(-3.846)	(0.696)	**(-2.585)**	**(-2.595)**
Lag Market return	-0.329**	-0.170	0.744**	-1.112***
	(-2.144)	(-0.763)	**(2.493)**	**(-4.278)**
Lag 10yrs rate	0.0751**	0.0457	0.0499	0.134**
	(2.011)	(1.078)	**(0.562)**	**(2.227)**
Market value	-1.45e-06	3.87e-06*	-1.2e-06	-1.5e-05***
	(-0.718)	**(1.734)**	(-0.375)	**(-2.902)**
Number of employees	3.01e-06**	4.08e-07	2.06e-06	1.15e-05**
	(2.447)	(0.487)	(0.886)	**(2.378)**
Confidence Index	-0.0110***	0.00254	-0.0149**	-0.0173***
	(-3.441)	(0.897)	**(-2.114)**	**(-2.632)**
Constant	-0.00119	0.00485	-0.00550	0.000327
	(-0.224)	(0.845)	(-0.438)	(0.0332)
Observations	3,360	980	980	1,400

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

This result suggests that larger spreads that we documented for short-maturities' bonds since the beginning of the crisis (see chapter II, section 3.8) have been increasingly driven by liquidity risks factors, rather than any other source of risk. Overall, this specification analysis reports a quite interesting evidence on the relationship between credit spreads and time-to-maturity. While the credit risk component seems to increase with time-to-maturity (higher impact of credit risk factors on bonds of long maturities), the overall impact of the other credit spread determinants seems to be larger for bonds of shorter maturities. This evidence puts indeed into doubt the traditional belief according to which longer-maturities present higher uncertainty, especially when the present is less certain[39].

Table III.14. Long maturities sub-sample:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0254**	0.000976	0.0304	0.0450*
	(2.179)	(0.0750)	(1.378)	**(1.779)**
Equity Return	-0.139***	-0.0337	-0.193**	-0.383***
	(-3.342)	(-0.788)	**(-2.114)**	**(-3.111)**
Historic volatility	9.705***	2.169	8.290***	19.92***
	(6.161)	(0.561)	**(3.924)**	**(4.615)**
10yrs treasury rate	-0.640***	-0.532***	-0.880***	-0.590***
	(-19.43)	**(-11.68)**	**(-11.83)**	**(-10.09)**
Market return	-0.785***	-0.571**	-0.602***	-0.757***
	(-6.462)	**(-2.170)**	**(-2.657)**	**(-3.289)**
Term slope 30-10y	-0.409***	-0.520***	-0.384***	-0.364***
	(-6.925)	**(-2.787)**	**(-3.315)**	**(-3.709)**
Business Climate	0.00489	0.0674*	-0.0142	-0.00443
	(0.216)	**(1.818)**	(-0.298)	(-0.105)
Bid-Ask spread	0.00567***	0.0446***	0.00907**	-0.000230
	(3.583)	**(10.76)**	**(2.453)**	(-0.117)
Market liquidity	0.217***	0.707	0.204***	0.306***
	(6.018)	(0.844)	**(4.365)**	**(2.801)**
lag spread	0.271***	0.329***	0.215***	0.264***
	(15.63)	**(11.06)**	**(6.895)**	**(9.213)**
lag equity return	-0.0225	0.00203	-0.0280	-0.0265
	(-0.564)	(0.0484)	(-0.334)	(-0.239)
Lag Market return	-0.0861	0.00716	0.370*	-0.404**
	(-0.767)	(0.0305)	**(1.667)**	**(-2.035)**
Lag 10yrs rate	0.127***	0.0831	-0.0240	0.217***
	(3.891)	(1.606)	(-0.319)	**(4.234)**
Market value	-1.54e-06	-2.72e-06	-5.53e-07	2.18e-06
	(-0.990)	(-0.938)	(-0.239)	(0.582)
Number of employees	4.55e-07	1.98e-07	-3.32e-07	2.40e-06
	(0.510)	(0.104)	(-0.264)	(1.204)
Confidence Index	-0.00682**	0.00289	-0.0176***	-0.00167
	(-2.512)	(0.826)	**(-2.985)**	(-0.319)
Constant	0.00146	0.00477	-0.0122	0.00334
	(0.340)	(0.685)	(-1.263)	(0.466)
Observations	3,240	945	945	1,350
Adj R-squared	0.307	0.348	0.345	0.327

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

[39] Few comparable empirical studies have addressed the relationship between credit spreads and time-to- maturity. Collin-Dufresne et al. (2001) addressed this relation and found higher R-squared for the short maturities. They concluded that their model behave badly for bonds with long time left until maturity.

6.4.2 Credit worthiness subsamples:

Next, we specify the results of Model 5 for different groups of bonds' creditworthiness. To do so, we repeated the regression in model 5 for two groups of bonds: bonds with rating above BBB- (i.e. investment grade bonds), and bonds with rating below BBB- (i.e. speculative grade bonds). Results of these regressions are reported in Tables III.15 and III.16[40]:

Table III.15. Investment grade bonds:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0144*	-0.00175	0.00323	0.00335
	(1.668)	(-0.196)	(0.161)	(0.242)
Equity Return	-0.0119	-0.0137	0.0840	0.206**
	(-0.313)	(-0.386)	(1.051)	**(2.299)**
Historic volatility	6.682***	-0.814	5.814***	13.21***
	(5.660)	(-0.284)	**(3.340)**	**(4.606)**
10yrs treasury rate	-0.514***	-0.484***	-0.804***	-0.389***
	(-20.11)	**(-17.18)**	**(-12.70)**	**(-8.964)**
Market return	-1.148***	-0.744***	-1.025***	-1.341***
	(-11.56)	**(-4.552)**	**(-5.115)**	**(-7.522)**
Term slope 30-10y	-0.355***	-0.497***	-0.0375	-0.391***
	(-7.735)	**(-4.356)**	**(-0.379)**	**(-5.360)**
Business Climate	0.0530***	0.0880***	-0.0271	0.0315
	(3.006)	**(3.874)**	(-0.665)	(1.003)
Bid-Ask spread	0.0115***	0.0454***	0.0114**	0.00206
	(4.877)	**(12.29)**	**(2.475)**	(0.599)
Market liquidity	0.301***	0.800	0.292***	0.428***
	(10.73)	(1.559)	**(7.264)**	**(5.220)**
lag spread	0.277***	0.248***	0.186***	0.333***
	(23.83)	**(11.62)**	**(8.639)**	**(18.50)**
lag equity return	-0.106***	0.0137	-0.142**	-0.325***
	(-3.047)	(0.394)	**(-2.005)**	**(-4.257)**
Lag Market return	-0.310***	0.00369	0.402**	-0.525***
	(-3.349)	(0.0251)	**(2.015)**	**(-3.371)**
Lag 10yrs rate	0.0863***	0.0864***	-0.000933	0.163***
	(3.471)	**(2.728)**	(-0.0147)	**(4.369)**
Market value	-6.2e-06***	-1.23e-06	-5.96e-06***	-1.5e-05***
	(-5.643)	(-0.916)	**(-3.176)**	**(-5.950)**
Number of employees	1.28e-06*	4.35e-07	-4.46e-07	5.2e-06***
	(1.648)	(0.477)	(-0.347)	**(2.707)**
Confidence Index	-0.0069***	0.00450**	-0.0171***	-0.00207
	(-3.276)	**(2.103)**	**(-3.393)**	(-0.528)
Constant	0.00116	0.00418	-0.0152*	0.000652
	(0.344)	(0.980)	(-1.821)	(0.117)
Observations	6,960	2,030	2,030	2,900
Adj R-squared	0.299	0.278	0.287	0.379

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

[40] Unfortunately, the different sub-ratings categories are not sufficiently represented by the bonds in this chapters' sample so we can check in detail the stylized fact 3.6 proposed in chapter II.

Table III.16. Speculative grade bonds:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0800***	0.0418**	0.0168	0.170**
	(2.887)	**(2.411)**	(0.316)	**(2.409)**
Equity Return	-0.399***	-0.176	-0.0162	-0.682***
	(-3.741)	(-1.309)	(-0.0784)	**(-3.844)**
Historic volatility	-0.629	-0.981	0.921	-3.784
	(-0.266)	(-0.218)	(0.212)	(-1.021)
10yrs treasury rate	-0.547***	-0.462***	-0.761***	-0.308**
	(-8.878)	**(-10.00)**	**(-5.510)**	**(-2.577)**
Market return	-1.302***	-0.902***	-1.444***	-1.212**
	(-5.394)	**(-3.253)**	**(-3.251)**	**(-2.545)**
Term slope 30-10y	-0.486***	-0.369*	-0.223	-0.291
	(-4.342)	**(-1.964)**	(-1.046)	(-1.441)
Business Climate	0.0745*	0.0735*	0.0203	0.00368
	(1.743)	**(1.938)**	(0.228)	(0.0415)
Bid-Ask spread	-0.000264	0.303***	-0.0397	0.000324
	(-0.0863)	**(3.663)**	(-0.705)	(0.0925)
Market liquidity	0.375***	-0.0818	0.362***	0.735***
	(5.491)	(-0.0959)	**(4.060)**	**(3.156)**
lag spread	0.288***	0.155***	0.234***	0.308***
	(11.80)	**(3.100)**	**(5.061)**	**(8.131)**
lag equity return	-0.181*	0.243*	-0.628***	0.0759
	(-1.894)	**(1.852)**	**(-3.612)**	(0.485)
Lag Market return	-0.0135	0.0220	1.196***	-0.789*
	(-0.0599)	(0.0890)	**(2.718)**	**(-1.917)**
Lag 10yrs rate	0.132**	-0.0587	-0.0386	0.276***
	(2.216)	(-1.075)	(-0.281)	**(2.725)**
Market value	-6.38e-06*	1.96e-06	-1.23e-05**	-7.93e-06
	(-1.678)	(0.720)	**(-1.977)**	(-0.692)
Number of employees	3.8e-06***	-1.51e-07	1.79e-05***	1.44e-05**
	(2.627)	(-0.244)	**(3.420)**	**(2.208)**
Confidence Index	-0.00890*	-0.00110	-0.0133	-0.0129
	(-1.737)	(-0.311)	(-1.219)	(-1.170)
Constant	-0.000931	0.0113	-0.0157	0.00432
	(-0.114)	(1.575)	(-0.861)	(0.280)
Observations	1,440	420	420	600
Adj R-squared	0.363	0.378	0.403	0.404

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

Analyzing the results of the regression in Tables III.15 and III.16 shows some interesting similarities with our previous findings. First, we note that credit spreads present higher sensitivity to the proposed determinants for the sub-sample of speculative grade bonds (adjusted R-squared of 29.9% for investment grade bonds against 36.3% for high yield bonds). This tends to confirm our previous observations of a higher sensitivity of credit spreads to the proposed determinants for sub-samples with higher levels of riskiness. Second, for both speculative and investment grade bonds we note that the model's linear fit increases from the pre-crisis to the Eurozone crisis periods. This increase is though more pronounced for the investment grade bonds from the subprime to the Eurozone crises periods (adjusted R-squared vary from 28.7% to 37.9% for investment grade bonds and from 40.3% to 40.4% for speculative grade bonds). This result brings support to our previous findings about an increase in the levels of risk priced by investors inside credit spreads since the beginning of the crisis. It completes it by the information that this increase was more drastic for the a priori less risky bonds (i.e. investment grade bonds), especially after April 2010. Similar results of higher sensitivity of credit spreads for lower grade bonds have been indeed documented by many previous empirical studies. For instance, Avramov et al. (2007) found that their set of credit spread determinant explain 67% of credit spreads changes for high yield bonds, while it explains only 35% of credit spreads for high grade bonds[41]. The low explanatory power associated to investment grade bonds brings some understanding to the low significance of our benchmark setup in Model 5. Indeed, our total bond sample is composed of up to 80% by investment grade bonds, which has generally more exploitable data. Further, considering individual determinants, we find no clear evidence in this specification analysis on a larger credit risk component priced inside speculative grade bonds, as might be expected. In particular, among the structural credit risk variables, leverage and equity return are found to have a greater impact on high-yield bonds, while volatility and the risk-free rate are found to have a larger effect on high-grade bonds. One intriguing result arises in this specification analysis from the relation between credit spreads and liquidity factors. Acharya and Pedersen (2005) and Chen and Lesmond (2007) found in their empirical analyses of credit spreads that liquidity factors have higher impact on credit spreads for speculative grade bonds (particularly Bid-Ask spread proxy). In contrast to this evidence, we find that liquidity factors have more impact on credit spreads for investment grade bonds, especially since the beginning of the crisis. This result highlights once again the important changes that the pricing of risk inside credit spreads have undergone since the onset of the subprime crisis, which are apparently unique in nature.

In summary, leading this specification on different categories of bond ratings was conclusive in many regards. Most of all, it highlights that the sensitivity of credit spreads to the proposed determinants relies much on the characteristics of the used bond sample. Bond-samples with different levels of riskiness are then expected to produce different results, making the comparison of the results between different studies harder.

[41] Collin-Dufresne et al. (2001), Ericsson et al. (2004), Zhang et al. (2005) are other comparable studies that found higher explanatory power for speculative grade bonds.

6.4.3 Firm-size sub-samples:

We propose finally to specify our results for different groups of firm-sizes. This will allow us to investigate the difference in risk pricing between the largest and smallest firms in our sample, and to assess the changes that this pricing have undergone since the beginning of the crisis. In particular, our attempt is to assess the specificity of the reaction of credit spreads for some of the largest firms in Europe that are thought to be "Too big to fail". To do so, we divided our initial sample into three groups of bonds according to their issuing-firm size, and re-estimated Model 5 regression, for each of the pre-crisis, the subprime crisis and the Eurozone crisis periods. The sub-samples of firm-sizes are chosen as follows: the "smallest firms" are chosen as the firms being at the same time in the first quartile of firms' number of employees and the first quartile of firms' market values; the "largest firms" are chosen as firms lying at the same time in the highest quartile of firms' number of employees and the highest quartile of firms market values; finally "middle-sized firms" are selected as firms not satisfying the two previous criteria (hence firms in the interquartile range of either market values or number of employees)[42]. Doing so, we placed, respectively, 13, 47, and 10 bonds in the smallest, middle-sized, and largest firms groups[43]. The results of the regressions for these three groups of bonds are Tables III.17, III.18, and III.19.

The results of this specification analysis bring some interesting insights on the relation between credit spreads changes and firm-size. First, with regard to models' explanatory power, we find that the sub-sample of smaller firms has a higher explanatory power (31.1%) than the sub-sample of the larger firms (30.9%). In agreement with our previous findings, this result can be interpreted as synonym of higher risks priced for smaller firms, even though the evidence is relatively small[44]. Turning to sub-periods analysis, we note particularly the difference of explanatory power between the largest and smallest firms in the pre-crisis period: the model explains 26% of credit spread changes for the largest firms while it accounts for up to 33% of credit spread changes for the smallest firms (7% difference). This difference slowly fades away as the crisis goes by and becomes of only 0.5% in the Eurozone crisis period (40.3% and 40.8% of adjusted R-squared for, respectively, the largest and the smaller firms). Everything otherwise equal,

[42] The designations "smallest firms", "Middle-sized firms", and "larges firms" are hence merely in relative terms with regard to the sample of this study. Applying this strict two-proxy criteria is expected to give us more rigorous results, especially for the smallest and largest firms' sub-samples.

[43] It is worth mentioning that 9 out of the 10 bonds in our largest firms sub-sample are issued by firms from the financial sector. This makes our results for the largest firms consistent with an evidence for the "Too big to fail" firms.

[44] Sub-samples with higher theoretic risk (like low rating firms) have had so far the highest explanatory power (with regard to adjusted R-squared)

Table III.17. Largest firms sub-sample:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0177	-0.00634	0.00239	0.0184
	(0.785)	(-0.446)	(0.0374)	(0.423)
Equity Return	-0.124**	-0.0114	-0.112	-0.288
	(-2.035)	(-0.357)	(-0.535)	(-1.134)
Historic volatility	-2.530	-3.525	-0.266	-5.584
	(-1.090)	(-0.699)	(-0.0735)	(-0.934)
10yrs treasury rate	-0.321***	-0.375***	-0.505***	-0.127
	(-5.350)	**(-7.225)**	**(-3.222)**	(-1.252)
Market return	-1.491***	-0.649**	-1.215**	-1.122**
	(-6.113)	**(-2.213)**	**(-2.272)**	**(-2.436)**
Term slope 30-10y	-0.451***	-0.0302	-0.103	-0.399**
	(-4.178)	(-0.148)	(-0.419)	**(-2.363)**
Business Climate	0.121***	0.117***	0.117	0.120
	(2.908)	**(2.870)**	(1.161)	(1.613)
Bid-Ask spread	0.0761	-0.225	0.115	-0.226
	(1.441)	(-0.925)	(1.493)	(-1.405)
Market liquidity	0.213***	-0.325	0.203**	0.666***
	(3.189)	(-0.361)	**(1.983)**	**(3.400)**
lag spread	0.269***	0.202***	0.207***	0.270***
	(9.883)	**(3.752)**	**(3.934)**	**(6.528)**
lag equity return	-0.112*	-0.00312	-0.414**	-0.130
	(-1.926)	(-0.102)	**(-2.203)**	(-0.665)
Lag Market return	-0.179	0.236	0.739	-0.460
	(-0.844)	(0.933)	(1.423)	(-1.151)
Lag 10yrs rate	0.0858	-0.0260	0.0618	0.175**
	(1.490)	(-0.462)	(0.400)	**(2.001)**
Market value	-3.6e-06**	1.45e-06	-2.26e-06	-9.94e-06*
	(-2.009)	(0.842)	(-0.665)	**(-1.826)**
Confidence Index	-0.0104**	0.00492	-0.0254**	-0.0106
	(-2.088)	(1.281)	**(-2.026)**	(-1.139)
Constant	0.00460	0.00559	-0.0134	0.00200
	(0.569)	(0.721)	(-0.625)	(0.134)
Observations	1,200	340	350	500
Adj R-squared	0.309	0.260	0.293	0.403

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

this result suggests the incidence of a readjustment in the pricing of risk between the smallest and the largest firms since the onset of the crisis. The spreads of the largest firms reflected apparently higher levels of the risk factors captured by our credit spread determinants since the onset of the crisis, which made them reach the levels priced inside the smallest firms (i.e. quite similar R-squared in the Eurozone crisis). Having said that, we note that the spreads of the smallest and largest bonds groups have different sensitivities to the determinants that we use.

Table III.18. Middle-sized firms sub-sample:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0208*	0.0179*	-0.00652	0.00751
	(1.902)	**(1.907)**	(-0.256)	(0.431)
Equity Return	0.00620	-0.0375	0.144	-4.91e-05
	(0.119)	(-0.523)	(1.605)	(-0.000514)
Historic volatility	7.706***	-3.775	7.346***	8.342***
	(6.097)	(-1.376)	**(3.727)**	**(3.325)**
10yrs treasury rate	-0.556***	-0.502***	-0.897***	-0.372***
	(-18.36)	**(-19.30)**	**(-12.15)**	**(-6.825)**
Market return	-1.238***	-0.591***	-1.187***	-1.311***
	(-10.01)	**(-3.677)**	**(-4.971)**	**(-5.831)**
Term slope 30-10y	-0.449***	-0.457***	-0.135	-0.411***
	(-8.238)	**(-4.369)**	(-1.173)	**(-4.465)**
Business Climate	0.0652***	0.0920***	-0.0189	0.0412
	(3.113)	**(4.444)**	(-0.396)	(1.035)
Bid-Ask spread	0.00728***	-0.0657	0.0115**	0.00281
	(2.713)	(-1.633)	**(2.380)**	(0.709)
Market liquidity	0.371***	0.826*	0.370***	0.498***
	(11.18)	**(1.760)**	**(7.922)**	**(4.768)**
lag spread	0.281***	0.144***	0.195***	0.334***
	(21.84)	**(5.635)**	**(8.268)**	**(16.60)**
lag equity return	-0.169***	0.0998	-0.207***	-0.194**
	(-3.614)	(1.513)	**(-2.582)**	**(-2.307)**
Lag Market return	-0.177	0.000560	0.656***	-0.784***
	(-1.509)	(0.00383)	**(2.710)**	**(-4.001)**
Lag 10yrs rate	0.0898***	0.00229	0.00383	0.204***
	(3.051)	(0.0756)	(0.0518)	**(4.410)**
Market value	-7.4e-6***	-2.1e-06*	-8.19e-06***	-1.3e-05***
	(-5.140)	**(-1.651)**	**(-3.384)**	**(-3.867)**
Confidence Index	-0.0083***	0.00306	-0.0175***	-0.00626
	(-3.318)	(1.558)	**(-2.983)**	(-1.262)
Constant	0.000978	0.00651*	-0.0214**	0.00311
	(0.242)	**(1.662)**	**(-2.167)**	(0.441)
Observations	5,640	1,645	1,645	2,350
Adj R-squared	0.313	0.288	0.312	0.367

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

This result suggests a different risk structure between these two groups of firms that we attempt to explore next[45]. Considering the structural credit risk proxies, we note that most of these variables became, unfortunately, insufficiently reliable to have certitude about their impact on credit spreads for the firm-size groups. The only reliable credit risk proxy is found to be the risk-free rate which presents some interesting results. First, in agreement with the findings of previous sections, we find that the risk-free rate presents a significant impact on credit spreads for

[45] As noted by the regression coeffecients (see tables 17 and 19)

Table III.19. Smallest firms sub-sample:

Variables	Full Sample	Pre-Crisis	Subprime Crisis	Euro Crisis
Leverage	0.0188	-0.0116	0.0263	0.0337
	(1.255)	(-0.514)	(0.964)	(1.165)
Equity Return	0.0519	-0.0112	-0.0389	-0.0731
	(0.359)	(-0.0511)	(-0.131)	(-0.311)
Historic volatility	0.173	4.231	-0.434	-5.765
	(0.0395)	(0.519)	(-0.0606)	(-0.695)
10yrs treasury rate	-0.561***	-0.475***	-0.807***	-0.472***
	(-12.09)	**(-5.610)**	**(-7.975)**	**(-6.602)**
Market return	-1.024***	-1.284***	-0.676**	-1.250***
	(-6.101)	**(-2.673)**	**(-2.275)**	**(-4.606)**
Term slope 30-10y	-0.112	-0.773**	0.0804	-0.101
	(-1.342)	**(-2.223)**	(0.507)	(-0.844)
Business Climate	-0.0372	-0.0128	-0.118*	-0.0562
	(-1.161)	(-0.186)	**(-1.808)**	(-1.074)
Bid-Ask spread	0.00597***	0.0456***	-0.183***	-0.000310
	(2.696)	**(8.484)**	**(-3.285)**	(-0.144)
Market liquidity	0.216***	1.273	0.209***	0.419***
	(4.268)	(0.820)	**(3.289)**	**(3.095)**
lag spread	0.274***	0.326***	0.108**	0.315***
	(11.31)	**(7.836)**	**(2.290)**	**(8.597)**
lag equity return	-0.0399	-0.0377	0.128	-0.119
	(-0.317)	(-0.183)	(0.523)	(-0.605)
Lag Market return	-0.411***	-0.320	-0.0134	-0.522**
	(-2.655)	(-0.724)	(-0.0471)	**(-2.239)**
Lag 10yrs rate	0.126***	0.210**	-0.0729	0.202***
	(2.729)	**(2.226)**	(-0.694)	**(3.194)**
Market value	-7.26e-06	-0.0002**	0.000163	8.54e-05
	(-0.105)	**(-2.029)**	(1.076)	(0.806)
Confidence Index	0.000911	0.00448	-0.00986	0.00912
	(0.237)	(0.688)	(-1.212)	(1.410)
Constant	0.00260	0.0143	-0.00395	-0.00186
	(0.426)	(1.093)	(-0.299)	(-0.209)
Observations	1,560	455	455	650
Adj R-squared	0.311	0.330	0.338	0.408

T-statistics are in parentheses: *** p<0.01, ** p<0.05, * p<0.1
(Statistical significance is indicated with boldfaces)

the whole sample analysis of both large and small firms groups. Second, with regard to the sub-periods analysis, we note interestingly that, while the impact of the risk-free rate kept almost the same level of significance for the smallest firms –unconditionally of the time period–, it loses much of its significance as the crisis goes by for the largest firms sub-sample (the risk-free rate becomes even non-significant in the Eurozone crisis period). This result is particularly worth emphasizing since it is the only case, among all the regression sub-samples analyzed so far, where the risk-free rate does not have a significant influence on credit spreads. This finding is appealing since it tends to confirm the hypothesis of a smaller credit risk component in the spreads of larger firms since the beginning of the crisis[46]. Furthermore, the observed decrease in the importance of credit risk factors inside the spreads of larger firms since the beginning of the crisis, combined to the increase in the adjusted R-squared of these latter, suggest that other factors became important determinants of the credit spread changes of the largest bonds since the onset of the crisis. Columns 3 and 4 of Table III.17 brings support to this hypothesis. We note, on the one hand, an increase in the coefficients of market liquidity (proxy of the tensions in the interbank market) and market return (proxy of systemic and contagion risk), since the outbreak of the subprime crisis, and on the other hand, an increase in the significance of the term slope in the Eurozone crisis period (macroeconomic and systemic risk proxies). This brings evidence that liquidity and market-wide risks became more important components of the spreads of the largest firms since the beginning of the crisis at the expense of credit risk.

In summary, specifying the results of Model 5 for different firm-size sub-samples provides many interesting insights. As expected, we found evidence of a higher sensitivity of credit spreads to the proposed determinants for the smallest firms sub-sample, suggesting that market participants perceive generally additional risk premiums for smaller firms. Concerning the largest firms, we found notably that credit spreads of these firms reflected lower levels of credit risk since the beginning of the crisis to the profit of market liquidity and market-wide risks.

7. Conclusion:

This chapter has attempted to investigate the determinants of credit spread changes with regard to the recent economic and financial turmoil. Using a sample of 70 Euro settled-corporate bond over July 2004-July 2014, we assessed the significance of a set of credit spread determinants covering: (*i*) credit risk, (*ii*) market-wide risks, (*iii*) liquidity risk, (*iv*) information asymmetries as well as (*v*) firm-size and risk premiums factors. Additionally, we specified the changes that the sensitivity of the spreads to these determinants have undergone between the pre-crisis, the subprime crisis and the Eurozone crisis periods.

Our conclusions are as follows. (*i*) With regard to the theoretical credit risk factors, we generally found evidence for a time-varying sensitivity of the spreads to the different credit risk factors. The crisis has presumably exacerbated the

[46] The smaller credit risk component for the largest firms can be also due to the implicit authorities' guarantees on the financial institutions debt, which constitute in this case 9 out of the 10 largest firms' bonds in our sample (see for instance OECD, 2012 "Implicit Guarantees for Bank Debt: Where Do We Stand" for more details about the concept of implicit guarantees).

difference between firms in such a way that credit spreads present generally higher sensitivity to the different credit risk factors in the subprime and the Eurozone crisis periods. As for the individual credit risk factors, we noted interestingly that credit spreads present a particularly high sensitivity to the risk-free interest rate in all the investigated sub-crisis periods. As for leverage ratios, we were able to bring support to the observations that we made in the previous chapter, as we found poor sensitivity of credit spreads to leverage ratios in the pre-crisis and the subprime crisis periods. In line with the structural models view, we showed additionally that credit risk constitutes the most represented risk inside corporate bonds' credit spreads, and this in all the investigated sub-periods.

(ii) With respect to the explored market-wide risk factors, we found overall evidence for a high sensitivity of the spread to the used macroeconomic and systemic risk factors. Only, the "LTROs", which we used as a proxy for authorities' action during the crisis were found to be insignificant, thus making the hypothesis of a negative relation between authorities' actions and credit spreads in need of further empirical investigations. Remarkably, we found that the significance of the factors that we used as proxies for the turbulence that markets witnessed during the crisis have increased substantially since July 2007 (e.g. the Eurostoxx50 and Vstoxx indexes as proxies of banks and governments defaults and bailouts). While the market-wide risk factors explained only 1.1% of credit spread changes in the pre-crisis period, their importance rose to explain, respectively, 7.4% and 5.7% of credit spread changes in the subprime and the Eurozone crisis.

(iii) Concerning the liquidity component of the spreads, we noticed that the subprime and Eurozone crisis periods coincided with an increase in the impact of market liquidity, combined with a decrease in the effect of bond-specific liquidity on credit spread changes. Additionally, we noted a decrease in the relative importance of the liquidity component in the spreads since the beginning of the crisis. Liquidity used indeed to be the second most important component of the spreads in the pre-crisis period, but then decreased to become only the fourth most important component behind, credit risk, market-wide risks and the delayed information component.

(iv) As far as the delayed information component is concerned, we found a proof for an increase in the impact of lagged variables since the beginning of the crisis, with a more drastic effect on the spreads in the Eurozone crisis period. Presumably, the crisis has increased information asymmetries between market participants and has put forward the imperfections of the price adjustment process in the corporate bond market. As such, the importance of the delayed information

component rose, to reach about 10.6% explanatory power in the Eurozone crisis period, compared to only 4.8% in the pre-crisis period.

(v) With regard to the explored additional factors, we found evidence for a link between investors' confidence (i.e. proxy of risk premiums) and credit spread changes, mainly in the subprime crisis period. Even though the relationship between this variable and credit spreads is found to be significant in the long run (i.e. the full sample period), the evidence is consistent with only a small effect of investors' confidence on credit spreads. Moreover, we explored the presence of a firm-size effect priced inside corporate bonds spreads. The evidence was consistent with the presence of a firm-size component, which was similarly small.

Overall, our results are consistent with a time varying sensitivity of the spreads to the proposed credit spread determinants, as well as a change in the structure of the components of the spreads since the beginning of the crisis. The analysis that we conducted over the full period of the study (i.e. ten years period) allowed us additionally to show that most of the credit spread determinants that we investigated have certain power in explaining credit spreads in the long run, with signs generally in line with theory and the made hypotheses. For robustness, we checked how well our set of credit spread determinants explain CDS spreads changes, which has pleaded rather for the robustness of these determinants. Remarkably, our comprehensive set of credit spread determinants was able to explain only 30.4% of credit spread changes. This low explanatory power can be partly attributed to the possible non-linear effects of the studied determinants, which can be hardly captured by the linear regression tool that we employed. Putting aside these non-linearities, we attempted, by the means of a principal component analysis of regression residuals, to understand the nature of the latent variation of credit spreads. In the same lines as Avramov et al. (2007), we found that the remaining variation of the spreads is driven by numerous relatively small factors. Conducting PCA on the residuals of different crisis sub-periods, we showed also that the number of factors that drive credit spread changes has increased since the beginning of the crisis.

Finally, we tried to specify our results by analyzing the determinants of credit spreads for different bond subsamples. Particularly, we tried to investigate the determinants of credit spread changes for some of the largest firms in Europe, which are thought to be "Too big to fail". Our results were conclusive in the sense that we found an evidence for a smaller credit risk component in the spreads of these firms since the beginning of the crisis. Their spreads were indeed increasingly driven by market liquidity and market-wide risks components.

So what inferences can we draw from these findings for the valuation of corporate bonds? Our main recommendations are the following. First, we showed that the theoretical credit spread determinants that we used are generally significant determinants of the spreads in the long run, with signs in line theory. This tends to support the robustness of these determinants for the valuation, especially for bonds with long remaining times until maturity (around ten years). Second, we believe that the theoretical models need to account more explicitly for some of the factors that emerged during the crisis and that we found to have a significant effect on credit spreads. These include the effects default contagion, firms' bailouts and other systemic risk components. Third, we think that a separate modeling should be considered for banks and large systemic institutions, contrary to what is done in the structural models where all firms are modeled similarly. These firms are found to have a different risk structure from the other firms, and are seemingly subject to a larger market-liquidity and default contagion risks. In addition, these firms present generally a "Too big to fail" profile, which make them, as opposed to the other firms, eligible to bailouts and rescue politics. Fourth, we believe that a more particular attention should be placed on the modeling of interest rates within the structural framework. This variable has indeed proven to be one of the most important credit risk factors, with a steady impact on the spreads in all the investigated sub-periods. Fifth, we think that the theoretical models of corporate bond valuation should account for all the changes in the components of the spreads that we endeavored to reveal throughout this chapter, in an appropriately specified crisis state. While our work has shed light on the possible changes that credit spread components may incur in a crisis context (i.e. increase in the importance of market-wide risks and information asymmetries in the context of crisis), further investigations seem necessary in order to determine the effective proportions in which these changes may happen.

In sum, all these proposition of enhancements set very high standards for the valuation of corporate bonds. Not only, the theoretical models should account for the shortcomings that we emphasized in chapter I, but they need as well to consider the stylized facts and the different effects of the crisis that we identified, respectively, in chapters II and III. Incorporating all these insights in the structural models seems to be a particularly challenging task, which may be hard to accomplish at least in the short run. In the following chapter, we propose a contribution to the modeling of corporate bonds which accounts for some of these insights.

Chapter IV

The term structure of credit spreads with firm rescue: a structural model

1. Introduction:

In the first chapter of this thesis, we have shown that the structural approach of corporate bond valuation presents the advantage of keeping a clear link between the economic fundamentals of the firm and the credit spreads of the valuated bond. We have also noted that this approach allows great flexibility when dealing with a particular situation of the modeled firm, all while being well established in terms of financial and economic theory. These attractive features, as well as the numerous shortcomings of the existing models, suggest that the structural valuation should be expanded.

In chapters II and III, we were interested in the empirical aspects of corporate bonds by analyzing the evolution and the determinants of credit spreads during the recent economic and financial turmoil. By doing so, we have been able to shed light on several empirical facts and results that can help improving the valuation of corporate bonds. For instance, we have shown that the main credit spread determinants suggested by the structural models are generally robust in the long run, which pleads in favor of their appropriateness for the modeling of corporate bonds. Additionally, we have noticed the emergence of many factors and phenomena during the crisis that were found to affect credit spreads, and that need to be considered in a more consistent and comprehensive corporate bond valuation. Among these factors, we noticed that the unprecedented wave of bailouts undertaken by the authorities during the crisis has had an impact on credit spreads. This factors has appeared in different ways. First, we documented that the increase in authorities' willingness to help the financial sector (e.g. approval of bailouts and LTROs by the central bank) has been generally reflected in a decrease in the overall credit spreads (i.e. stylized fact 3.3 of chapter II, and the empirical analysis of chapter III). Second, we reported that the bailouts of some large firms (particularly financial institutions) has resulted, at least temporarily, in a decrease in their credit spreads (i.e. stylized fact 3.10 of chapter II). Moreover, since the bailouts concerned generally large firms (particularly large financial institutions due to the possible adverse economic consequences that their failure can cause), one can see the credit spreads of these firms as reflecting some of the possibility of their rescue in case of distress. In this regard, we have also pointed in the previous chapters some interesting empirical findings. First, we noticed that a change in the size of a firm (which may reflect a change in the possibility of its bailout) exert an impact on its credit spreads (i.e. the firm size effect investigated in chapter III). Second, we documented that large firms present generally lower credit spreads than smaller firms, which can be associated, at least to some extent, with their higher probabilities of bailout (i.e. stylized fact 3.9 of chapter II). Third, we reported that the gap between the spreads of large and small firms has increased during the crisis period, where, the bailouts have reached a high level (i.e. stylized fact 3.9 of chapter II). And finally, we have found that the credit spreads of large firms reflected a smaller credit risk component since the beginning of the crisis, which can be linked, at least to some extent, to their higher probabilities of rescue in case of distress (i.e. the specification analysis of credit spread determinants proposed in chapter III). These effects can be additionally linked to the notion of "implicit guarantee" that the recent financial crisis has put forward. The actions of governments or central banks during the crisis (bailouts and lender of last resort for financial institutions) have raised indeed concern about the possibility of an increase in investors' risk taking due to the presence of a guarantee from authorities for the banking sector even if their situation turn bad[1]. Since the bond samples that we used in our empirical analysis were mainly comprised of financial firms, one can see the decrease in the spreads of large firms that we documented as reflecting some of this effect.

In light of these empirical evidences, we propose in this chapter a contribution to the valuation of corporate bonds which accounts for the possibility of firms to be bailed out in case of distress, and that attempts to capture some of the empirical facts discussed above.

[1] See for instance OECD's Financial Market Trends (2012): "Implicit Guarantees for Bank Debt: Where Do We Stand".

More specifically, we develop here a structural model of corporate bond valuation that captures one of the aspects of the crisis, namely the bailouts. Since it is not possible so far to overcome the risk-neutral valuation, we decide to use this technique as is the tradition within the structural setup. In doing so, we try to capture some of the best ideas that have been developed by the previous structural models, and we try to improve them by considering one aspect that has been shown to have effect on the spreads. In particular, we build our model on the ideas of Merton (1974), Black-Cox (1976), Collin-Dufresne and Goldstein (2000) and Zhou (2001). Following the latter, we start by making an assumption about the evolution of the firm's assets over time. In doing so, we test two different assumptions for the dynamics of the firm value. First, as in Merton (1974), Black-Cox (1976), Collin-Dufresne and Goldstein (2000), we assume that the firm value follows a geometric Brownian motion (i.e. a proxy of stable economic conditions). Second, as in Zhou (2001), we assume that the firm value follows a jump-diffusion process (i.e. a proxy of a period of tensions or economic crisis). Given these dynamics, we assume, as in Black-Cox (1976), that the bond contract contains a safety covenant allowing the bondholders to force the bankruptcy or the reorganization of the firm if it performs poorly at a certain date compared to a pre-specified boundary level. In contrast to the previous structural models (which assume generally that bankruptcy occurs at the first time the firm goes into default) we assume here that, once in distress, the firm has the possibility to negotiate a bailout plan that has a probabilistic outcome. In case of bailout approval, the bondholders allow the firm to continue its activity, which may reimburse fully it creditors at maturity. In case of bailout disapproval, the firm makes bankruptcy at the first default date. Semi analytical formulas for the price of the risky debt and its credit spread are derived in this context. The model is also extended by a numerical analysis of the term structure of credit spreads generated by the model, and also by the sensitivity of the credit spreads to the main model's parameters.

In agreement with the economic intuition, our model generates smaller (larger) credit spreads for firms with higher (lower) probabilities of receiving a bailout. Additionally, by assuming that higher probabilities of bailout approval are associated with large firms, we manage to link the size of a firm to its credit spreads. Thereby, we find that our model generates lower credit spreads for larger firms (those which have higher probabilities of being rescued), while it generates greater credit spreads for smaller firms (those which have smaller chances of benefiting from a bailout). As such, we allow our model to reproduce some of the empirical facts that we discussed above, namely the effect of rescue operations on credit spreads, and the link that exists between the size of a firm and its credit spreads.

Overall, the model that we propose in this chapter brings the following improvements to the existing corporate bonds models. First, it considers more realistic bankruptcy mechanisms as it allows the firm to continue its activity in the case it succeeds to be bailed out. Second, it considers more realistic capital structures, as it is allows the modeled firm to alter its initial capital structure when it benefits from a rescue package. Third, this model considers the effect of a jump-diffusion dynamics for the firm value, which allows to capture some of the effects of the crisis on the spreads. Finally, this model reproduces some effects of the empirical findings discussed within the previous chapters, mainly by allowing the model to generate lower credit spread for the firms that have higher chances to be bailed-out.

The rest of this chapter is structured as follows. In section 2, we present the basic economic framework for the model in the case where the firm value follows a geometric Brownian motion. In section 3, we reconsider the model in case the firm value follows a jump-diffusion dynamics, while section 4 concludes the chapter. Proofs of the proposed formulas are placed in Appendices IV.1-4.

2. The term structure of credit spreads with firm rescue: the basic economic framework:

This model considers the valuation of a zero-coupon corporate bond issued by a firm subject to financial distress and a rescue procedure. In what follows, we present the main model assumptions under which we derive the bond's credit spreads. First, we start by assuming that the firm value follows a geometric Brownian motion (as in most of the previous structural models), before modifying this assumption in the following section to account for jumps on the firm value. Doing so will allow us, on the one hand, to compare the results of our model to the results of the structural models that use the geometric Brownian motion assumption, and on the other hand, to investigate the impact of the introduction of the jumps (supposed to capture some of the effects of the crisis on firm values) on the valuation setup. We start by presenting the model's assumptions, before deriving credit spreads and testing numerically the main implications of the model on credit spreads.

2.1. Model assumptions:

A.1. Capital structure and firm value dynamics:

Following Merton (1974), we assume that a firm has a capital structure, at date T_0, comprised of assets $V_0 > 0$, equities $E \geq 0$, and a single zero-coupon bond issue with face value $D > 0$ and maturity T_2. The evolution of the firm's assets over time is then assumed to follow a geometric Brownian motion with respect to the following stochastic differential equation:

$$dV_t = (r - \kappa)V_t \, dt + \sigma_v V_t \, d\widetilde{\mathbb{W}}_t \qquad (1)$$

Where r is the constant risk-free interest rate; κ the constant pay-out rate, σ_v the constant volatility of the firm's assets and $\widetilde{\mathbb{W}}_t$ a standard Brownian motion under the risk-neutral measure $\mathbb{Q}$. The diffusion process in equation (1) is assumed to capture the "normal" fluctuations in the firm value. This can be associated to a situation of stable economic conditions, which causes only marginal changes in the firm's value. In contrast to many previous structural models, we give here the possibility for the firm to alter its initial capital structure. This may occur in the case where the firm value hits a certain distress barrier, but the firm succeeds to negotiate a bailout package. The nature of this distress barrier and the bailout negotiation process are detailed in what follows.

A.2. The distress barrier:

We assume next that the bond contract contains a safety covenant that gives the bondholders the right to bankrupt or force the reorganization of the firm if it is doing poorly compared to a pre-specified standard. This pre-specified standard is assumed to be a constant barrier level $b > 0$ that the firm must have at a known date $T_1 \in (0, T_2)$[2]. In this setup, the bondholders are assumed to examine the firm value at the date T_1, and two cases arise. (i) Either the value of the firm's assets is superior to the boundary level (i.e. $V_{T1} \geq b$), in this case the firm is allowed to continue normally its activity until date T_2; or (ii) the firm value is inferior to the barrier level (i.e. $V_{T1} < b$), situation in which the firm is assumed to be in distress, and may be forced to bankruptcy by the bondholders. Once in distress, we assume here that the firm has the possibility to negotiate a bailout plan that convinces the bondholders to let it avoid bankruptcy. The bailout negotiation process is discussed in what follows.

A.3. The bailout negotiation process:

We assume afterwards that, once in distress (i.e. $V_{T1} < b$), the firm enters automatically into a negotiation process with the government, or other financial

[2] The date T_1 can be considered as the date at which the firm's accounting reports are published. The barrier level b can be chosen numerically in order to consider different scenarios, but an interesting scenario can be $b = De^{-r(T_2 - T_1)}$ (i.e. the firm must have at least the discounted value of the face-value of the bond in T_1)

authorities, in order to be bailed-out and avoid bankruptcy[3]. The outcome of this negotiation –denoted R–, and the approval of the bailout plan are assumed to be to be probabilistic, with a probability "p" to succeed and "$1-p$" to fail. In turn, these probabilities of success or failure of the negotiation are assumed to be impacted by the size of the firm, which is supposed to be exogenous. As such, two situations arise. (i) In the case of success of the negotiation (i.e. approval of the bailout plan), the firm obtains a rescue package in the form of a new debt of nominal value $\delta = D - V_{T1}$ and maturity T_2 (i.e. the received rescue package is assumed to be equal to the difference between the value of the firm's assets in T_1, and the face-value of its initial debt D)[4]. In this case, the bondholders accept to give the firm an opportunity to continue its activity until the maturity of the bond T_2, since they have a chance to recover the full face-value of the debt D. (ii) In the opposite case (i.e. failure of the negotiation and disapproval of the bailout), the firm is assumed to become bankrupt in T_1. The total mechanisms of bankruptcy in this framework are detailed in what follows.

A.4. Bankruptcy mechanisms:

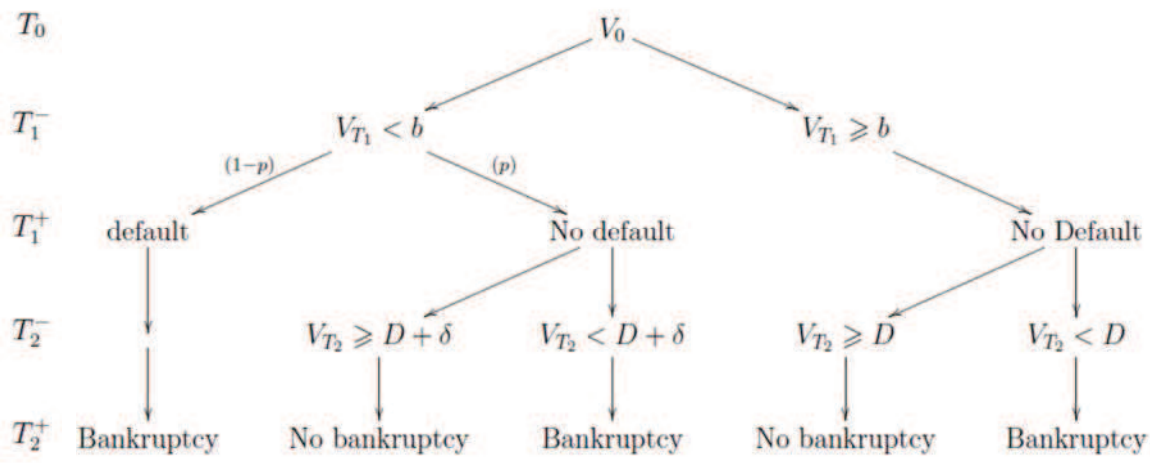
In this valuation setup, the firm value is assumed to be examined in two different dates: T_1 and T_2. In each of these dates, the decision of bankruptcy or survival of the firm is made, in light of assumptions A.2 and A.3, according to the following scheme:

- If the firm value at date T_1 is superior to the distress barrier (i.e. $V_{T1} \geq b$), the firm continues its activity until T_2;
- On the opposite, if the firm value at date T_1 is inferior to the distress barrier (i.e. $V_{T1} < b$), the firm gets into the bailout negotiation process. In the case of success of the negotiation and the approval of the bailout (i.e. $R = \delta$), the firm continues its activity up to T_2; in the opposite case (i.e. $R = 0$), the firm goes bankrupt in T_1.
- Finally, if the firm survives it until T_2, (i.e. in the cases where $V_{T1} > b$ or in the case where the recue negotiation succeeds, i.e. $R = \delta$), two possibilities arise in T_2. Either the firm produces enough cash flows to pay the face value of the bond D (besides the rescue package δ in the case it received a bailout); or it is liquidated. These mechanisms are summarized in Figure IV.1.

[3] Hence bankruptcy is assumed to be the worst outcome for the shareholders.

[4] The maturity of the new debt (i.e. the rescue package) is assumed for simplicity to be similar to the initial debt. The new debt is also assumed to be of similar priority to the initial debt. Different scenarios for the amount of the rescue package can be considered easily.

Figure IV.1. Bankruptcy mechanisms



A.5 Bondholder's payoffs:

With regard to the previous assumptions, the holder of this corporate bond expects to receive one of the following payoffs in T_2:[5]

- The face-value of the debt D, in the case where the firm value is above the distress barrier in T_1 (i.e. $V_{T1} > b$), and has made enough cash flows to pay the face value of the debt in T_2 (i.e. $V_{T2} > D$);
- The face-value of the debt D, in the case where the firm succeeds to negotiate a bailout in T_1 (i.e. $R = \delta$) and has made enough cash flows to pay the face value of the debt and the rescue package in T_2 (i.e. $V_{T2} > D + \delta$)
- The recovery level $\alpha_1 = (1 - w_1)D$, in the case where the firm has sufficient assets in T_1 but defaults in T_2.
- The recovery level $\alpha_2 = (1 - w_2)D$, in the case where the firm is bailed-out in T_1 but fails to meet its total debt obligation in T_2.
- The recovery level $\alpha_3 = (1 - w_3)D$, in the case where the firm value is under the distress barrier in T_1 and the bailout negotiation does not succeed.

In the last three cases, the recovery α_i, for $i = 1 \dots 3$, is assumed to be a fixed proportion $(1 - w_i)$ of the face value of the debt at maturity, with w_i the write down-rate. We assume additionally that the probability that the firm value falls

[5] The assumption that the bondholders are paid at the maturity of the bond, even if the firm defaults in T_1, is made for expositional convenience. It is indeed a classic assumption within the structural models (see for instance Zhou, 2001).

below the recovery level α_i in case of default is negligible (inferior to 10^{-2}).[6] These payoffs are summarized in Table IV-1:

Table IV-1: Bondholders payoffs:

T_1^-	T_1^+	T_2^-	Payoff in T_2^+:
$if\ V_{T1} \geq b$	and	$if\ V_{T2} \geq D$	$\to\ D$ (i)
		$if\ V_{T2} < D$	$\to\ \alpha_1$ (ii)
$if\ V_{T1} < b\ \to negociation$	$if\ R = 0$		$\to\ \alpha_3$ (iii)
	$if\ R = \delta\ \to$	$if\ V_{T2} \geq D + \delta$	$\to\ D$ (iv)
		$if\ V_{T2} < D + \delta$	$\to\ \alpha_2$ (v)

A.6. The risk-free rate:

The term structure for the risk-free interest rate is assumed to be flat and constant for all maturities. This assumption is made for convenience and can be easily extended toward stochastic interest rates.

A.7. Market characteristics:

Following the previous structural models, we assume for simplicity that there are no transactions costs or taxes, and that all securities are divisible. In addition, we assume that each investor can buy and sell as much assets as he wants at the market price. Considering these assumptions can be indeed of interest since it allows us a close comparison between the results of our model and the results of the previous structural models that use these assumptions, such as the models of Merton (1974), Black-Cox (1976), Collin-Dufresne and Goldstein (2000) and Zhou (2001) presented in chapter I.

2.2. Deriving credit spread:

Based on the previous assumptions, the price of the risky bond issued by this corporation is given at date $t = 0$ by the following expectations[7]:

[6] This assumption is made so that the firm has always enough remaining assets to pay the recovery level α_i. The rates w_1, w_2, w_3 can be also chosen in such a way that this probability becomes even lower.

[7] The proof for this derivation is provided in appendix IV.2

$$P(0,T) = e^{-r(T_2)} \Bigg\{ \mathbb{E}^{\mathbb{Q}} \Bigg(\underbrace{D\ \mathbf{1}_{\{V_{T1} \geq b\ ;\ V_{T2} \geq D\}}}_{(i)} \Bigg) + \mathbb{E}^{\mathbb{Q}} \Bigg(\underbrace{\alpha_1\ \mathbf{1}_{\{V_{T1} \geq b\ ;\ V_{T2} < D\}}}_{(ii)} \Bigg)$$
$$+ \mathbb{P}(R=0)\ \mathbb{E}^{\mathbb{Q}} \Bigg(\underbrace{\alpha_3\ \mathbf{1}_{\{V_{T1} < b\}}}_{(iii)} \Bigg) + \mathbb{P}(R=\delta)\ \mathbb{E}^{\mathbb{Q}} \Bigg(\underbrace{D\ \mathbf{1}_{\{V_{T1} < b\ ;\ V_{T2} \geq D+\delta\}}}_{(iv)} \Bigg)$$
$$+ \mathbb{P}(R=\delta)\ \mathbb{E}^{\mathbb{Q}} \Bigg(\underbrace{\alpha_2\ \mathbf{1}_{\{V_{T1} < b\ ;\ V_{T2} < D+\delta\}}}_{(v)} \Bigg) \Bigg\} \quad (2)$$

Where $\mathbf{1}\{\}$ is the indicator function; the entities $(i), (ii), (iii), (iv)$ and (v) correspond, respectively, to the payoffs of the bond for each of the cases described in Table IV-1; and $\mathbb{P}(R=\delta)$, $\mathbb{P}(R=0)$ correspond respectively to the probabilities of success and failure of the bailout negotiation. Solving equation (2) yields to the following semi-analytical solution[8]:

$$P(0,T) = e^{-r(T_2)} \Bigg\{ D\ \mathbb{E}^{\mathbb{Q}} \Big(\mathbf{1}_{\{V_{T1} \geq b\}} N\big(d_1(V_{T1})\big) \Big) + \alpha_1 \mathbb{E}^{\mathbb{Q}} \Big(\mathbf{1}_{\{V_{T1} \geq b\}} N\big(d_2(V_{T1})\big) \Big)$$
$$+ (1-p) \Big(\alpha_3\ N\big(d_3(V_0)\big) \Big) + p \Big(D\ \mathbb{E}^{\mathbb{Q}} \Big(\mathbf{1}_{\{V_{T1} < b\}}\ N\big(d_4(V_{T1})\big) \Big) \Big)$$
$$+ p \Big(\alpha_2\ \mathbb{E}^{\mathbb{Q}} \Big(\mathbf{1}_{\{V_{T1} < b\}}\ N\big(d_5(V_{T1})\big) \Big) \Big) \Bigg\} \quad (3)$$

Where:

$$\alpha_i = (1 - w_i)D\ ;\ \text{For } i = 1 \ldots 3$$

$$d_1(V_{T1}) = \frac{\ln\left(\frac{V_{T1}}{D}\right) + \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_2 - T_1)}{\sigma\sqrt{T_2 - T_1}}$$

$$d_2(V_{T1}) = \frac{\ln\left(\frac{D}{V_{T1}}\right) - \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_2 - T_1)}{\sigma\sqrt{T_2 - T_1}}$$

$$d_3(V_0) = \frac{\ln\left(\frac{b}{V_0}\right) - \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_1)}{\sigma\sqrt{T_1}}$$

[8] The proof of the solution in equation (3) is provided in appendix IV.3.

$$d_4(V_{T1}) = \frac{\ln\left(\frac{V_{T1}}{D+\delta}\right) + \left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)}{\sigma\sqrt{T_2-T_1}}$$

$$d_5(V_{T1}) = \frac{\ln\left(\frac{D+\delta}{V_{T1}}\right) - \left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)}{\sigma\sqrt{T_2-T_1}}$$

Next, the yield to maturity of the bond in this framework is then given by:

$$Y(0,T) = -\frac{1}{T_2}\ln\left(\frac{1}{D}\big(P(0,T)\big)\right) \tag{4}$$

$$= -\frac{1}{T_2}\ln\Bigg\{e^{-r(T_2)}\Bigg[\mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1}\geq b\}}N\big(d_1(V_{T1})\big)\Big) + \mathbb{E}^{\mathbb{Q}}\Big((1-w_1)\mathbf{1}_{\{V_{T1}\geq b\}}N\big(d_2(V_{T1})\big)\Big)$$
$$+ (1-p)\Big((1-w_3)N\big(d_3(V_0)\big)\Big) + p\,\mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1}<b\}}\,N\big(d_4(V_{T1})\big)\Big)$$
$$+ p\,\mathbb{E}^{\mathbb{Q}}\Big((1-w_2)\mathbf{1}_{\{V_{T1}<b\}}\,N\big(d_5(V_{T1})\big)\Big)\Bigg]\Bigg\} \tag{5}$$

Finally, the corresponding credit spread of the bond is given by:

$$S(0,T) = Y(0,T) - r \tag{6}$$

$$= -\frac{1}{T_2}\ln\Bigg\{e^{-r(T_2)}\Bigg[\mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1}\geq b\}}N\big(d_1(V_{T1})\big)\Big) + \mathbb{E}^{\mathbb{Q}}\Big((1-w_1)\mathbf{1}_{\{V_{T1}\geq b\}}N\big(d_2(V_{T1})\big)\Big)$$
$$+ (1-p)\Big((1-w_3)N\big(d_3(V_0)\big)\Big) + p\,\mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1}<b\}}\,N\big(d_4(V_{T1})\big)\Big)$$
$$+ p\,\mathbb{E}^{\mathbb{Q}}\Big((1-w_2)\mathbf{1}_{\{V_{T1}<b\}}\,N\big(d_5(V_{T1})\big)\Big)\Bigg]\Bigg\} - \underbrace{\left(-\frac{1}{T_2}\ln\big(e^{-r(T_2)}\big)\right)}_{r}$$

Using $\ln(a) - \ln(b) = \ln(a/b)$ in the previous equation we obtain:

$$S(0,T) = -\tfrac{1}{T_2}\ln\Bigg\{\mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1}\geq b\}}N\big(d_1(V_{T1})\big)\Big) + \mathbb{E}^{\mathbb{Q}}\Big((1-w_1)\mathbf{1}_{\{V_{T1}\geq b\}}N\big(d_2(V_{T1})\big)\Big)$$
$$+ (1-p)\Big((1-w_3)N\big(d_3(V_0)\big)\Big) + p\,\mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1}<b\}}\,N\big(d_4(V_{T1})\big)\Big)$$
$$+ p\,\mathbb{E}^{\mathbb{Q}}\Big((1-w_2)\mathbf{1}_{\{V_{T1}<b\}}\,N\big(d_5(V_{T1})\big)\Big)\Bigg\} \tag{7}$$

In what follows, we analyze numerically the credit spreads generated by our model.

2.3. Numerical results:

We run next a series of numerical simulations of the credit spreads generated from our model, which we represent graphically by the means of the "term structure of credit spreads". To do this, we compute the spreads from equation (7) for different values of the time to maturity T_2, and we represent the obtained values in a scatter plot where T_2 stands in the horizontal axis. Using this representation will allow us, on the one hand, to compare the results of our model to the results of the main structural models that we analyzed in chapter I, and on the other hand, to present graphically the impact of the firm rescue feature on the credit spreads generated by the model. We start by discussing the benchmark setup for the term structure of the spreads before comparing our results to the results of the previous models and specifying the impact of the probability of bailout on the term structure of the spreads[9].

Figure IV.2. The term structure of credit spreads

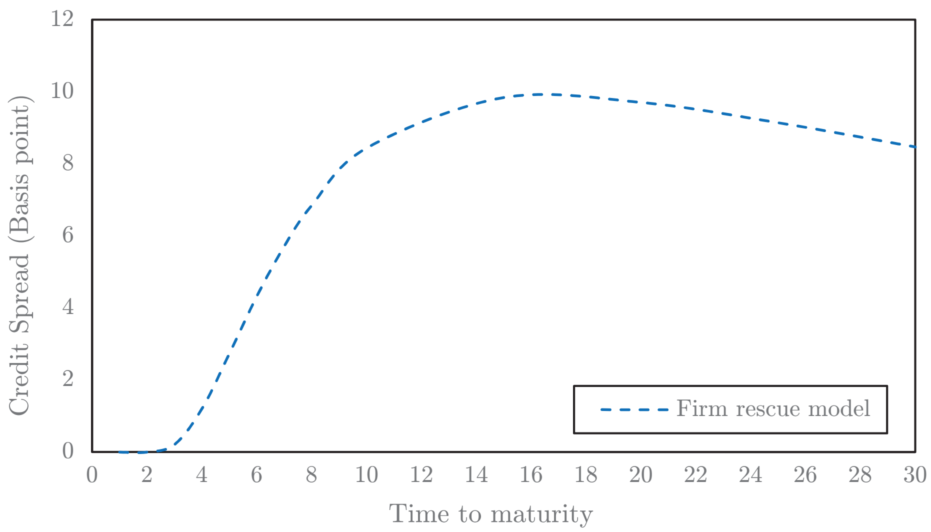


Figure IV.2 presents the term structure of credit spreads computed from our firm rescue model. To have so, we set in equation (7) the leverage level $L = 40\%$; the risk-free rate $r = 0.06$; the asset volatility $\sigma_v = 0.2$; the pay-out rate $\kappa = 0.03$; the write-down rates $w_1 = w_2 = w_3 = 0.2$; the probability of success of the negotiation $p = 0.5$; the distress boundary level $b = 39$; the distress verification

[9] The numerical simulations are done using Visual Basic for Excel and SCILAB numerical computations' software.

date $T_1 = 1$. Using this setup, we computed credit spreads for maturities T_2 going from two to thirty years[10].

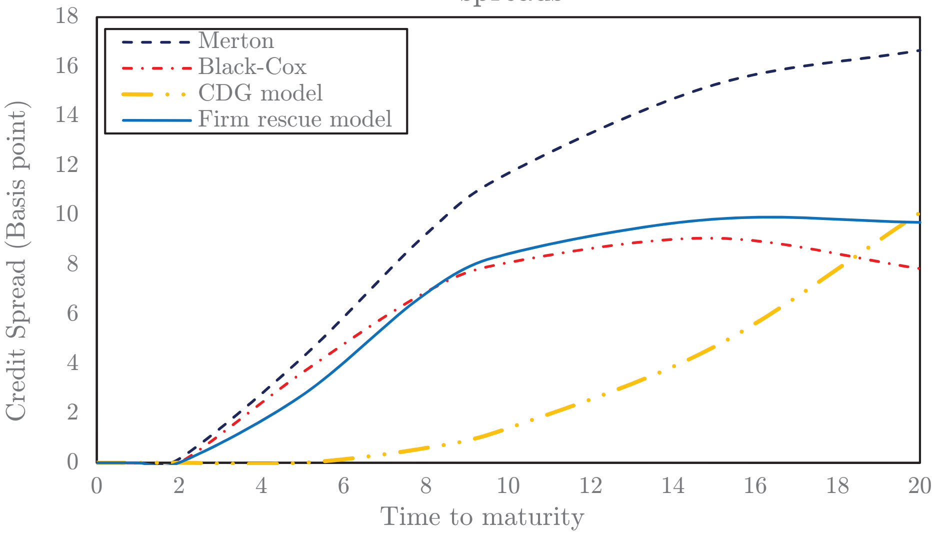
Figure IV.2 shows that, under the chosen parameters, the term structure of credit spreads obtained from our model is hump-shaped. As for the short term credit spreads, we find in the same vein, as most of the structural models discussed in chapter I, that our model generates near-zero short-term credit spreads. These near-zero spreads are again a direct consequence of the assumption that the asset value follows a geometric Brownian motion. As a matter of fact, the event of bankruptcy is indicated in this setup by the proximity of the firm value to the bankruptcy barriers (i.e. the distress barrier in T_1 or the face-value of the debt in T_2). Since the initial firm value here is far from these boundaries (i.e. low initial leverage ratio), the continuous diffusion path of the geometric Brownian motion makes it hard for bankruptcy to happen before a certain time. Consequently, both the short-term probabilities of default and the credit spreads remain at near-zero levels. As for the long term credit spreads, we note that for the chosen parameters our firm rescue model generates larger long-term credit spreads (e.g. about 10 bps for the twenty years maturity), which means that it predicts more chances of bankruptcy for longer maturities. That being said, we note that, similarly to the models of Merton (1974) and Black-cox (1976), the shape of the term-structure depends much on the chosen initial leverage level. For low leverage ratios, the hump of the term structure goes further in time and remains flat for a long period, while it comes closer to short maturities, and does not last long for larger leverage ratios. This observation is a consequence of both the geometric Brownian motion assumption chosen for the asset value (which increases exponentially over time), as well as the chosen bankruptcy conditions (comparing the firm value to the distress barrier or to the firm's liabilities). The hump of the spreads appears at the period where the firm value is the closest to the bankruptcy boundary, but then fades away in line with the decrease of the chances of bankruptcy caused by the exponential increase of the firm value.

Further, Figure IV.3 compares the credit spreads generated from our model to the credit spreads generated from the models of Merton (1974), Black-cox (1976) and Collin-Dufresne and Goldstein –CDG– (2000) for equivalent parameter values[11]:

[10] Hence the minimum interval between T_1 and T_2 is of 1 year.

[11] This figure considers the same parameter values for the models of Merton (1974), Black-Cox (1976) and Collin-Dufresne and Goldstein (2000) as in Figure I.8 of chapter I (see section 5.2 of chapter I). The parameters for our model are the same as in Figure IV.2.

Figure IV.3. Impact of the rescue option on credit spreads



Comparing these term structure provides interesting insights. First, Figure IV.3 confirms the previous insights about the proximity of the four models with respect to the short-term credit spreads. Again, this stems from the similar assumption made by these models about the dynamics of the firm value as well as the predictability of the default-bankruptcy stopping time[12]. Second, Figure IV.3 shows that our model generates spreads quite similar to the model of Black-Cox (1976) in terms of levels and the structure by term. This relative similarity can be explained by the safety covenant feature that our model shares with the model of Black-Cox (1976). As in Black-Cox (1976), our firm rescue model contains indeed a distress barrier which allows the bondholders to check the solvability of the firm before maturity (i.e. in T_1), in order to protect their debt claim. Thereby, our model generates, in the same lines as Black-Cox (1976), lower credit spreads than those generated by the model Merton (1974) where this feature is not available.

That being said, Figure IV.3 shows that there are some differences between the term structure of the spreads generated from our model and that of Black-Cox (1976). These differences can be attributed to our different treatment of the safety covenant feature. While bankruptcy occurs in the first random time at which the firm value hits a certain boundary in Black-Cox (1976), in our model

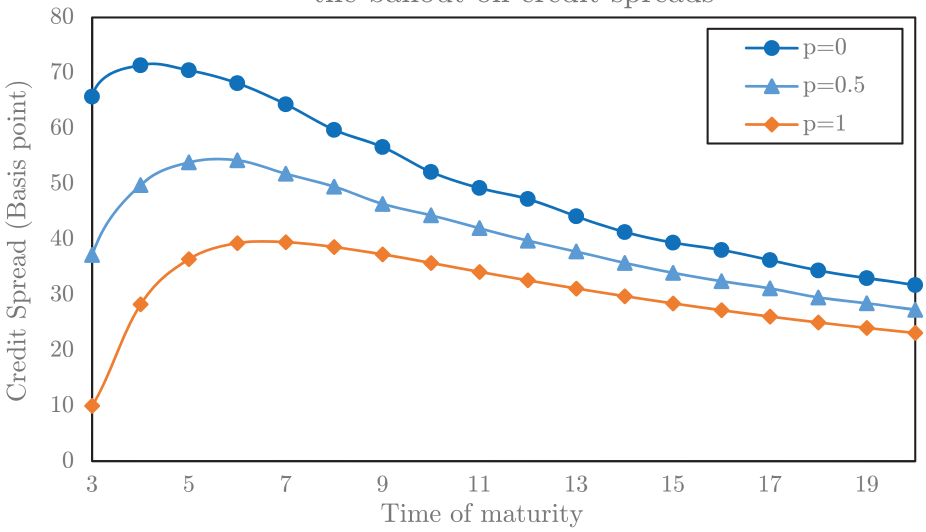
[12] As argued in chapter I (see for instance section 7.1), under the geometric Brownian motion assumption, and with complete information on the firm value and the default barrier, default becomes a predictable stopping time which makes the model generate near-zero short term credit spreads. To overcome this shortcoming, literature proposed introducing jumps on the firm value or incomplete information on the firm value and/or the default boundary. In the following section, we consider the effect of jumps on the firm value.

the date of the verification of the assets is known in advance, and the firm may continue its activity in our setup if ever it succeeds to be bailed out.

Finally, Figure IV.3 shows also that our model generates a different term-structure to that of CDG (2000) even though both models give the firm the possibility to alter its capital structure over time. CDG (2000) allows, however, the firm to increase or decrease its leverage without constraints, in line with the continuous movements of the asset value, while our model gives the firm the possibility to increase its leverage only: (*i*) at selected times, (*ii*) if it is doing poorly compared to a pre-specified standard, or (*iii*) under the condition of success of the negotiation of the bailout. Since firms do not have the possibility to increase their leverage ratios without constraints in practice, our assumptions and the term structures generated by our model are arguably more realistic.

Furthermore, compared to the Models of Merton (1974), Black-Cox (1976), and Collin-Dufresne and Goldstein (2000), our firm rescue model is a function of an additional parameter, namely the probability of negotiation success and approval of the bailout "p" (conversely, the probability of negotiation failure and bailout disapproval "$1-p$"). Figure IV.4 specifies the impact of different values of this parameter on the term structure of credit spreads generated from our model:

Figure IV.4. Impact of the probability of approval of the bailout on credit spreads



In order to make this simulation, we set in equation (7) the leverage level $L = 70\%$; the risk-free rate $r = 0.06$; the asset volatility $\sigma_v = 0.2$; the pay-out rate $\kappa = 0.03$; the write-down rates $w_1 = w_2 = w_3 = 0.2$; the distress boundary level $b = 69$; the distress verification date $T_1 = 2$; and then we calculated credit spreads for maturities T_2 going from three to twenty years. This computation is presented in Figure IV.4 for the probabilities of bailout approval: $p = 0$; $p = 0.5$ and $p = 1$.[13]

Figure IV.4 shows interestingly that larger probabilities of negotiation success (i.e. approval of the bailout plan) are consistently associated with a decrease in the credit spreads generated from our model. For instance, for a maturity of five years, the model generates a credit spread of 70bps in the case where the bailout will never be approved (i.e. $p = 0$), while it predicts a credit spread of 36bps in the case where the bailout will always be approved (i.e. $p = 1$). In agreement with the economic intuition, higher probabilities of receiving a financial aid (i.e. the bailout) are associated in our model to a decrease in the probabilities of bankruptcy of the firm, and accordingly to smaller credit spreads. Of course it is of interest to give some interpretation to the likelihood of approval or disapproval of the bailout. It seems indeed logical to think that large financial institutions have higher chances of being rescued in case of distress, in view of the disastrous effects that their bankruptcy may cause on the economy (e.g. the collapse of Lehman Brothers), or by dint of the size of their network. One can hence intuitively link large financial institutions have a "p" that tends towards 1, while smaller firms from other economic sectors have a "p" that tends towards 0.[14] Under this consideration, our model is found to be consistent with lower credit spreads for large firms (those which have an important negotiation power), while it generates higher credit spreads for smaller firms (those having small chances of being rescued). This result is noteworthy because it allows us to replicate, at least to some extent, some of the empirical findings of chapters II and III. These include the observed decrease in the spreads of the bailed-out firms after the bailouts (i.e. stylized fact 3.10 of chapter II), the observed lower credit spreads for larger firms (i.e. stylized fact 3.9 of chapter II), and finally the smaller credit risk component inside the spreads of large financial institutions (i.e. the specification analysis of credit spread determinants for different firm sizes provided in chapter III). In what follows, we reconsider the results our model in the case where the firm value follows a jump-diffusion process.

[13] As mentioned earlier, for low initial leverage levels, the probability that the firm value hits the distress barrier at short maturities is very low (due to the continuous diffusion property of the geometric Brownian motion). This makes the effect of the bailout-approval probability on the spreads hardly noticeable for low leverage ratios and short T_1. As such, we increased here the leverage to 70% and the verification date T_1 to two years. The credit spreads are accordingly calculated starting from $T_2 = 3$, to keep at least a one year interval between T_1 and T_2.

[14] Making more explicit the relationship between the size of the firm and its negotiating power constitutes a principal point in our future research agenda.

3. The term structure of credit spreads with firm rescue: the jump-diffusion dynamics:

We propose next to reconsider our firm rescue model for the case where the firm value follows a jump diffusion process. Considering this assumption seems indeed attractive from a theoretical point of view, since it allows to capture some of the effects of the crisis, which was found in previous chapters to have a considerable impact on credit spreads. While keeping the other assumptions unchanged, we replace the assumption A.1 made previously by the following assumption A.1'.

A.1'. Capital structure and firm value dynamics:

Similarly to A.1, we assume that the firm has a capital structure, at date T_0, comprised of assets $V_0 > 0$, equities $E \geq 0$, and a single zero-coupon bond issue with face value $D > 0$ and maturity T_2. Following Zhou (2001), we assume here however that the evolution of the firm's assets over time follows a jump-diffusion process with respect to the following dynamics:

$$d\hat{V}_t = (r - \lambda\vartheta)\hat{V}_t dt + \sigma_v \hat{V}_t d\widetilde{\mathbb{W}}_t + (j_t - 1)\hat{V}_t dN_t \tag{8}$$

Where:

- ϑ, σ_v and λ are positive constants;
- r is the constant risk-free interest rate;
- $\widetilde{\mathbb{W}}_t$ is a Brownian motion under the risk-neutral measure;
- N_t is a Poisson process which counts the random number of jumps on the firm value until time "t". N_t is a function of the exogenous intensity parameter λ, which specifies the average rate at which the jumps occur.
- $j_t > 0$ is the random jump size, and $(j_t - 1)$ is the increase in the firm value due to the jump that has the expected value $\vartheta = \mathbb{E}(j_t - 1)$. The jump size can be indeed set to follow any arbitrary probability distribution. Following Zhou (2001) we assume that the jump size follows a log-normal distribution where $J_t = \ln(j_t) \sim N(\mu_j, \sigma_j^2)$[15]. Under this assumption, the expected value of the –increase in the firm value due to jump– becomes equal to : $\vartheta = \mathbb{E}(j_t - 1) = \exp(\mu_j + \sigma_j^2/2) - 1$[16].

[15] Saying that j_t follows a log-normal distribution returns equivalently to saying that the log of j_t follows a normal distribution. We denote here the log of j_t by J_t.

[16] Since the expected value of a log-normal variable (here j_t) is equal to: $\exp(\mu_j + \sigma_j^2/2)$, it is obvious that the expected value of $(j_t - 1)$ is equal to: $\exp(\mu_j + \sigma_j^2/2) - 1$.

Under the dynamics of equation (8), the firm value is assumed to be affected by three sources of randomness. The Brownian motion $\widetilde{\mathbb{W}}_t$, the number of jumps N_t, and the size of the jumps j_t. These latter are assumed to be mutually independent. With all the above specifications, the jump-diffusion dynamics in equation (8) can be interpreted as follows. The firm value follows the same diffusion path of a geometric Brownian motion, with a drift equal to $(r_t - \lambda\vartheta)$ and a constant volatility σ_v[17]. This diffusion path may however witness N_t jumps in the interval of length "t"[18]. At each random jump time, the firm value may rise or fall by a random amount j_t[19]. This dynamics captures hence the "normal" fluctuations in the firm value, as well as the effect of any type of shock that may cause the firm value to change considerably over a small time interval. Under the right parametrization (i.e. with regard to λ and j_t), the jump-diffusion dynamics can hence allow us to capture some of the effects of the crisis on the firm value, even though the link is not very explicit. As shown, in chapters II and III the crisis caused a considerable impact on credit spreads and their determinants; making this assumption allows us to capture, at least to some extent, some of these effects. Additionally, by considering this jump-diffusion process, we allow the model to capture some of the skewness and excess kurtosis that can be expected on the returns of the firm, which are not accounted for by the geometric Brownian motion assumption[20].

Finally, similarly to A.1, we give here the firm the possibility to alter its initial capital structure in the case where the firm value hits the distress barrier, but then succeeds to negotiate a bailout package. In what follows, we derive the price of the bond and its credit spread under this new dynamics for the firm value.

---

[17] The firm value increases hence with the interest rate and decreases with the jump intensity and average size of the jumps.

[18] From the model's perspective, the number of jumps is a pseudo-random number, generated from the probability distribution of a Poisson process, which is as follows :

$$P(N_t = k) = \frac{e^{-\lambda t}(\lambda t)^k}{k!}$$

This is indeed nothing but a Poisson distribution with a parameter λt. The generated number of jumps $N_t = k$ is hence affected by the jump intensity parameter λ (which is specified by the modeler) and the length of the time interval "t".

[19] j_t is also a pseudo-random number generated from a log-normal distribution, with parameters μ_j and σ_j^2.

[20] It is now accepted that many financial time series exhibit skewness and excess kurtosis, and are therefore not normally distributed (see for instance Rama Cont, 2000).

3.1. Deriving credit spread:

Based on this modified assumption for the firm value dynamics (i.e. A.1'), and keeping all the assumptions A.2 to A.7 unchanged, the price of the risky corporate bond at date $t = 0$ can be given by the following expectations:

$$\hat{P}(0,T) = e^{-r(T_2)} \Bigg\{ \mathbb{E}^{\mathbb{Q}}\Bigg(\underbrace{D\ \mathbf{1}_{\{\hat{V}_{T1}\geq b\ ;\ \hat{V}_{T2}\geq D\}}}_{(i)}\Bigg) + \mathbb{E}^{\mathbb{Q}}\Bigg(\underbrace{\alpha_1\ \mathbf{1}_{\{\hat{V}_{T1}\geq b\ ;\ \hat{V}_{T2}< D\}}}_{(ii)}\Bigg)$$
$$+ \mathbb{P}(R=0)\ \mathbb{E}^{\mathbb{Q}}\Bigg(\underbrace{\alpha_3\ \mathbf{1}_{\{\hat{V}_{T1}< b\}}}_{(iii)}\Bigg) + \mathbb{P}(R=\delta)\ \mathbb{E}^{\mathbb{Q}}\Bigg(\underbrace{D\ \mathbf{1}_{\{\hat{V}_{T1}< b\ ;\ \hat{V}_{T2}\geq D+\delta\}}}_{(iv)}\Bigg)$$
$$+ \mathbb{P}(R=\delta)\ \mathbb{E}^{\mathbb{Q}}\Bigg(\underbrace{\alpha_2\ \mathbf{1}_{\{\hat{V}_{T1}< b\ ;\ \hat{V}_{T2}< D+\delta\}}}_{(v)}\Bigg)\Bigg\} \quad (9)$$

Where $\mathbf{1}\{\}$ is the indicator function; entities $(i),(ii),(iii),(iv)$ and (v) correspond respectively to the payoffs of the bond for each of the cases described in Table IV.1, while $\hat{V}_{T1}$ and $\hat{V}_{T2}$ correspond, respectively, to the values of the firm's assets in T_1 and T_2 under the jump-diffusion dynamics provided in equation (8)[21]. Unfortunately, we are unable to derive closed-form solutions for the price of the bond in this setting. We rely hence on Monte numerical simulation methods in order to compute the relevant bond price and credit spreads.

Next, the yield to maturity of the bond in this framework is obtained numerically from the price of the given in equation (9), and the following equation:

$$\hat{Y}(0,T) = -\frac{1}{T_2}\ln\left(\frac{1}{D}\left(\hat{P}(0,T)\right)\right) \quad (10)$$

Finally, using the yields computed from equation (10) and the risk-free rate r, the credit spread of the bond is obtained from:

$$\hat{S}(0,T) = \hat{Y}(0,T) - r \quad (11)$$

In what follows we analyze numerically the credit spreads generated by our model under this jump-diffusion dynamics assumption.

[21] This equation is derived in the same way as equation (2) (proof is provided in Appendix IV.3.

3.2. Numerical results:

Figure IV.5 presents the term structure of credit spread generated from our firm rescue model under the assumption A.1'. To better specify the effect of the jumps, we computed credit spreads for the jump-size parameters $\sigma_j = 0$; $\sigma_j = 1.7$; $\sigma_j = 2$ and $\sigma_j = 2.4$. The remaining parameters are the jump intensity $\lambda = 0.05$ and the jump-size mean $\mu_j = 0$, the leverage level $L = 40\%$; the asset volatility $\sigma_v = 0.2$; the risk-free rate $r = 0.06$; the pay-out rate $\kappa = 0.03$; the write-down rates $w_1 = w_2 = w_3 = 0.2$; the probability of the success of the negotiation $p = 0.5$; the distress boundary level $b = 39$ and the distress verification date $T_1 = 1$:

Figure IV.5. Impact of jump size on credit spreads

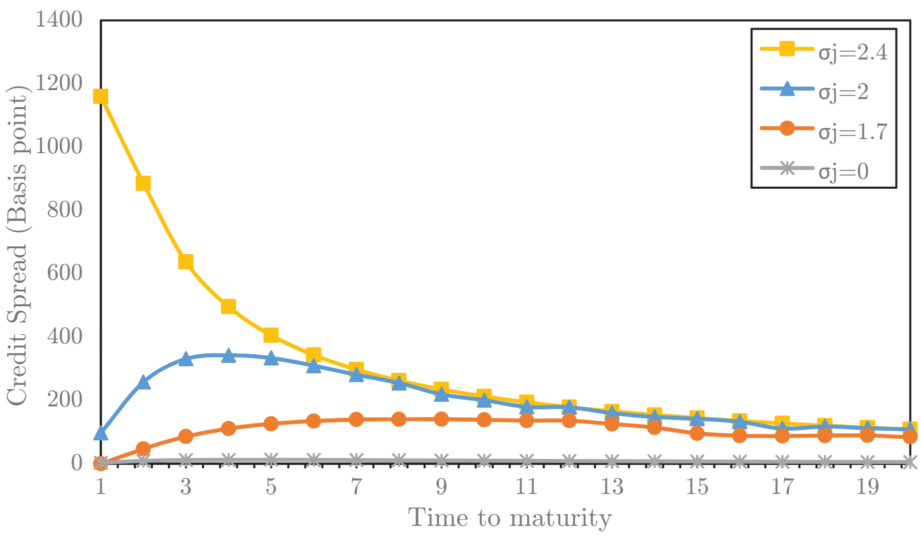


Figure IV.5 shows that introducing jumps on the firm value changes considerably the levels and the term structure of the spreads. First, we note that the model generates generally larger credit spreads under the jump-diffusion dynamics. For instance, for a bond with a ten years maturity, the model predicts a credit spread of 200 bps for a jump standard deviation $\sigma_j = 2$, while it predicted a credit spread of only 9 bps under the geometric Brownian motion dynamics. These larger spreads are indeed caused by the higher likelihood of the firm value to hit the distress barrier following a sudden jump on its value. These large credit spreads are interesting since they are closer to those observed in reality, particularly in a context of crisis.

Second, Figure IV.5 shows that the credit spreads predicted by the model increase in line with the increase of the jump-size parameter σ_j. For instance, for a corporate bond with a ten years maturity, the model predicts a credit spread of 140 bps for $\sigma_j = 1.7$, while it predicts a credit spread of about 202 bps for $\sigma_j =$

2.4.[22] Higher levels of σ_j increase the size of the jumps that can occur on the firm value, makes the firm more likely to hit the bankruptcy boundary, which results logically in an increase in the credit spreads. Since an increase in the amplitude of the jumps that occur on the firm value can be associated to a period of crisis (e.g. stock market crash or deep decrease in the firm's cash flows) one can see the model as capable of replicating some of the shocks that firms have witnessed during the crisis, by generating consistently larger spreads. Additionally, we assumed here for convenience that the intensity at which the jumps occur (i.e. λ) is small, which means that the firm can undergo only few jumps with more or less large sizes (i.e. different values of σ_j). Increasing the jump intensity is found to result in more jumps on the firm value, which are consistently associated with a high volatility of the spreads, in agreement with the ones that were observed in the context of crisis.

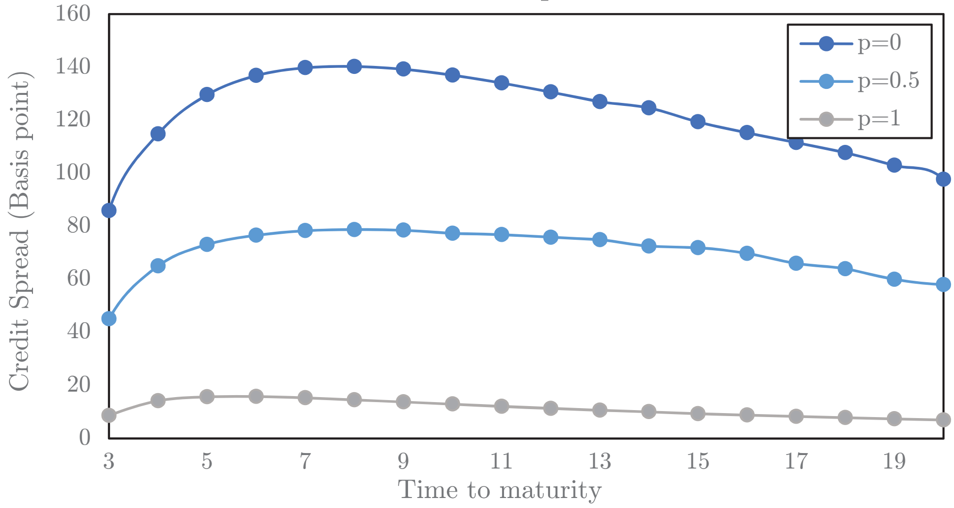
Further, Figure IV.5 shows interestingly that the model is capable of generating high short-term credit spreads, even for firms with low initial leverage ratios (here L=40%), which was not possible under the geometric Brownian motion assumption. This can be explained by the fact that the firm value can jump at any time to make the firm reach the distress barrier at the verification date. Finally, we note that the model can be parameterized under A.1' in such a way as to generate flat, downward or upward sloping credit spread term structures[23]. All these observations tend to bring support to the higher flexibility and the better appropriateness of the jump-diffusion dynamics despite the higher volatility of the results and the absence of any analytical or semi-analytical solution for the model. We specify next the results of the model for different values of the probability of approval or disapproval of the bailout under A.1'.

Furthermore, Figure IV.6 presents the term structures of credit spread generated from equation (11) for the probabilities of bailout approval $p = 0$; $p = 0.5$ and $p = 1$. The remaining parameters are the leverage level $L = 40\%$; the distress boundary level $b = 39$; the distress verification date $T_1 = 3$, the risk-free rate $r = 0.06$; the asset volatility $\sigma_v = 0.2$; the pay-out rate $\kappa = 0.03$; the write-down rates $w_1 = w_2 = w_3 = 0.2$ and the jump parameters $\lambda = 0.05$, $\sigma_j = 1.5$ and $\mu_j = 0$.

[22] For $\sigma_j = 0$ the model reduces to the case where the firm value follows a geometric Brownian motion.

[23] Note that term structures of the spreads obtained under A.1' are generally less smooth than the ones obtained under the geometric Brownian motion assumption. This is generally due to the higher levels of randomness implied by the jump-diffusion dynamics. This randomness is found to be even larger in the case of a higher jump intensity λ. The choice of the jump parameters needs hence a particular attention since it can change considerably the levels and the shapes of the spreads generated by the model.

Figure IV.6. Impact of the probability of approval of the bailout on credit spreads under A.1'



The results in Figure IV.6 tend generally to confirm our previous findings provided in Figure IV.4. Larger probabilities of success of the negotiation (i.e. approval of the bailout plan) are associated with a decrease in the credit spreads generated from our model also under the jump-diffusion dynamics. For instance, for a bond with a maturity of 5 years, the model generates a credit spread of about 130 bps in the case where the bailout will never be approved (i.e. $p = 0$), while it generates a credit spread of about 16 bps in the case where the bailout will always be approved (i.e. $p = 1$). In agreement with our findings under A.1, higher chances of receiving a bailout are associated with a decrease in the probabilities of bankruptcy of the firm, and accordingly with smaller credit spreads. As we have previously indicated, we can think large financial institutions have a "p" that tends towards 1, while smaller firms from other economic sectors have generally a "p" that tends towards 0. Under this consideration, and in view of the used jump diffusion process used for the firm value, we can interpret the results of our model as follows. In a context of crisis (i.e. higher and numerous jumps on the firm value), the model generates lower credit spreads for bonds issued by larger firms (since they have a more important negotiating power), while it generates higher credit spreads for smaller firms (since they have only small chances to be rescued). Since we consider here mainly the default component of the spreads, this results tends hence to support the empirical findings that we documented in chapters II and III about the effects of bailouts as well as the specificities of the spreads for different firm sizes.

4. Conclusion:

If firms in general, and large financial institutions in particular, can be rescued when their situation turns bad, it is natural to expect their credit spreads to account for this fact. In this study, we developed a simple model where a firm in distress has the possibility to be bailed out by the means of a new debt, and can hence continue its activity with a probable payback of its creditors. Inspired by the bailout procedures initiated during the recent financial turmoil, we introduced into the corporate valuation setup a process of rescue negotiation allowing for different probabilities of approval or disapproval of the bailout. In agreement with economic intuition, we show numerically that higher probabilities of receiving a financial aid (i.e. the bailout) are associated in our model with smaller credit spreads. Moreover, by assuming that high probabilities of bailout approval are associated with large firms (for instance due to the disastrous impact their bankruptcy can cause), we manage to link the size of a firm to its credit spread. Thereby, our model is able to predict smaller credit spreads for larger firms (those which have a more important negotiating power), while it generates greater credit spreads for smaller firms (those which have small chances of being rescued). This result is found additionally to hold for two different assumptions about the firm-value dynamics, namely in the case where the firm value follows a geometric Brownian motion (i.e. a proxy of stable economic conditions), and the case where the firm value follows a jump-diffusion process (i.e. a proxy of a period of tensions or economic crisis). In line with Zhou (2001), we show, however, that the jump-diffusion dynamics allows the model: (*i*) to deviate from the near-zero short credit spreads implied by many previous structural models, (*ii*) to predict larger credit spreads levels that are more consistent with the credit spread observed in reality, and (*iii*) to generate different shapes for the term structure of credit spreads including flat, upward or downward term structures.

The implications of this model are noteworthy in the sense that it allows us to reproduce, at least to some extent, some of the empirical findings of chapters II and III. These include the observed decrease in the spreads of the bailed-out firms after the bailouts (i.e. stylized fact 3.10 of chapter II), the observed lower credit spreads for larger firms (i.e. stylized fact 3.9 of chapter II), and the smaller credit risk component inside the spreads of large financial institutions (i.e. the specification analysis of credit spread determinants for different firm sizes provided in chapter III). In addition to these results, our model allows us to address some of the drawbacks of the existing structural models. These include: (*a*) the simple bankruptcy mechanisms (i.e. Merton drawback (*iv*) discussed in chapter I); (*b*) the simple capital structure (i.e. Merton drawback (*iii*) discussed in chapter I); and (c) the near-zero credit spreads implied by many structural models (i.e. Merton drawback (vi) discussed in chapter I).

Finally, the model which we have proposed in this chapter can be extended in many different ways which could be the object of future works. First, it can be easily expanded to account for certain conventional features of the structural models. These include, for instance, coupon payments in the same vein as Collin-Dufresne and Goldstein (2000), stochastic interest rates in the same vein as Vasicek (1977) or different probability distributions for the size of the jumps as in Kou and Chen (2009). Second, this valuation framework could be prolonged in such a way as to account for a more complex bailout negotiation process. This process may explicitly take into consideration the impact that the firm's bankruptcy may have on other firms or on the economy; or can also consider the possibility of an endogenous bankruptcy triggered by the firm's management. Third, the model might be extended so as to deal with the specificities of the capital structure of a financial institution (e.g. as in Pennacchi, 2010 or Glasserman and Nouri, 2012), in order to deal with the different risk levels comprised in the assets of a bank. Fourth, this setup can be adapted in such a way as to provide insights about the optimal rescue package for firms in distress. Fifth, another natural extension of this framework is by calibrating it to market data for instance as in Huang and Huang (2003) or Tarashev (2008). Finally, this model could be reconsidered in order to account for some of the most recent extensions of the structural models discussed in chapter I. These include for instance a regime-switching economic cycle in the same spirit as Hackbarth, et al. (2006) and Chen (2010), or by introducing liquidity premium as in Ericsson and Renault (2006) or Chen, Cui et al. (2014).

Conclusion

This thesis has attempted to bring some contributions to the valuation of corporate bonds by drawing lessons from the existing theoretical models and the movements of the credit spreads during the recent economic and financial crisis.

In the **first chapter** we analyzed the coherence of the structural approach of corporate bond valuation from the stand points of hypotheses and numerical results. In doing so, we have put a particular emphasis on the models of Merton (1974), Black-Cox (1976), Collin-Dufresne and Goldstein (2000) and Zhou (2001). First, with regard to the models' hypothesis, we showed that the mathematics of these models translate well the relationship between the capital structure of the firm and default, which allows an economic interpretation of the causes of default and the credit spreads of valuated bond. Additionally, we noted that this approach is well-established in terms of financial theory (e.g. option theory and capital structure theory), which makes it appealing for the sake of a more consistent and "economically consistent" valuation of corporate bonds. Further, we showed throughout this chapter that the hypotheses of the structural approach have improved considerably since Merton's (1974) seminal paper. Many efforts have been made in order to include more realistic features and to enhance the modeling framework. Interesting examples include: (*i*) the model of Zhou (2001), who considers jumps on the firm value, which can be seen as consistent with a period of tension or economic crisis (thereby, this model is consistent with a mixture between the structural and reduced form approaches); (*ii*) the model of Ericsson and Renault (2006) who model the impact of liquidity shocks and information asymmetries on the valuation of corporate bonds; or (*iii*) Lindset et al. (2013) who consider the existence of information asymmetries in the modeling setup. Despite the numerous existing efforts, we underlined throughout this theoretical analysis that the existing corporate bond models still suffer from many drawbacks, which emanate mainly from the unrealistic hypotheses on which these the models are based. For instance, most of the existing models use the efficient-market hypothesis, which has strongly been questioned in recent years (e.g. B. Guerrien, 2011 and N. Bouleau, 2013). In addition, we note that only little effort has been made so far to put aside the risk-neutral valuation, or to include explicitly the effects of economic cycles or crisis. Likewise, the existing models can be extended to account for more realistic capital structures of the modeled firms, more realistic bankruptcy mechanisms, or to deviate from the absolute priority rule. Additionally, most models neglect the effect of liquidity risk, systemic or default contagion risks as well as information asymmetries (this latter is found in chapter III to have a considerable effect on corporate bonds' returns).

With regard to the models' results, the numerical analyzes we made on the credit spreads of the models of Merton (1974), Black-Cox (1976), Collin-Dufresne and Goldstein (2000) and Zhou (2001) were conclusive in many respects. Above all, we showed that, despite its analytical attractiveness, the geometric Brownian motion assumption for the evolution of the firm value implies near-zero default probabilities and credit spreads for short maturities. This makes the results of these models highly questionable and to some extent misleading especially in a crisis context. In this regard, the assumption that the firm value follows a jump-diffusion process, as proposed by Zhou (2001) seems more consistent with the credit spreads which can be observed in practice (including in a crisis context), as it allows the model to generate high short-term credit spreads. Moreover, we showed by the means of the numerical analyses that we presented in this chapter that, by definition, leverage plays an important role in the levels and the term structures of the credit spreads that the structural models generate. As such, precluding the firm from altering its leverage level over time (as it can be done in the real world) is found numerically to have a significant effect to the levels of credit spreads and their structure by term. A particular attention must be then given to the evolution of the debt of the modeled firm, since this may affect considerably the results of the model.

In the **second chapter**, we have shed light on the levels and movements of credit spreads that were observed during the crisis in order to draw some conclusions for the valuation of corporate bonds. We identified, first, a set of ten stylized facts about the evolution of credit spreads during the crisis which can be gathered in three main groups of results. (*i*) The first group includes the numerous factors which we found to have an impact on credit spreads during the crisis, and which have not been, or have been only sparsely, considered by the theoretical models of corporate bond valuation. These are for instance: (*a*) default contagion risk (e.g. the collapse of a bank or the default of a country is found to be associated with an increase in the overall credit spreads); (*b*) the risk of collapse of an entire economic or financial system (e.g. the threat of the breakup of the Eurozone is found to be associated with increase in the spreads); (*c*) the bailouts and the rescue politics (e.g. the bailout of some major financial institutions or governments is found to be linked, at least temporarily, to a reduction in their spreads); (*d*) the actions undertaken by the central banks and the different governments to stabilize the financial system (e.g. the creation of the Financial Stability Board, the creation of the European Financial Stability Facility, the agreement of the Long Term Refinancing Operations –LTROs– had presumably considerable effects on the reduction of the spreads). (*ii*) The second group of results includes the changes in paradigm that credit spreads display during the crisis, which are not predicted by the theoretical corporate bond models. For instance, we noted (*a*) that the sensitivity of the spreads to leverage ratios decreased substantially during the crisis, and (*b*) that the relation between credit spread and time to maturity has changed since the onset of the crisis (longer maturities became consistent with lower credit spreads since the beginning of the crisis). (*iii*) The third group of stylized facts comprises some well-documented phenomena in the economic and financial literature that can help in explaining the levels and the movements of the spreads during the crisis. These include: (*a*) the paradoxes of tranquillity and credibility (respectively, Minsky, 1975, 1977; Borio and Shim, 2007), which helps understanding the low credit spreads that prevailed in the pre-crisis period and the upsurge of these latter since the beginning of the crisis. (*b*) The phenomena of flight-to-quality and flight-to-liquidity, which explain the observed sudden increases in corporate bond yields during the crisis, as well as the higher credit spreads which were observed for the firms of smaller sizes since the onset of the crisis. (c) The financial instability hypothesis (Minsky, 1975; 1977; 1982), which gives some insight on the increased fragility of the financial sector since the beginning of the crisis and the need for the authorities' actions to stabilize it.

Afterwards, we carried in this same chapter a Principal Component Analysis (PCA) of credit spreads levels. Our goal was to check if there occurred a change in the pricing dynamics in the corporate bond market since the outbreak of the subprime crisis. We found, first, that the same five principal components of credit spreads explained a larger proportion of these latter since the beginning of the crisis. We interpret this result as consistent with an increase in the sensitivity of the spreads to these five components since July 2007. Second, we found evidence for a substantial increase in the sensitivity of the spreads to the first principal component since the onset of the crisis. If the principal component of credit spreads is to be attributed to default risk, as claimed by most of theoretical structural models, our evidence is hence consistent with the assumption of a higher sensitivity of credit spreads to default risk since the beginning of the economic and financial turmoil. Finally, we documented through this PCA an increase in the correlations between the spreads of the different corporations during the subprime crisis, which was even more important during the Eurozone crisis. This result implies that the factors that affect credit spreads levels became increasingly common since the beginning of the crisis. Overall, this PCA allowed us to shed light on two different pricing paradigms between before and after July 2007. The continuity of the second paradigm since July 2007 (higher credit spread levels, quite similar credit spread components, higher credit spread correlations) suggests a permanent change in the pricing of risk inside the corporate bond market.

In the **third chapter**, we proposed to complete the empirical evidence proposed in chapter II, by exploring, by the means of statistical regressions techniques, the most significant factors in explaining credit spread changes. More specifically, we analyzed the effect of a set determinants derived from the analyses that we proposed in chapters I and II, as well as some new factors, on credit spreads changes. The determinants that we introduced covered: (*i*) credit risk, (*ii*) market-wide risks, (*iii*) liquidity risk, (*iv*) information asymmetries, as well as (*v*) firm-size and risk premiums factors. On top of that, we specified the changes that the sensitivity of the spreads to these determinants have undergone between the pre-crisis, the subprime crisis and the Eurozone crisis periods.

Our findings were as follows. Overall, we found that all the factors which we explore have a certain power in explaining credit spreads in the long run, with signs generally in line with theory and the proposed hypotheses. Our results provide evidence in favor of the appropriateness, and even the necessity, of taking these factors into account in a more consistent valuation of corporate bonds. Turning to the sub-periods analysis (i.e. pre-crisis, the subprime crisis and the Eurozone crisis periods) and the sub-components analysis (i.e. the analysis of credit spread determinants by group of factors), we found evidence for a time-varying sensitivity of the spreads with respect to the proposed credit spread determinants, as well as a change in the structure of the components that affect the spreads since the beginning of the crisis. (*i*) With regard to the theoretical credit risk factors, we found that credit risk constitutes the most represented risk inside corporate bonds' credit spreads (in all the investigated sub-periods), in agreement with the view of the structural models. Additionally, we found that credit spreads present generally higher sensitivity to the different credit risk factors in the subprime and the Eurozone crisis periods. As for the individual credit risk factors, we showed that credit spreads present a particularly high sensitivity to the risk-free interest rate in all the investigated sub-periods. This drives us to think that interest rates constitute one of the major factors that drives credit risk and credit spreads, and thus deserves a particular attention within corporate bond modeling. As for leverage ratios, we were able to bring support to the observations that we made in chapter II about a weak sensitivity of credit spreads to leverage ratios, mainly in the pre-crisis and the subprime crisis periods.

(*ii*) With respect to the explored market-wide risk factors, we found, overall, evidence for a high sensitivity of the spreads to macroeconomic and systemic risk factors. Above all, we showed that the proportion of credit spread movements explained by market-wide risk factors rose considerably since the beginning of the crisis (1.1% of in the pre-crisis period and, respectively, 7.4% and 5.7% of credit spread changes in the subprime and the Eurozone crisis). Among these market-wide risk factors, we tested for instance the effect of "LTROs", as a proxy for monetary authorities' action in helping the financial sector during the crisis. This variable presented a negative relation with credit spreads (hence an increase in authorities' help decreases the corporate credit spreads).

(iii) As for the liquidity component of the spreads, we mainly found that the subprime and Eurozone crises periods coincided with an increase in the effect of market liquidity on credit spread changes. Additionally, we noticed a decrease in the relative importance of the liquidity component of the spreads since the beginning of the crisis. According to this evidence, the role of liquidity risk, which used to be the second most important component of the spreads in the pre-crisis period, decreased to become only the fourth most important component (behind, credit risk, market-wide risks and the delayed information component).

(iv) Concerning the delayed information component which we explored, we found evidence for an increase in the impact of lagged variables since the beginning of the crisis, with a more significant impact on the spreads in the Eurozone crisis period. Presumably, the crisis has increased information asymmetries among market participants and has given a more important role to market imperfections in the price adjustment process in the corporate bond market. As such, we found that the importance of the delayed information component rose, to reach about 10.6% of the explanatory power during the Eurozone crisis period, as compared to only 4.8% in the pre-crisis period.

(v) As far as the explored additional factors that we explored are concerned, we found evidence of a link between investors' confidence (i.e. proxy of risk premiums) and credit spread changes, mainly in the subprime crisis period. However, we found that the effect of investors' confidence on credit spreads is small. Moreover, we explored the existence of a firm-size effect priced by corporate bonds spreads (that may convey a change in the probability that firms would be rescued in case of distress). Our findings were consistent with a significant sensitivity of the spreads to changes in firm sizes, which was however small.

Remarkably, the comprehensive set of determinants and risk factors that we explored was able to explain only 30.4% of credit spread changes. This low explanatory power can be partly attributed to the possible non-linear effects of the studied determinants, which can be hardly captured by the linear regression tool that we employed. Putting aside nonlinearities, we attempted, by the means of a principal component analysis of regression residuals, to understand the nature of the latent variation of credit spreads. In the same lines as Avramov et al.

(2007), we found that the remaining variation of the spreads is driven by numerous relatively small factors. Conducting a PCA on the residuals of different crisis sub-periods, we showed also that the number of factors which drive credit spread changes has increased since the beginning of the crisis.

Finally, we tried in this third chapter to complement our results by analyzing the determinants of credit spreads for different bond subsamples. Particularly, we tried to investigate the determinants of credit spread changes for some of the largest firms in Europe, which are thought to be "Too big to fail". Our results were conclusive in the sense that we found evidence for a smaller credit risk component in the spreads of these firms since the beginning of the crisis. The credit spreads of these firms were more driven by market liquidity and market-wide risks components.

On the basis of the results of the theoretical and empirical analyses presented in previous chapters, the **fourth chapter** of this thesis proposed a contribution to the modelling of corporate bonds. Starting from the observed empirical effect of the bailouts of large firms on credit spreads, we developed a simple model where a firm in distress has the possibility to be bailed-out by the means of a new debt, and can hence continue its activity with a probable payback of its creditors. In doing so, we introduced into the corporate valuation setup a process of rescue negotiation allowing for different probabilities of approval or disapproval of the bailout. In agreement with the economic intuition, we showed numerically that higher probabilities of receiving a financial aid (i.e. the bailout) are associated in our model to smaller credit spreads. Additionally, by assuming that high probabilities of bailout approval are associated with large firms (for instance due to the disastrous impact their bankruptcy can cause), we managed to link the size of a firm to its credit spread. Thereby, our model is found to predict smaller credit spreads for larger firms (those which have a more important negotiating power), while it generates greater credit spreads for smaller firms (those which have few chances of being rescued). This result is found also to hold for two different assumptions about the dynamics of the firm value, namely in the case where the firm value follows a geometric Brownian motion (i.e. a proxy for stable economic conditions), and the case where the firm value follows a jump-diffusion process (i.e. a proxy of a period of tensions or economic crisis). In line with Zhou (2001), we showed however that the jump-diffusion dynamics allow the model: (*i*) to deviate from the near-zero short credit spreads implied by many previous structural models, (*ii*) to predict larger credit spreads levels which are more consistent with the credit spreads observed in the real world, and (*iii*) to generate different shapes for the term structure of credit spreads including flat, upward or downward term structures.

The implications of this model are noteworthy as they allow us to reproduce, at least to some extent, some of the empirical findings of chapters II and III. These include the observed decrease in the spreads of the bailed-out firms after the bailouts, the lower credit spreads observed for larger firms, and the smaller credit risk component that were found in the spreads of large financial institutions. On top of that, this model allowed us to tackle some of the drawbacks of the existing structural models that we discussed in chapter I. These include: (*a*) the simple bankruptcy mechanisms drawback, (*b*) the simple capital structure drawback, and (*c*) the small short-term credit spreads implied by many structural models.

While this work has answered some interesting theoretical and empirical research questions, it has also raised some new questions that will require future researches in corporate bond valuation and risk modeling.

First of all, the model we proposed in chapter IV can be extended in many different ways. (*i*) It can easily be expanded to account for some conventional features used in the previous corporate bond models. These include for instance coupon payments in the same vein as Collin-Dufresne and Goldstein (2000), stochastic interest rates in the same vein as Vasicek (1977), different probability distributions for the size of the jumps as in Kou and Chen (2009). (*ii*) Our model could be prolonged in such a way as to account for a more complex bailout negotiation process. For instance, this process could account explicitly, for the impact that the firm's bankruptcy may have on other firms or the economy, or can account for the possibility of an endogenous bankruptcy triggered by the firm's management. (*iii*) The model might also be extended so as to account for the specificities of the capital structure of a financial institution, such as the different risk levels comprised in the assets of a bank. Doing so will allow the model to become more closely-associated with the modelling of "Too big to fail" firms (which concern mainly financial institutions) and would thus bring insight to investors and regulators about the issue. This represents one of the priority paths for our future research, since it will allow us to address the issue of implicit guarantees, which received an increasing concern in recent years. (*iv*) In the same lines, our model can be adapted in such a way as to provide insights about the optimal rescue package for a firm in distress. (*v*) Another natural extension of this framework is by calibrating it to market data for instance as in Huang and Huang (2003) or Tarashev (2008). (*vi*) Our model could be also reconsidered in order to account for some of the ideas of the most recent extensions of the structural models discussed in chapter I. These include, for instance, a regime-switching economic cycle in the same spirit as Hackbarth, et al. (2006) and Chen (2010), or by introducing liquidity premium as in Ericsson and Renault (2006) or Chen, Cui et al. (2014).

Furthermore, the analyses that we proposed in chapters II and III allowed us to shed some light on many empirical facts that need to be considered in a more consistent corporate bond valuation. First, we found that corporate bond models should account more explicitly for some of the factors that emerged during the crisis and that we found to have a significant effect on credit spreads. In addition to bailouts, for which we accounted for in our model, we documented that macroeconomic conditions, default contagion risk and other systemic risk components have significant effects on corporate bonds returns. Second, we suggest that a separate modeling should be considered in the future for banks and large systemic institutions, contrary to what is done in the structural models where all firms are modeled similarly. Banking and financial firms have been found to have a different risk structure from the other firms, and are seemingly subject to a larger market-liquidity and default contagion risks. In addition, these firms present generally a ”Too big to fail” profile, which makes them have relatively easier access to bailouts as compared to firms from other sectors. Some recent efforts have been in fact proposed by literature for the modeling bank's capital structure (e.g. Pennacchi, 2010 or Glasserman and Nouri, 2012). These studies remain however relatively scarce and need further extensions. Third, we suggest that a more particular attention should be placed on the modeling of interest rates within the structural framework of corporate bond pricing. As mentioned above, this variable has proven to be one of the most important credit risk factors, with a steady impact on the spreads in all the investigated sub-periods. Finally, another path for research consists in accounting for all the changes in the components of the spreads, and nonlinearities that we endeavored to reveal throughout the third chapter of this thesis, in an appropriately specified crisis state. One way of achieving this can be by the means of regime switching Markov processes, in the same vein as the recent studies of Chen et al. (2010), and Chen et al. (2014).

As a matter of fact, many of the extensions proposed above have been explored in the frame of our research. These could not however be accomplished in the limit of this dissertation mainly due to the cost that their achievement imply in terms of mathematical difficulty and time. This work has been also confronted to some other difficulties during its elaboration. For instance, the availability of data was a major obstacle against having a larger corporate bond sample, as well as exploring the effect of some other factors (e.g. default history, transactions volumes, detailed balance sheet information etc.).

Our final remark for this work is a reflection about the valuation models that our work has attempted to improve. These models are indeed necessary to deal with the complexity of the risks inherent to corporate bonds, and to give a certain value to these investments. However, it is important to keep in mind that, despite their mathematical sophistication, these models are generally a simplification of reality, and can never reproduce fully reality. In this sense, if there is default risk in a contract, there will almost always be a certain element of gambling, since it is impossible to know with certainty when a company may default. Additionally, as noted by E. Derman (2011): "*even though financial models employ the mathematics and style of physics, they are fundamentally different from the models that science produces. In physics you're playing against God, and He doesn't change His laws very often. In finance you're playing against God's creatures, agents who value assets based on their ephemeral opinions".* This means that even if we manage to improve the models in such a way as to account for the lessons of the crisis, the economic reality can always change in the future to make things even more difficult.

Bibliography

Acharya, V. V. (2002). Corporate Bond Valuation and Hedging with Stochastic Interest Rates and Endogenous Bankruptcy. *Review of Financial Studies*.

Acharya, V., & Pedersen, L. (2005). Asset pricing with Liquidity Risk. *Journal of Financial Economics*, 375-410.

Acharya, V., Huang, J., Subrahmanyam, M., & Sundaram, R. (2006). When does strategic debt-service matter? *Economic Theory 29, 363-378*.

Altman, E. (1992). Revisiting the high yield bond market. *Financial Management*, 21:78-92.

Amato, J., & Remolona, E. M. (2005). The Pricing of Unexpected Credit Losses. *BIS Working Papers, No. 190.*

Amihud, Y., & Mendelson, H. (1986). Asset Pricing and the Bid-Ask Spread. *Journal of Financial Economics*, 223–49.

Andersen, G., T., Bollerslev, T., & Diebold, F. X. (2004). Some like it smooth, and some like it rough: untangling continuous and jump components in measuring, modeling, and forecasting asset return volatility. *Duke University, Working Paper*.

Anderson, R. W., Sundaresan, S., & Tychon, P. (1996). Strategic Analysis of Contingent claims. *European Economic Review*.

Annaert, J., De Ceuster, M., Van Roy, P., & Vespro, C. (2009). What determines euro area bank CDS spreads? In National Bank of Belgium,. *Financial Stability Review*.

Artus, P., Betbeze, J.-P., De Boissieu, C., & Capelle-Blancard, G. (2008). *La crise des subprimes.* Realise en PAO au Conseil d'Analyse Economique par Christine Carl.

Avramov, D., Jostova, G., & Philipov, A. (2007). Understanding Changes in Corporate Credit Spreads. *Financial Analysts Journal, Volume 63 • Number 2.*

Aydogan, A., & Tetlock, P. C. (2011). How Important Is Mispricing. *University of Texas at Austin and Columbia University, Working Paper*.

Beber, A., Brandt, M. W., & Kavajecz, K. A. (2008). Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market. *The Review of Financial Studies*.

Bhamra, H. S., Kuehn, L.-A., & A. Strebulaev, I. (2009). The Levered Equity Risk Premium and Credit Spreads: A Unified Framework. *Review of Financial Studies*.

Bhattacharjee, A., Higson, C., Holly, S., & Kattuman, P. (2002). Macro economic instability and business exit: determinants of failures and acquisitions of large UK firms. *Cambridge Working Papers in Economics 0206*.

Bielecki, T., & Rutkowski, M. (2002). Credit Risk: Modeling, Valuation and Hedging. *Springer Finance.*

BIS. (2004). International convergence of capital measurement and capital standards. *Bank for International Settlements*.

Black, F., & Cox, J. C. (1976). Valuing Corporate Securities: Some Effects of Bond. *Journal of Finance*.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy, Vol. 81, No. 3 (May - Jun., 1973), pp. 637-654*.

Borio, C., & Shim, I. (2007). What can (macro)-prudential policy do to support monetary. *BIS Working Papers, no 242*.

Boss, M., & Scheicher, M. (2002). The Determinants of Credit Spread Changes in the Euro Area. *BIS Working Paper n. 12*.

Boucher, C., & Derhy, A. (2008). La grande moderation et la valorisation des actions. *Revue d'economie politique, Dalloz, vol. 118(5)*, p. 683-709.

Boucher, C., & Maillet, B. (2011). The Riskiness of Risk Models. *Centre d'Economie de la Sorbonne, Working paper*.

Bouleau, N. (2013). L'efficience : Une imposture scientifique reussie ? *Finance et environnement*.

Briys, E., & De Varenne, F. (1997). Valuing risky fixed rate debt: An extension. *Journal of Financial and Quantitative Analysis, 32:239-248,*.

Bunn, P., & Redwood, V. (2003). "Company accounts based modelling of business failures and the implications for financial stability. *Bank of England, Working Paper No.210*.

Caballero, R., & Krishnamurthy, A. (2008). Collective risk management in a flight to quality episode. *Journal of Finance 2195-2230*.

Caballero, R., & Krishnamurthy, A. (2008). Musical Chairs: A Comment on the Credit Crisis. *Financial Stability Review Banque de France*.

Campell, J., & Taksler, G. (2003). Equity volatility and corporate bond yields. *Journal of F inance*, 58, 2321-2350.

Capelle-Blancard, G. (2011). *Finance d'entreprise.* Pearson Education France.

Capponi, A., & Cvitanic, J. (2009). Credit Risk Modeling with Misreporting and Incomplete Information. *International Journal of Theoretical and Applied Finance*.

Cetin, U., Jarrow, R., Protter, P., & Yildirim, Y. (2004). Modeling Credit Risk With Partial Information. *The Annals of Applied Probability*, 1167–1178.

Chan-Lau, J. A. (2006). Market-Based Estimation of Default Probabilities and Its Application to Financial Market Surveillance. *IMF Working Paper*.

Chen, H. (2007). Macroeconomic conditions and the puzzles of credit spreads and capital structure. *MIT, Working paper* .

Chen, H. (2010). Macroeconomic Conditions and the Puzzles of Credit Spreads and Capital Structure. *NBER Working Paper*.

Chen, H., Cui, R., He, Z., & Milbradt, K. (2014). Quantifying Liquidity and Default Risks of Corporate Bonds over the Business Cycle. *MIT Sloan School of Management and NBER working paper*.

Chen, H., Xu, Y., & Yang, J. (2012). Systematic Risk, Debt Maturity, and the Term Structure. *MIT Sloan and NBER, Working Paper*.

Chen, L., Lesmond, D., & Wei, J. (2007). Corporate yield spreads and bond liquidity. *Journal of Finance 62 (1), 119-149*.

Chen, L., Lesmond, D., & Wei, J. (2008). Corporate Yield Spreads and Bond Liquidity. *Journal of Finance*, 119-149.

Chen, N., & Kou, S. G. (2009). Credit Spreads, Optimal Capital Structure, And Implied Volatility With Endogenous Default and Jump Risk. *Mathematical Finance*, 343–378.

Colander, D., Haas, A., & Juselius, K. (2009). The Financial Crisis and the Systemic Failure of Academic Economics. *Univ. of Copenhagen Dept. of Economics Discussion Paper*.

Collin-Dufresne, P., & Goldstein, R. S. (2000). Do Credit Spreads Reflect Stationary. *Journal of Finance, Vol. 56, No. 5 (Oct., 2001), pp. 1929-1957.*

Collin-Dufresne, P., Goldstein, R., & Martin, J. (2001). The determinants of credit spread changes. *Journal of Finance 56, 2177–2207*.

Couderc, F., & Renault, O. (2005). Times-to-Default: Life Cycle, Global and Industry Cycle Impacts. *FAME Research Paper No. 142*.

Cox, J. C., Ingersoll Jr., J. E., & Ross, S. A. (1985b). A theory of the term structure of interest. *Econometrica*, 53:385-407.

Creditreform. (2015). Corporate Bonds in Europe 2005-2014. *Creditreform, Working paper*.

Cremers, M., Driessen, J., & Maenhout, P. (2008). Explaining the level of credit spreads: option-implied jump risk premia in a firm value model. *Review of Financial Studies*, 21 (5), pp. 2209-2242.

Cremers, M., Driessen, J., Maenhout, P., & Weinbaum, D. (2004). Individual stockoption stock option prices and credit spreads,. *Vale ICF, Working Paper 04-14*.

Crosbie, P. J., & Bohn, J. R. (2002). Modelling Default Risk. *Working Paper, KMV Corporation*.

Dao, T. B., & Jeanblanc, M. (2005). A Double Exponential Structural Jump Diffusion Model with Endogenous Default Barrier. *Universite d'Evry Val d'Essonne, Working Paper, .*

Davydenko, S. (2005). When do firms default? *University of Toronto Working Paper*.

De Jong, F., & Driessen, J. (2005). Liquidity Risk Premia in Corporate Bond Markets. *Tilburg University, Working paper*.

Delianedis, G., & Geske, R. (2001). The Components of Corporate Credit Spreads: Default, Recovery, Tax, Jumps, Liquidity, and Market Factors. *UCLA Working Paper,.*

Di Cesare, A., & Guazzarotti, G. (2010). An analysis of the determinants of credit default swap spread changes before and during the subprime financial turmoil. *Banca d'Italia, Working Paper N: 749*.

Dionne, G., François, P., & Maalaoui-Chun, O. (2009). Credit spread changes within switching regimes. *Canada Research Chair in Risk Management, Working Paper 09-01*.

Driessen, J. (2003, 2005). Is default event risk priced in corporate bonds? *Review of Financial Studies*, 165-195.

Duffie, D. (2005). Credit risk modelling with affine processes. *Journal of Banking and Finance 29, 2751-2802*.

Duffie, D., & Lando, D. (2001). Term Structure of Credit Spreads with Incomplete Accounting Information. *Econometrica 69, 633-664*.

Duffie, D., & Singleton, K. (2003). Credit Risk: Pricing, Measurement and Management. . *Princeton University Press,.*

Duffie, D., & Singleton. J., K. (1999). Modeling Term Structures of Defaultable Bonds. *The Review of Financial Studies*.

Easley, D., Hvidkjaer, S., & O'Hara, M. (2002). Is information risk a determinant of asset returns? *Journal of Finance*, 2185-2221.

ECB. (2010). The ECB's Response to The Financial Crisis. *European Central Bank Monthly Bulletin, October 2010*.

ECB. (2011). The ECB's Non-Standard Measures - Impact and Phasing-out. *European Central Bank, Monthly Bulletin July 2011*.

ECB. (2013). The ECB's non-standard monetary policy measures the role of institutional factors and financial structure. *European Central Bank, Working Paper Series No 1528, April 2013*.

ECB. (2014). Euro area risk-free interest rates: Measurement Issues, Recent developments and Relevance to monetary policy. *European Central Bank Monthly bulletin, July 2014*.

Eklund, T., Larsen, K., & Bernhardsen, E. (2001). Model for analysing credit risk in the enterprise sector. *Norges Bank Economic Bulletin Q3 01*.

Elizalde, A. (2005a). Credit Risk Models I: Default Correlation in Intensity Models. *CEMFI working paper*.

Elizalde, A. (2005b). Credit Risk Models II: Structural Models. *CEMFI Working Paper*.

Elizalde, A. (2005c). Credit Risk Models III: Reconciliation Structural - Reduced Models,. *CEMFI Working Paper*.

Elton, E., Gruber, M., Agrawal, D., & Mann, C. (2001). Explaining the rate spread on corporate bonds. *Journal of Finance 56, 247–277*.

Eom, Y. H., Helwege, J., & Huang, J. Z. (2003). Structural Models of Corporate Bond Pricing: An Empirical Analysis. *Review of Financial Studies 17, 499-544*.

Ericsson, J., & Renault, O. (2006). Liquidity and credit risk. *Journal of Finance* , 61, 2219 2250.

Ericsson, J., & Reneby, J. (2005). Estimating Structural Bond Pricing Models. *Journal of Business 78, 707-736*.

Ericsson, J., Jacobs, K., & Oviedo, R. (2009). The Determinants of credit default swap. *Journal of Financial and Quantitative Analysis,*, 109-132.

Ericsson, J., Reneby, J., & Wang, H. (2007). Can structural models price default risk? Evidence from bond and credit derivative markets. *Mimeo, electronic copy available at: http://ssrn.com/abstract=637042.*

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance, Vol. 25, No. 2*.

Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics 25, 23-49*.

Farhi, E., & Panageas, S. (2004). The real effects of stock market mispricing at the aggregate: Theory and Empirical Evidence. *NBER, Working Paper*.

Forte, S., & Peña, J. (2011). Credit Spreads: Theory and Evidence About The Information Content of Stocks, Bonds and CDSs. *Journal of Banking and Finance*, 2013-2025.

Fortet, R. (1943). Les fonctions aleatoires du type de Markov associees a certaines equations lineaires aux derivees partielles du type parabolique. *J. Math. Pures Appl.*, 22:177–243.

Francois, P., & Morellec, E. (2004). Capital Structure and Asset Prices: Some Effects of Bankruptcy Procedures. *Journal of Business, vol. 77, no. 2, pt. 1.*

Frank, N. (2009). Linkages between asset classes during the financial crisis, accounting for market microstructure noise and non-synchronous trading. *Oxford-Man Institute of Quantitative Finance, Working Paper*.

Franks, J., & Torous, W. (1989). An Empirical Investigation of U.S. Firms in Reorganization. *Journal of Finance 44, 747-769*.

Galai, D., Raviv, A., & Wiener, Z. (2005). Liquidation Triggers and The Valuation. *Working Paper, School of Business Administration, The Hebrew University of Jerusalem*.

Gatfaoui, H. (2004). Risque de Defaut et Risque de Liquidite : Une Etude de Deux Composantes du Spread de Credit. *Revue des Sciences de Gestion, n: 210*, p. 123-134.

Gatfaoui, H. (2005). How Does Systematic Risk Impact US Credit Spreads ? A Copula Study. *Banque & marches*, p. 5-16.

Gatfaoui, H. (2008a). Credit Risk and Market Risk: Analyzing US Credit spreads. *SSRN, Electronic copy available at: http://ssrn.com/abstract=1404640*.

Gatfaoui, H. (2008b). From Fault Tree to Credit Risk Assessment: A Case Study. *International Research Journal of Finance and Economics*, p. 379 - 401.

Gatfaoui, H. (2008c). *Une Histoire du Risque de Defaut.* Publibook, 14 novembre 2008.

Gatfaoui, H. (2009). Is Corporate Bond Market Performance Connected with Stock Market Performance? *Bankers, Markets & Investors*, p. 46-59.

Gatfaoui, H. (2010). Investigating the dependence structure between credit default swap spreads and the U.S. financial market. *Annals of Finance, Volume 6, Issue 4*, p. 511-535.

Gatfaoui, H., Martey Addo, P., De Peretti, P., & Runge, J. (2014). The kiss of information theory that captures systemic risk. *Centre d'Economie de la Sorbonne, Working Paper*.

Geske, R. (1977). The Valuation of Corporate Liabilities as Compound Options. *Journal of Financial and Quantitative Analysis*, 541-552.

Geske, R. (1979). The Valuation of Compound Options. *Journal of Financial Economics*, 63-81.

Giesecke, K. (2004). "Correlated default with incomplete information. *Journal of Banking and Finance 28, 1521-1545*.

Giesecke, K. (2005). Default and Information. *Working Paper, Cornell University*.

Giesecke, K., & Goldberg, L. R. (2004). Sequential defaults and incomplete information. *Journal of Risk 7, 1-26*.

Giordano, L., & Siciliano, G. (2013). Real-world and risk-neutral probabilities in the regulation on the transparency of structured products. *CONSOB, working papers*.

Glasserman, P., & Nouri, B. (2012). Contingent Capital with a Capital-Ratio Trigger. *Management Science*, 1–18.

Goldstein, R. (2009). Can Structural Models of Default Explain the Credit Spread Puzzle? *FRBSF Economic Letter*.

Gomes F., J., & Schmid, L. (2010). Equilibrium Credit Spreads and the Macroeconomy. *London Business School, Working paper*.

Greatrex, C. A. (2008). The credit default swap market's determinants. *Department of Economics, Fordham University, Discussion Paper No. 2008-05*.

Group, S. S. (2009). Risk Management Lessons from the Global Banking Crisis of 2008.

Guerrien, B. (2011). L'imbroglio de la theorie dite « des marches efficients ¸. *Chicago Booth School of Business, working paper*.

Guo, X., Jarrow, R. A., & Zeng, Y. (2006). Credit risk models with incomplete information. *Mathematics of Operations Research*, 34 (2), 320–332.

Hackbarth, D., Miao, J., & Morellec, E. (2006). Capital structure, credit risk, and macroeconomic conditions. *Journal of Financial Economics, 82 (2006) 519–550*.

Hausman, J. A. (1251-1371). Specification tests in econometrics. *Econometrica*.

Helwege, J. (1999). How long do junk bonds spend in default? *Journal of Finance 54, 341-357*.

Hendricks, D. (2009). Defining Systemic Risk. *Financial Reform Project, Briefing Paper 1: Defining Systemic Risk*.

Hilberink, B., & Rogers, L. C. (2002). Optimal Capital Structure and Endogenous Default. *Finance and Stochastics 6, 237-263*.

Hotchkiss, E. (1995). Postbankruptcy performance and management turnover. *Journal of Finance 50, 3-21*.

Hotchkiss, E. S., & Ronen, T. (1999). The informational efficiency of the corporate bond market: an intraday analysis. *Working Paper*.

Houweling, P., & Vorst, T. (2005). Pricing default swaps: empirical evidence. *Journal of International Money and Finance*, 1200-1225.

Hsu, J., Saa-Requejo, J., & Santa-Clara, P. (2004). Bond Pricing with Default Risk. *UCLA Working Paper*.

Huang, J. Z. (1997). Default Risk, Renegotiation, and the Valuation of Corporate Claims. *Ph.D. Dissertation, NYU*.

Huang, J. Z., & Huang, M. (2003). How Much of the Corporate-Treasury Yield Spread is Due to Credit Risk? *Penn State and Stanford Universities, Working Paper*.

Hull, J. (2012). *Options, Futures and Other Derivatives.* Pearson Education; 8 edition.

Hull, J., & White, A. (2001). aluing Credit Default Swaps II: Modelling Default Correlations. *Journal of Derivatives 8, 12-22*.

Hull, J., Nelken, I., & White, A. (2004). Merton's Model, Credit Risk, and Volatility Skews. *Journal of Credit Risk 1, 3-28*.

Hull, J., Predescu, M., & White, A. (2004). The relationship between credit default swap spreads bond yields and credit rating announcements. *University of Toronto, Working paper*.

Jarrow, R. A., & Protter, P. (2004). Structural versus reduced form models: a new information based perspective. *Journal of Investment Management 2, 1-10*.

Jarrow. A, R., & Turnbull. M, S. (1995). Pricing Derivatives on Financial Securities Subject to Credit Risk. *The Journal of Finance*.

Jean-Blanc, M. (2000). Modelling of Default Risk: An Overview,". *Theory and Practice Higher Education Press, Beijing*.

Jeanblanc, M., & Rutkowski, M. (2000). Modelling of Default Risk: An Overview. *Mathematical Finance: Theory and Practice, 171-269*.

Jeanblanc, M., Bielecki R., T., & Rutkowski, M. (2009). Credit Risk Modeling. *Center for the Study of Finance and Insurance, Center for the Study of Finance and Insurance*.

Jimenez, G., & Saurina, J. (2004). Collateral, type of lender and relationship banking as determinants of credit risk. *Journal of Banking and Finance*, 2191-2212.

Jimenez, G., & Saurina, J. (2005). Credit cycles, credit risk, and prudential regulation. *BIS, Working Paper*.

Jobert, A., & Rogers, L. C. (2006). Option pricing with Markov-Modulated dynamics. *SIAM Journal of Control and Optimization*, 2063-2078.

Jolliffe, I. (2002). *Principal Component Analysis.* Springer.

Jones, P., Mason, S., & Rosenfeld, E. (1984). Contingent Claim Analysis of Corporate Capital Structures: An Empirical Investigation. *Journal of Finance 39, 611-625*.

Jonsson, H., Schoutens, W., Fang, F., Oosterlee, & W., C. (2009). Fast Valuation and Calibration of Credit Default Swaps Under Levy Dynamics. *Delft University of Technology, Working Paper*.

Joro, T., & Na, P. (2002). Derivatives and credit risk: credit risk modeling for catastrophic events. *Proceedings s of the 2002 Winter Simulation Conference*.

Junior, L. S. (2011). Correlation of financial markets in times of crisis. *Insper, Instituto de Ensino e Pesquisa, Working Paper*.

Kay, G. (2005). Default and Information. *Working Paper, Cornell University.*

Kijima, M. (2002). Stochatic Processes with Applications in Finance. *Boca Raton FL: Chapman and Hall*.

Kim, I. J., Ramaswamy, K., & Sundaresan, S. M. (1993). Does default risk in coupons affect the valuation of corporate bonds? : A contingent claims model. *Financial Management 22, 117-131*.

Kou, S. G. (2002). A Jump Diffusion Model for Option Pricing. *Management Science*, 48, 1086–1101.

Kou, S., & Wang, H. (2003). First passage times of a jump diffusion process. *Advances in Applied Probability*, 35, pp. 504-531.

Le Courtois, O., & Quittard-Pinon, F. (2006). Risk-neutral and Actual Default Probabilities with an Endogenous Bankruptcy Jump-diffusion Model. *Asia Pac. Financ. Market* , 13, 11–39.

Leland, H. (1994). Corporate debt value, bond covenants, and optimal capital structure. *Journal of Finance, 49:1213-1252*.

Leland, H. E. (2004). Predictions of Default Probabilities in Structural Models of Debt. *Journal of Investment Management*.

Leland, H., & Toft, K. (1996). Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. *Journal of Finance, 51:987*.

Lindset, S., Lundb, A.-C., & Perssonc, S.-A. (2013). Credit Risk and Asymmetric Information: A Simplified Approach. *Journal of Economic Dynamics and Control*, 98–112.

Longstaff, F. A. (2004). The Flight-to-Liquidity Premium in U.S. Treasury Bond Prices. *Journal of Business*.

Longstaff, F., & Schwartz, E. (1995). A simple approach to valuing risky fixed and floating rate. *Journal of Finance*.

Longstaff, F., Mithal, S., & Neis, E. (2005). Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market. *Journal of Finance*, 2213-2253.

Longworth, D., & Duguay, P. (2007). The Financial System Review and Financial Stability. *Bank of Canada, working paper*.

Lyden, S., & Saraniti, D. (2001). An empirical examination of the classical theory of corporate security valuation. *SSRN Working Paper*.

Madan, D. B., & Schoutens, W. (2007). Break on Through to the Single Side. *The Journal of Credit Risk*, 4(3): 3-20.

Mayordomo, S., & Pena, J. I. (2012). An Empirical Analysis of the Dynamic Dependences in the European Corporate Credit Markets: Bonds vs. Credit Derivatives. *Spanish Securities Markets, Working paper, Electronic copy available at: http://ssrn.com/abstract=1719287*.

Mehra, R. (2012). The Equity Premium Puzzle Revisited. *NBER, Working Paper*.

Mella-Barral, P., & Perraudin, W. (1997). Strategic Debt Service. *Journal of Finance*.

Mello, A., & Parsons, J. (1992). Measuring the agency cost of debt. *Journal of Finance 47, 1887-1904*.

Merton, R. C. (1974). On the pricing of Corporate Debt : The risk structure of interest rates. *The Journal of Finance, 29*(2), 449–470.

Minsky, H. P. (1975). John Maynard Keynes. *New York: Columbia University Press*.

Minsky, H. P. (1977). The financial instability hypothesis. An interpretation of Keynes and an alternative to «standard¸ theory. *Nebraska Journal of Economics and Business*, 59-70.

Minsky, H. P. (1982). Can "It" Happen Again? In Can "It" Happen Again?: Essays on Instability and Finance. *3-13. Armonk, N.Y.: M. E. Sharpe*.

Minsky, H. P. (1986). Stabilizing an Unstable Economy. *New Haven (CT), Yale University Press*.

Minsky, H. P. (1992). Reconstituting the Financial Structure: The United States. *Hyman P. Minsky Archive Paper 18, Levy Economics Institute of Bard College*.

Modigliani, F., & Miller, M. (1958). The Cost of Capital, Corporation Finance and the Theory of Investment. *American Economic Review*, 48, 261–297.

Moldovan, I. (2012). Stock Markets Correlation: before and during the Crisis Analysis. *Theoretical and Applied Economics* , 111-122.

Moreaux, F. (2004). Valuing Corporate Liabilities When the Default Threshold is not an Absorbing Barrier. *University of Rennes Working Paper*.

Morrison, E. (2003). Bankruptcy Decision-Making: An Empirical Study of Small-Business Bankruptcies. *Columbia Law and Economics Working Paper No. 239*.

Musiela, M., & Rutkowski, M. (1997). *Martingale Methods in Financial Modeling*. Springer Verlag.

Naumer, H.-J., Gasquet, O., & Nacken, D. (2011). « Je m'appelle « Bond ¸, « Corporate Bond ¸. *Allianz Global Investors, PortfolioPraxis: Akademie*.

Nielsen, T., Saa-Requejo, J., & Santa-Clara, P. (1993). Default risk and interest rate risk: The term structure of default spreads. *INSEAD working paper*.

Norden, L., & Weber, M. (2004). *Journal of Banking and Finance* , 2813-2843.

Opler, T. C., & Titman, S. (1997). The debt-equity choice: An analysis of issuing firms. *Ohio-State University, Working Paper*.

Opler, T. C., Titman, S., & Saron, M. (1997). Designing Capital Structure To Create Shareholder Value. *Journal of Applied Corporate Finance.*, 21-32.

Orlean, A. (1999). Le pouvoir de la finance [The finance power]. *Odile Jacob, Paris*.

O'Sullivan, A., & Sheffrin, S. M. (2003). *Economics: Principles in action.* Pearson Prentice Hall.

Pennacchi, G. (2010). A Structural Model of Contingent Bank Capital. *FRB of Cleveland, Working Paper No. 10-04* .

Perraudin, W., & Taylor, A. (2003). Liquidity and Bond Market Spreads. *Bank of England, Working Paper*.

Rajan, U., Seru, A., & Vig, V. (2009). The Failure of Models That Predict Failure: Distance, Incentives and Defaults. *Chicago GSB Research Paper*.

Renault, O., & Ericsson, J. (2005). Liquidity and Credit Risk. *International Center for Financial Asset Management and Engineering, Working paper*.

Saa-Requejo, J., & Santa-Clara, P. (n.d.). Bond pricing with default risk. *Anderson Graduate School of Management, Working Paper*.

Schatzschneider, W. (2000). CIR model in financial markets. *Anahuc university, Working Paper*.

Schich, S., & Lindh, S. (2012). Implicit Guarantees for Bank Debt: Where Do We Stand? *OECD Journal: Financial Market Trends, Volume 2012 Issue 1*.

Schonbucher, P. J. (2000). Factor Models for Portfolio Credit Risk. *Department of Statistics, Bonn University, Working Paper*.

SEC. (2014). What Are Corporate Bonds? *Office of Investor Education and Advocacy, Investor BulletIn No. 149* , elctronic copy available at: http://www.sec.gov/investor/alerts/ib˙corporatebonds.pdf.

Shiller, R. J. (1999). Measuring Bubble Expectations and Investor Confidence . *NBER Working Paper, (http://papers.nber.org/papers/w7008.pdf)* .

Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. *Journal of Economic Perspectives*, 83-104.

Shiller, R. J., & Case, K. E. (1989). The Efficiency of the Market for Single-Family Homes. *American Economic Review*, 125-37.

Shimko, D. C., Tejima, N., & Van Deventer, D. R. (1993). The Pricing of Risky Debt when Interest Rates are Stochastic. *The Journal of Fixed Income*.

Shleifer, A., Vishny, R. W., & Lakonishok, J. (1994). Contrarian Investmen, Extrapolation and Risk. *The Journal of Finance*.

Shlens, J. (2009). A Tutorial on Principal Component Analysis. *University of California, San Diego, Working Paper*.

Shreve, S. (2004). *Stochastic Calculus for Finance II.* Springer-Verlag New York Inc.

Sloan, R. G. (1996). Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings. *The Accounting Review*, 289-315.

Smith, L. I. (2002). A tutorial on Principal Components Analysis. *Working Paper*.

Stultz M., R. (2009). Risk management failures: what are they and when do they happen. *Cornerstone research Working paper*.

Sundaram, R. K. (2001). The Merton/KMV Approach to Pricing Credit Risk. *NYU, Working Paper*.

Surya, B. A., & Yamazaki, K. (2012). Toward a Generalization of the Leland-Toft Optimal Capital Structure Model. *arXiv : 1109.0897.*

Sy, W. (2008). Credit risk models: why they failed in the credit crisis . *Australian Prudential Regulation Authority.*

Tang, D., & Yan, H. (2007). Liquidity and Credit Default Swap Spreads. *Working Paper.*

Tarashev, N. A. (2008). An empirical evaluation of structural credit risk models. *International Journal of Central Banking.*

Tendulkar, R., & Hancock, G. (2014). Corporate Bond Markets: A Global Perspective. *IOSCO Research, Staff Working Paper.*

Tychon, P., & Vannetelbosch, V. (1997). Debt Valuation and Marketability Risk. *Universite Catholique de Louvin, Working Paper.*

Unal, H., Madan, D., & Guntay, L. (2003). Pricing the Risk of Recovery in Default with APR Violation. *Journal of Banking & Finance, 1001–1025.*

Vasicek, O. (1977). Equilibrium characterization of term structure. *Journal of Financial Economics 5,177–188.*

Vasicek, O. (2002). Loan portfolio value. *RISK.*

Vernimmen, P. (4th Edition (17 octobre 2014)). *Corporate Finance: Theory and Practice.* John Wiley & Sons.

W. Hubbard, D. (2009). *The Failure of Risk Management: Why it's Broken and How to Fix it.* John Wiley & Sons.

Wang, D. F. (1999). Pricing defaultable debt: some exact results . *International Journal of Theoretical and Applied Finance.*

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data. *MIT Press.*

Yo, U., & Thompson, H. E. (2006). Bond prices in a debt priority structure with absolute priority rule deviation. *The Quarterly Review of Economics and Finance.*

Zhang, B. Y., Zhou, H., & Zhu, H. (2005). Explaining Credit Default Swap Spreads with Equity Volatility and Jump Risks of Individual Firms . *BIS Working Papers, No 181.*

Zhou, C. (2001). The term structure of credit spreads with jump risk. *Journal of Banking & Finance.*

Zhu, H. (2004). An empirical comparison of credit spreads between the bond market and the credit default swap market. *BIS Working Papers, No. 160.*

Appendices

Appendix I

About corporate bonds:

According to the European Central Bank glossary, a corporate bond is a tradable debt security that represents a "promise on the part of the issuer (i.e. the borrower or the corporation) to make one or more payment(s) to the holder (i.e. the lender or the investor) at a specified future date or dates[1]. It usually carries a specific rate of interest (the coupon) and/or are sold at a discount to the amount that will be repaid at maturity". (Source: European Central Bank, 2004, Annual Report: 2004, ECB, Frankfurt, Glossary).

To be better understood, corporate bonds need to be considered on two different levels: the primary market (where corporate bonds are newly issued) and on the secondary market (where the bonds are traded between investors after issuance). The following lines summarize the main features of these two markets.

I.1. Corporate bonds in the primary market:

I.1.1 The need for corporate bond issuance:

In order to meet a financing need, a corporation may resort to capital markets by issuing a "corporate bond". Along with equities, bank loans and lines of credit, bonds consist indeed of one of the major sources of financing for corporates. Generally speaking, the bond market allows corporations to have access to a larger and more flexible funding than typical bank loans. With regard to these large amounts, corporate bond finding is generally used for significant investment activities such as mergers and acquisitions (M&A) or business expansions; it can be though used for corporates' ongoing operations or for refinancing purposes.

I.1.2 Corporate bond issuers:

No clear consensus emerges from markets or economic literature about the structure of corporate bond issuers. Generally speaking, a corporate bond can be

[1] Corporations are "artificial entities that are created by state statute, and that are treated much like individuals under the law, having legally enforceable rights, the ability to acquire debt and to pay out profits, the ability to hold and transfer property, the ability to enter into contracts, the requirement to pay taxes, and the ability to sue and to be sued. The rights and responsibilities of a corporation are independent and distinct from the people who own or invest in them. A corporation simply provides a way for individuals to run a business and to share in profits". (Source: Nolo's Plain-English Law Dictionary).

seen as a debt instrument issued by a corporation in order to meet a financing need. Since corporations can be public, private, quasi-public or non-profit, all the bonds issued by these entities (including hence corporations from the public sector) can be largely designed as corporate bonds[2]. The term "Corporate bond" is found sometimes to encompass bonds issued by governments in other currencies or bonds issued by supranational organizations[3]. More commonly, "corporate bonds" design bonds issued by corporations from the private sector (for instance by industrial, financial and services companies), by associations, or any other private legal entity[4]. In this thesis, we design by corporate bonds all bonds issued by firms from the private sector, as well as bonds issued by firms from that the public sector that have at least a small portion of their capital held by privates. We assume indeed that bonds issued by fully public firms don't have the same riskiness as firms including privates.

I.1.3 Corporate bond investors:

By buying a corporate bond, an investor buys a portion of the debt of the issuing corporation and is considered thus as lending money to this corporation. Investors, however, purchase corporate bonds for various reasons. The main ones are: (*i*) because corporate bonds offer known fixed incomes (the coupon rate and the frequency of coupon payments are fixed at the time of issuance of the bond); (*ii*) because they provide interesting returns that are higher on average than the returns on government bonds; (*iii*) because they give a large and flexible investing possibilities (different corporate bonds features according to the needs of investors); and (*iv*) because investors can sell again their bonds before their maturity on the secondary markets if ever they need to.

I.1.4 The corporate bond contract:

Every corporate bond contract has specific features that make it different from any other bond contract in the market. Some of these features are invariable throughout the life of the bond while others are not. Table I-1 summarizes the main features of the corporate bond contract and sheds light, when it is the case, on the features that vary during the life of the bond.

---

[2] Public corporations are legal entities that undertake commercial activities on behalf of an owner government. They include typically cities and towns that help the state to function at the local level. Private corporations are in business to make money, whereas nonprofit corporations generally are designed to benefit the general public. Quasi-public corporations would be considered private, but their business serves the public's needs, such as by offering utilities or telephone service. (Source: Nolo's Plain-English Law Dictionary).

[3] See O'Sullivan and M. Sheffrin (2003) or the US "Office of Investor Education and Advocacy" (SEC) bulletins.

[4] See for instance, G. Capelle-Blancard (2011), or Allianz investors' services by Naumer. H et. Al (2011).

Every corporate bond contract has specific features that makes it different from any other bond contract in the market. Some of these features are invariable throughout the life of the bond while others are not. Table I-A.1 summarizes the main features of the corporate bond contract and sheds light, when it is the case, on the features that vary during the life of the bond.

Table I.A.1: Main features of a corporate bond contract:

N:[5]	Feature	Description
	Issuer	Designation of the corporation that issues the bond contract.
A	Amount	The total amount of money borrowed by the corporation.
D	Nominal, face or par value	The total amount of the debt contracted by the corporation is generally divided into a certain number of units called nominal value (similarly face or par value). The issuer of the bond pays interest to the holder on the base of this nominal value and, unless otherwise specified, it is the amount of that has to be repaid by the issuer at the end of the bond contract (i.e. the maturity).
P	Bond price	The actual value at which the bond is sold. At issuance, the bond price (issue price) may be fixed to be higher than the face value (bond issued at a premium), lower than the face value (bond issued at a discount) or equal to the face value (bond issued at par). Afterwards, the bond is sold on secondary markets at different prices which are usually presented as a percentage of the nominal value. The difference between the price of the bond and its nominal value provides the bondholder a return that makes purchasing the bond sometimes worthwhile even if the bond pays no interest.
	Date of issue	The date on which interest on the bond begins to accrue.
	Settlement date	The date on which the trade of the bond must be settled. It may be different from the date of issue.
	Normal redemption date	This is the date on which the bond (seen here as a loan) is amortized; the bond is hence said to be redeemed. Similar to bank loans, redemption can be at maturity; in equal slices (constant amortization); or in fixed instalments. The terms of the bond contract may also include options for the issuer to make earlier redemptions. Many other financial innovations exist for redemption methods, such as redemption by lottery[6].
T	Maturity	Corresponds to the period of time for which the bond remains outstanding. It goes from the issue date to the final redemption date where the principal is repaid with interest. It is generally superior to one year.

[5] This column contain a notation of each feature that will used in subsequent formulations.

[6] Some bonds issues contain a "sinking-fund" provision that means that a certain portion of the issue must be retired each specified period. The bonds retired are sometimes selected by lottery.

C	Coupon	This is the periodic interest that the bond holder (i.e. the lender) receives between the date of the issue and the maturity. It is generally presented in term of a coupon rate (or nominal rate) and is calculated on the base of the nominal value. A corporate bond may pay no coupons and it is then called a zero-coupon bond (or a discount bond). The coupon rate can be constant throughout the life of the bond (i.e. fixed rate bond) or floating on the base of another reference rate (i.e. floating rate bond).
Y	Yield to maturity	The yield to maturity is the rate of return earned by an investor who buys the bond assuming that he will hold it until maturity. It depends mainly on the price of the bond, the coupon rate (if any) and naturally on the time left to maturity. The yield to maturity varies hence throughout the life of the bond.
S	Credit Spread	The credit spread is the difference between the yield to maturity of the bond and that on a benchmark bond used by the market. In the euro area, the benchmark for long-term debt is most often the German government bond yield or the Interest Rate Swap (IRS) rate. Along with the yield to maturity, the spread is a key aspect for bonds in general and corporate bonds in particular[7].
R	Rating	The rating or credit rating is an evaluation of the ability of the issuer to pay back its debt obligation provided by an "independent" Rating Agency. These are mainly: Standard and Poor's, Fitch and Moody's. These rating agencies can decide to rate a specific issue or to give an absolute rating for the issuer (rating given to first-ranking debt). In Europe, rating agencies generally rate companies at their request, which enables them to access privileged information (e.g. medium-term plans, contacts with management). Rating agencies check the debtor's ability to pay back its debt and the likelihood of default, and attribute a rating ranging from AAA, for the debtors with the highest ability to meet their debt obligation, to C for the most risky debtors; D rating is attributed for entities in Default (in this thesis we use the rating system provided by Standard & Poor's as the benchmark rating system.). Broadly, ratings between AAA and BBB- are referred to as Investment-grade (also high grade), and those between BB+ and D are referred to as High-yield (also speculative grade or non-investment grade). Investment grade entities have higher ability to meet their debt obligations and consist thus of a more secure investment compared to High-yield bonds.
	Guarantee	The principal and interest payments of the bond can be guaranteed by the issuer of the bond, by a collateral (such as property, equipment, or other assets that the company owns) or by a third party such as the parent company of the issuer. Corporate bonds that have no guarantee pledged to them are often called unsecured or "debentures".

[7] The spread and yield to maturity will be considered with more details in what follows.

I	Indenture and covenants	The bond indenture specifies the legal terms of the bond contract while the bond covenants precise the rights of the bondholder and the obligations of the issuer (for instance the recovery rules of the capital of the bondholder in the case of default of the issuer). The obligations of the issuer may include maintaining certain financial performance, providing financial statements, interdiction from taking certain actions while the bond is active such as selling the company or merging it with another company. After the issuance of the bond, these terms can be hardly modified during the life of the bond[8]. Hence, in order to have more freedom, many corporate issuers prefer to issue bonds without covenants.
	Optional and Special features	The corporate bond contract may specify other special features such as optionality (a corporate bond can be callable or puttable), convertibility (the bond can be converted into shares of the issuing company), exchangeability (the bond can be exchanged into shares of any other) etc. Many financial innovations exist nowadays with regard to the special features of the bond.
	Listing	Market place of the bond issuance

I.2. Corporate bonds in the secondary market:

As opposed to a bank loan, the corporate bond contract presents the particularity of being transferable between different investors after issuance. The market where the bonds are traded after issuance is called the secondary market, and consist broadly of stock exchanges, money markets, mortgage markets and interbank markets. This secondary corporate bond market is generally an over-the-counter market, where brokers act usually as intermediaries between bond investors[9]; nonetheless, some corporate bonds are listed on stock exchanges[10]. Whether on the organized or over-the-counter markets, corporate bonds are quoted in the secondary market, which allows investors to buy and sell them at prices that are not necessarily the same as their issue price (i.e. the price at which they were sold at issuance). The price at which a bond is bought or sold will fluctuate hence during the life of the bond on the basis of a variety of factors. In

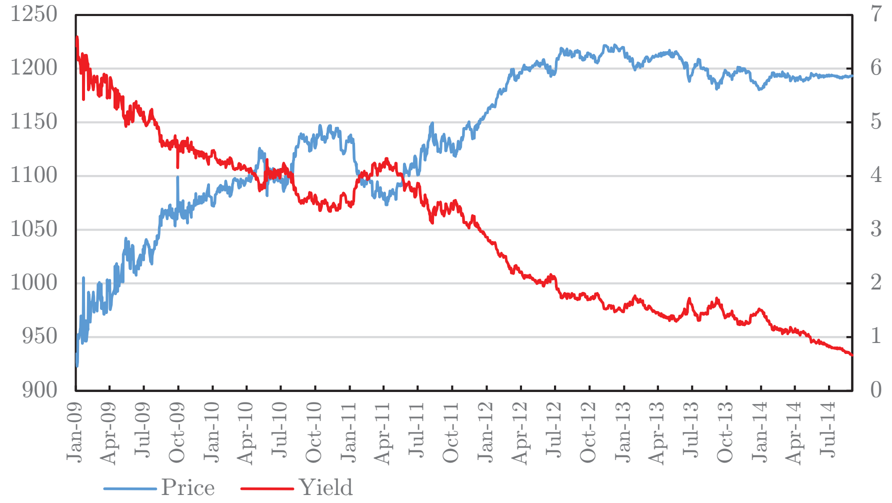
[8] This requires at least an approval by the majority of the bond holders.

[9] An over the counter (OTC) market is decentralized market where the trade takes place off exchange and directly between the purchasing and selling parties. It is hence less regulated than organized markets such as stock exchanges.

[10] The corporate bond trade in the secondary markets suffers generally from a lack of transparency (since trade is generally executed on secondary markets it can be done between two participants without other market participants being aware of the price at which the transaction was effected), and a low liquidity. Recent efforts have been made to improve these, such as the creation of the NYSE Euro corporate bond trading platform in June 2011, called the "NYSE BondMatch". Source: Banque de France bulletins.

step with these fluctuations, the yield to maturity of the bond (henceforth "YTM" or "yield") will also vary throughout the life of the bond:[11]

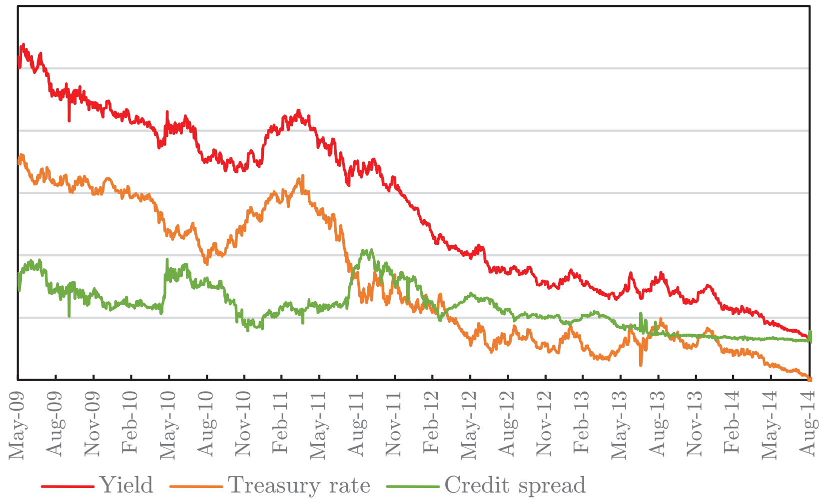
Figure I.A.1 - Corporate bond price and yield in the secondary market



Corporate bond: Airbus GRP 5,5% 25/09/2018, Source: Six-financial and autour calculations

In parallel, the credit spread over an equivalent treasury rate will also fluctuate on the secondary market:[12]

Figure I.A.2 - Corporate bond yield and credit spread in the secondary market



Corporate bond: Airbus GRP 5,5% 25/09/2018 EUR; Treasury rate: German BUND, 4.25 04/07/18. Source: Six-financial and autour calculations.

[11] An opposite relation is be observed between the price and the yield of the bond (Figure I.A.1)

[12] Ceteris paribus, an increase in the yield to maturity of the bond will be generally associated with an increase in its credit spread (see Figure I.A.2).

Appendix II

Credit spread sample and statistics

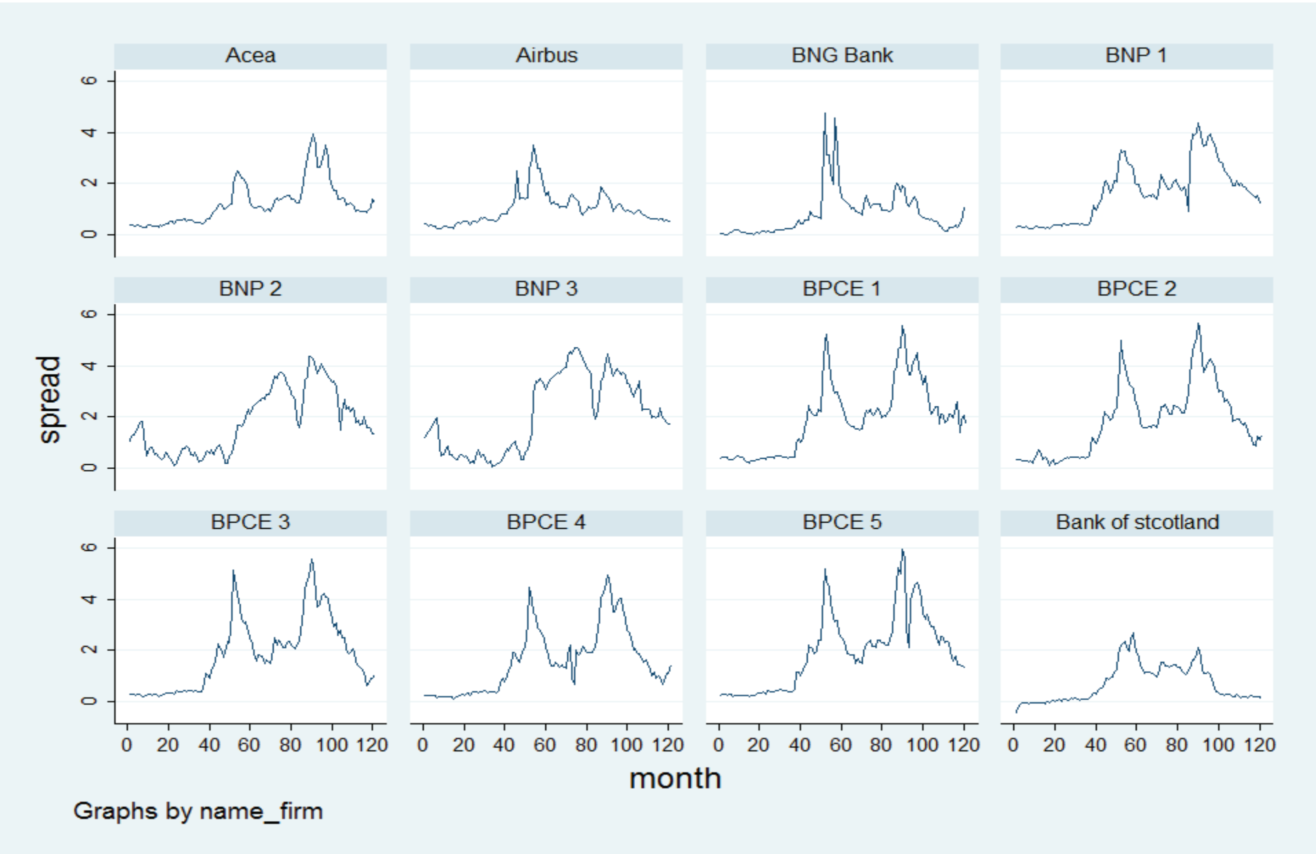
This part regroups all the appendices of chapter II.

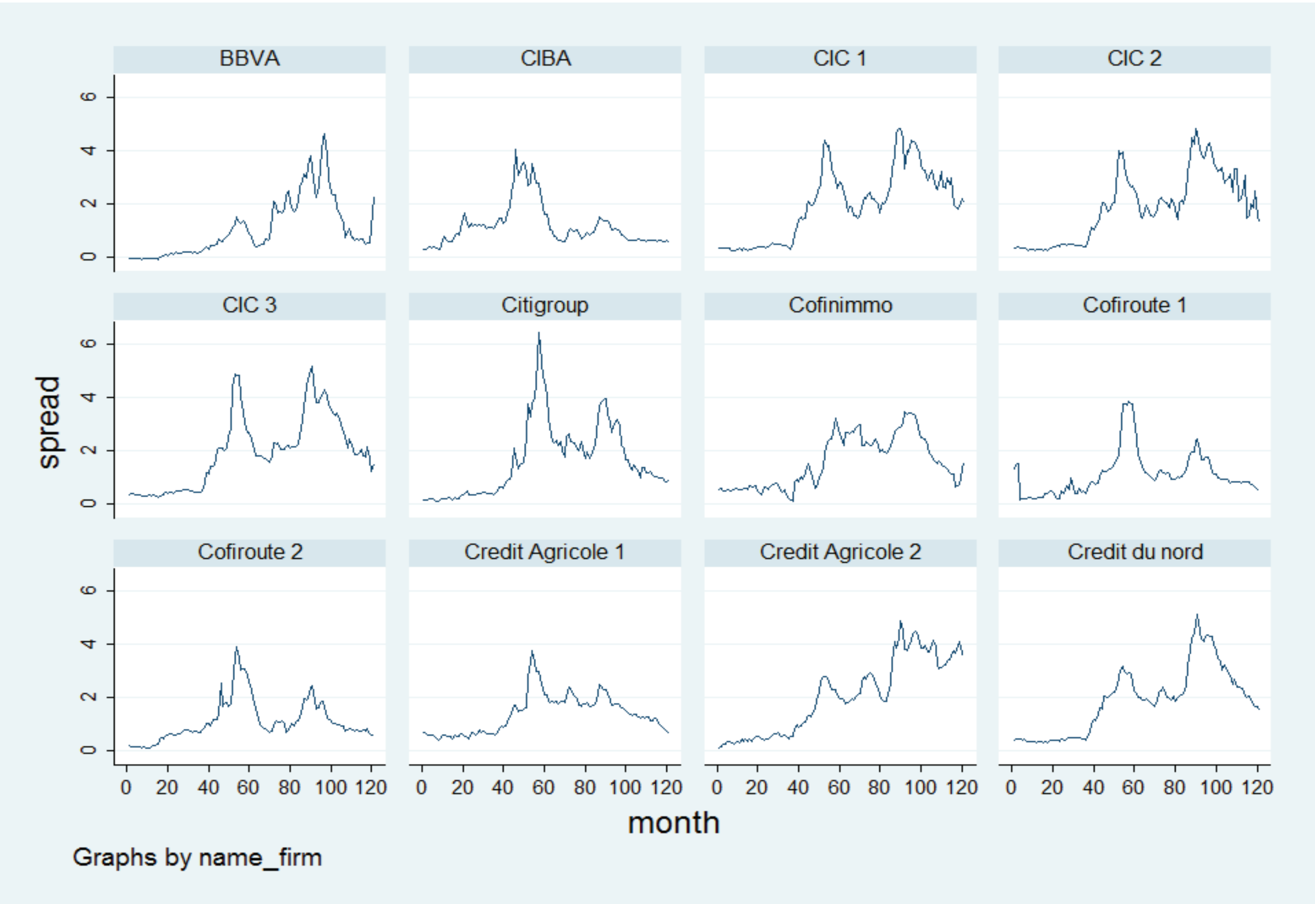
Appendix II.1. The corporate bond sample:

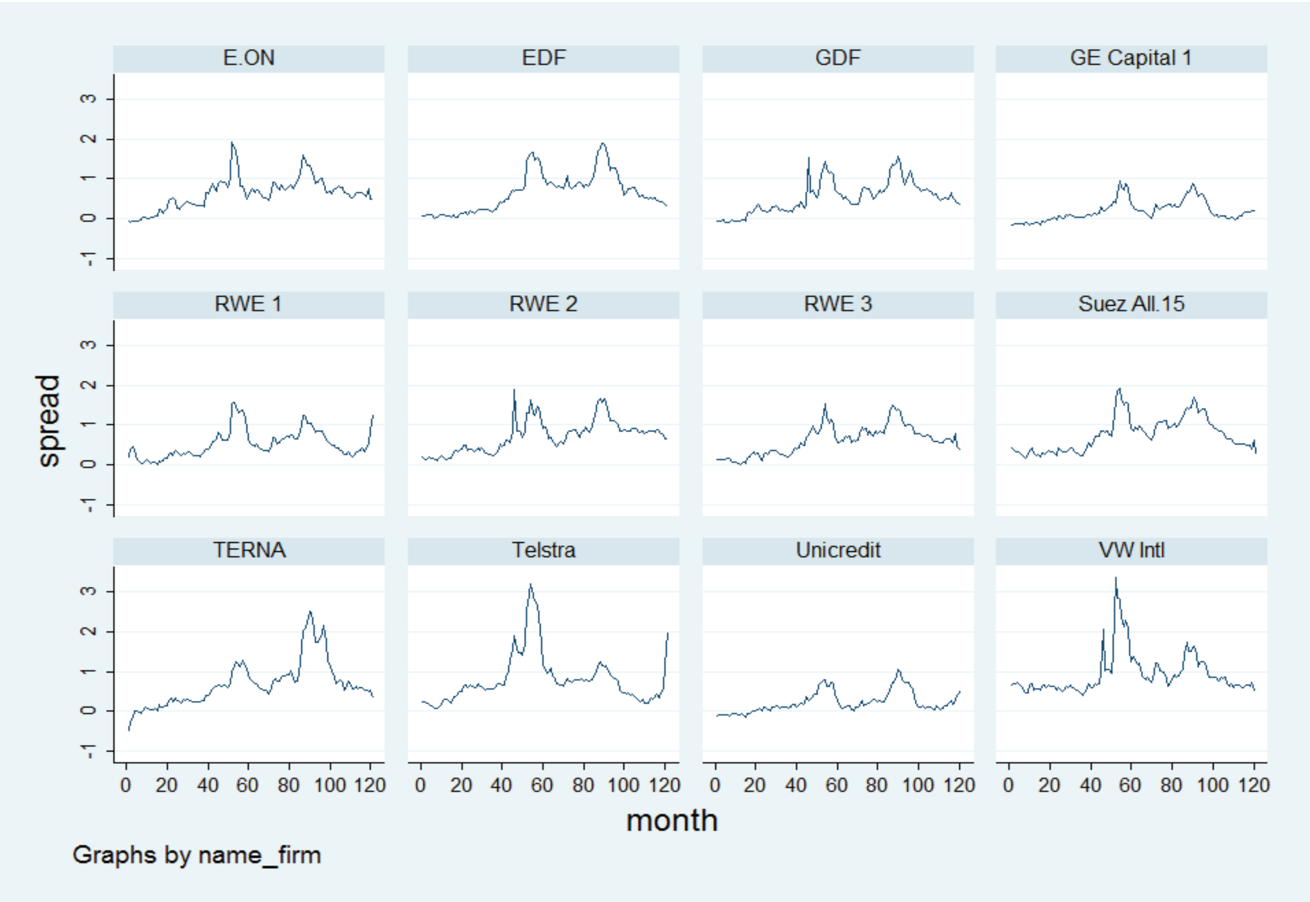
N°	ISIN	Bond issuer	Sector	Maturity	Rating - S&P
1	XS0196712086,XX,186	Acea	Industry - cars	2014	BBB
2	XS0176914579,XX,186	Airbus	Industy -aircraft	2018	A
3	FR0000189219,XX,25	BNP Paribas	Financial	2015	A+
4	XS0124669515,XX,186	BNP 1	Financial	2016	A+
5	XS0124269506,XX,186	BNP 2	Financial	2016	A+
6	FR0010091041,XX,25	BPCE 1	Financial	2014	A
7	FR0000189227,XX,25	BPCE 2	Financial	2015	A
8	FR0000188948,XX,25	BPCE 3	Financial	2015	A
9	FR0000188625,XX,25	BPCE 4	Financial	2014	A
10	FR0010049643,XX,25	BPCE 5	Financial	2016	A
11	XS0201674594,XX,186	Bank of stcotland	Financial	2014	A+
12	ES0413211055,XX,186	BBVA	Financial	2014	BBB
13	XS0170386998,XX,186	CIBA	Industry - chemicals	2018	A+
14	FR0000189177,XX,25	CIC 1	Financial	2016	AA−
15	FR0000188781,XX,25	CIC 2	Financial	2015	AA−
16	FR0000188930,XX,186	CIC 3	Financial	2015	AA−
17	XS0197646218,XX,186	Citigroup	Financial	2019	BBB
18	XS0193197505,XX,186	Cofinimmo	Real estate	2014	BBB+
19	FR0000487217,XX,186	Cofiroute 1	Industry -services	2016	A−
20	FR0000473993,XX,186	Cofiroute 2	Industry -services	2018	A−
21	DE0007572745,XX,13	Commerbank 1	Financial	2022	BBB+
22	DE0008029513,XX,13	Commerbank 2	Financial	2018	BBB+
23	XS0183046431,XX,47	Credit Agricole 1	Financial	2015	A
24	FR0010095513,XX,25	Credit Agri.	Financial	2016	A
25	FR0010082933,XX,25	Credit du nord	Financial	2016	A
26	XS0148579153,XX,186	E.ON	Industry - energy	2017	A−
27	FR0000487258,XX,186	EDF	Industry - energy	2016	AA−
28	BE0119550466,XX,186	Elia System	Industry - energy	2019	A−
29	XS0182242247,XX,186	Finmeccanica	Industry - aircraft	2018	BBB−
30	XS0196047723,XX,186	Fortis 1	Financial	2014	A

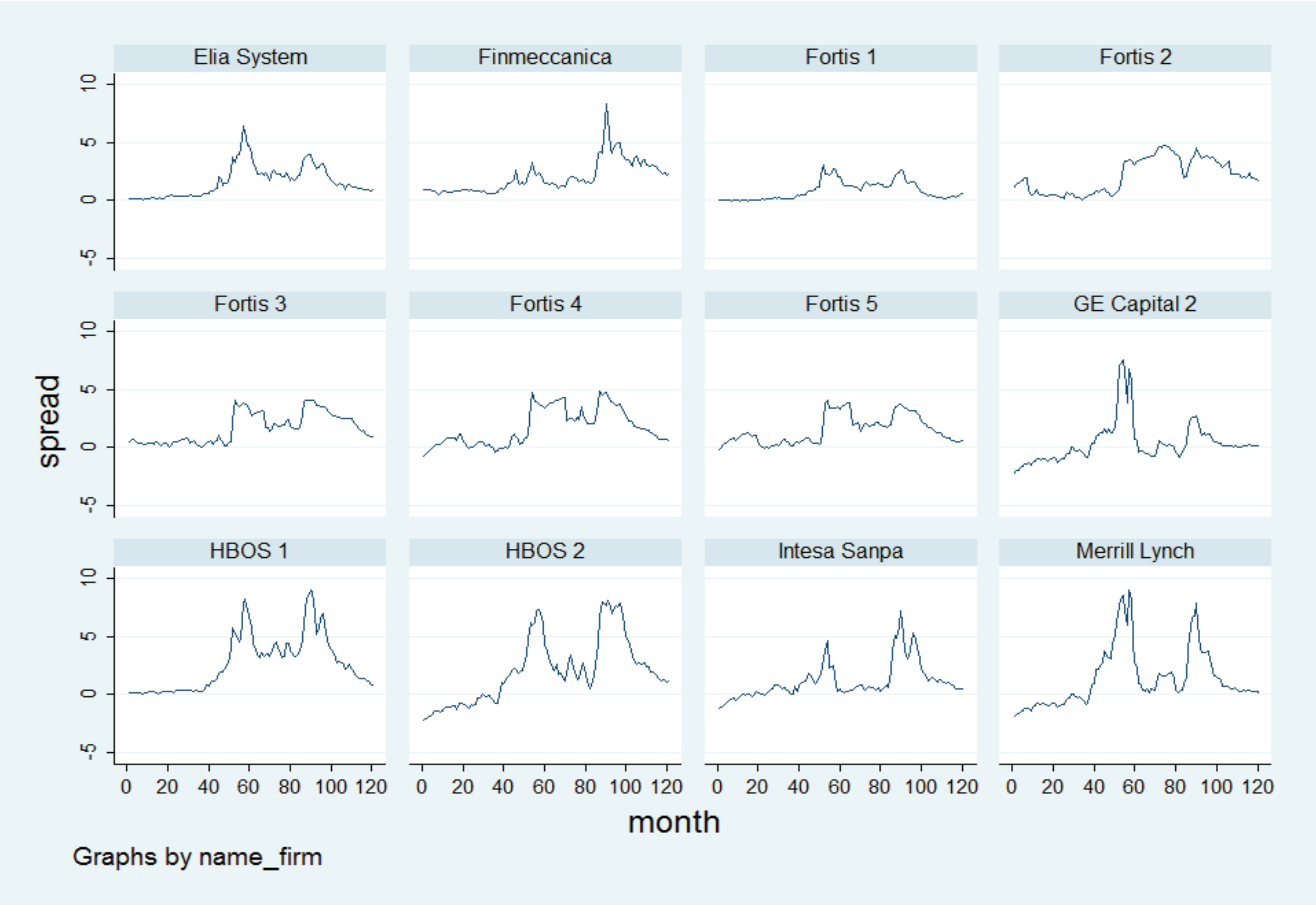
31	XS0201484382,XX,186	Fortis 2	Financial	2016	A
32	XS0122720732,XX,186	Fortis 3	Financial	2016	BBB
33	XS0208412063,XX,186	Fortis 4	Financial	2014	BBB
34	XS0196988587,XX,186	Fortis 5	Financial	2014	BBB
35	FR0000472334,XX,186	GDF	Industry - energy	2018	A+
36	XS0195116008,XX,186	GE Capital 1	Financial	2014	A+
37	XS0197508764,XX,186	GE Capital 2	Financial	2014	A+
38	XS0165449736,XX,186	HBOS-Lloyds 1	Financial	2015	A
39	XS0192560653,XX,186	HBOS-Lloyds 2	Financial	2016	A
40	XS0201271045,XX,186	Intesa Sanpa	Financial	2014	BBB
41	XS0197079972,XX,186	Merrill Lynch	Financial	2014	BBB
42	XS0196302425,XX,186	RWE 1	Industry - energy	2014	BBB+
43	XS0172851650,XX,186	RWE 2	Industry - energy	2018	BBB+
44	XS0127984747,XX,186	RWE 3	Industry - energy	2016	BBB+
45	FR0000188724,XX,25	SG 1	Financial	2014	A
46	FR0000189110,XX,25	SG 2	Financial	2015	A
47	XS0110673950,XX,186	SG 3	Financial	2015	A
48	FR0010016790,XX,25	SG 4	Financial	2015	A
49	FR0010042226,XX,25	SG 5	Financial	2016	A
50	FR0010071027,XX,25	SG 6	Financial	2016	A
51	FR0010154906,XX,25	SG 7	Financial	2017	A
52	FR0000475741,XX,186	Suez All.15	Industry - energy	2015	A+
53	XS0196578255,XX,186	Telstra	Telecomunication	2014	A
54	XS0203714802,XX,186	TERNA	Industry - energy	2014	BBB+
55	DE000HV0A1M8,XX,186	Unicredit	Financial	2014	BBB+
56	XS0168881760,XX,186	VW Intl	Industry - cars	2018	A−
57	XS0204395213,XX,186	Arcelor Fin 1	Industry - other	2014	BB+
58	XS0194455340,XX,186	Arcelor Fin 2	Industry - other	2014	BB+
59	ES0414950594,XX,186	Bancaja 1	Financial	2014	BB
60	ES0414950560,XX,186	Bancaja 2	Financial	2016	BB
61	XS0210870415,XX,186	Banca Popolare	Financial	2015	BB
62	XS0215451559,XX,186	BancoPopolare	Financial	2015	BB−
63	XS0203341424,XX,186	Gr Edit	Press	2014	BB−
64	XS0203156798,XX,186	Italease Bca	Financial	2014	BB−
65	XS0123488602,XX,186	KBL	Financial	2016	BB
66	XS0196630270,XX,186	Lafarge	Industry - construction	2014	BB+
67	FR0010130823,XX,25	Radian	Financial	2014	BB
68	XS0167127447,XX,186	RBS	Financial	2015	BB
69	XS0184373925,XX,186	Telecom Italia	Telecomunication	2019	BB+
70	XS0205040305,XX,186	Veneto Banca	Financial	2014	BB
71	XS0203831432,XX,186	Wendel	Financial	2014	BB
1	XS0176675485,XX,186	RATP	Utility	2014	AAA
2	FR0000488017,XX,186	CNAutoroutes	Utility	2017	AAA
3	FR0010000448,XX,186	SNCF	Utility	2018	AAA
4	FR0000483075,XX,186	Res.Ferre.France	Utility	2020	AAA

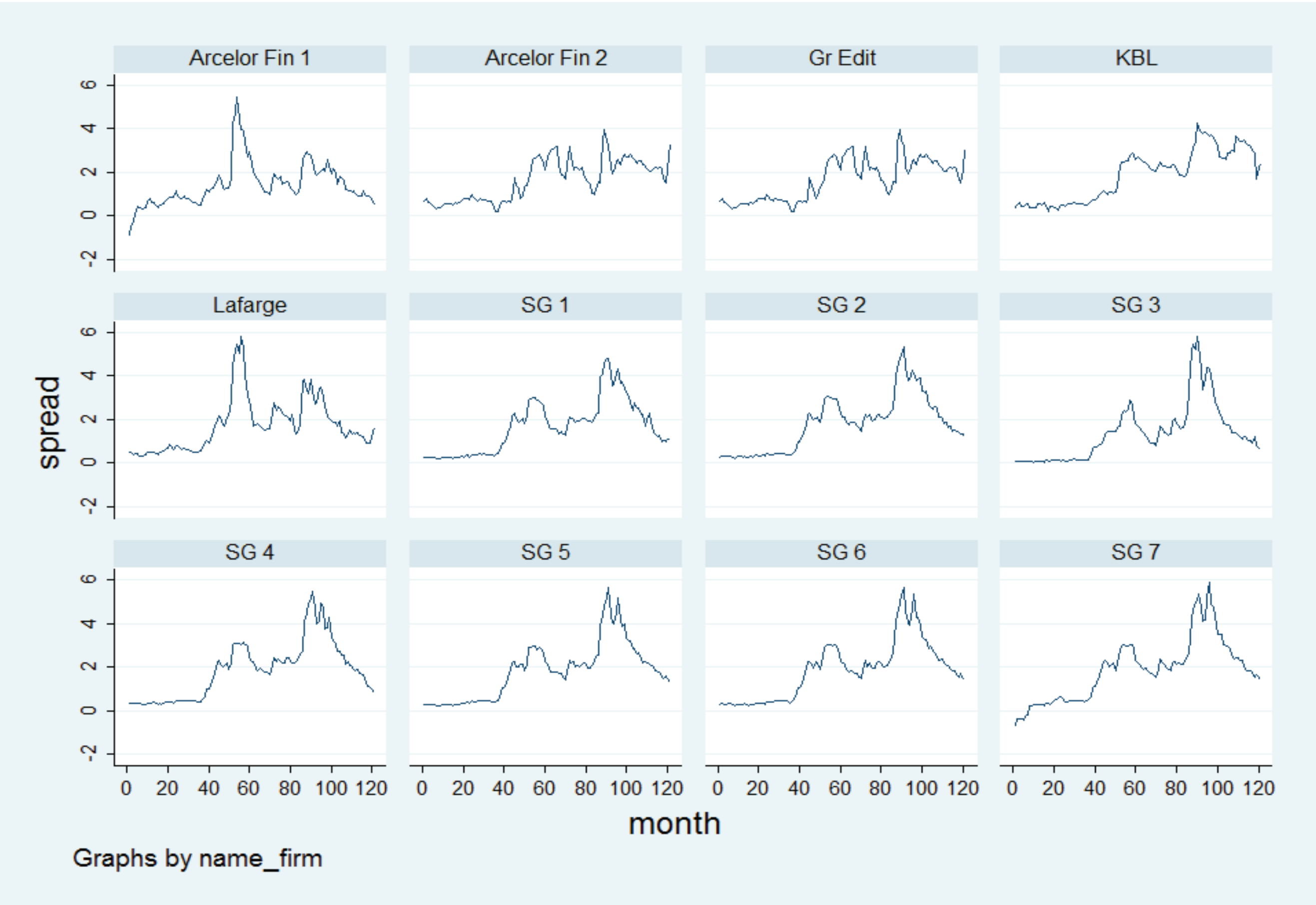
Appendix II.2. Credit spreads:



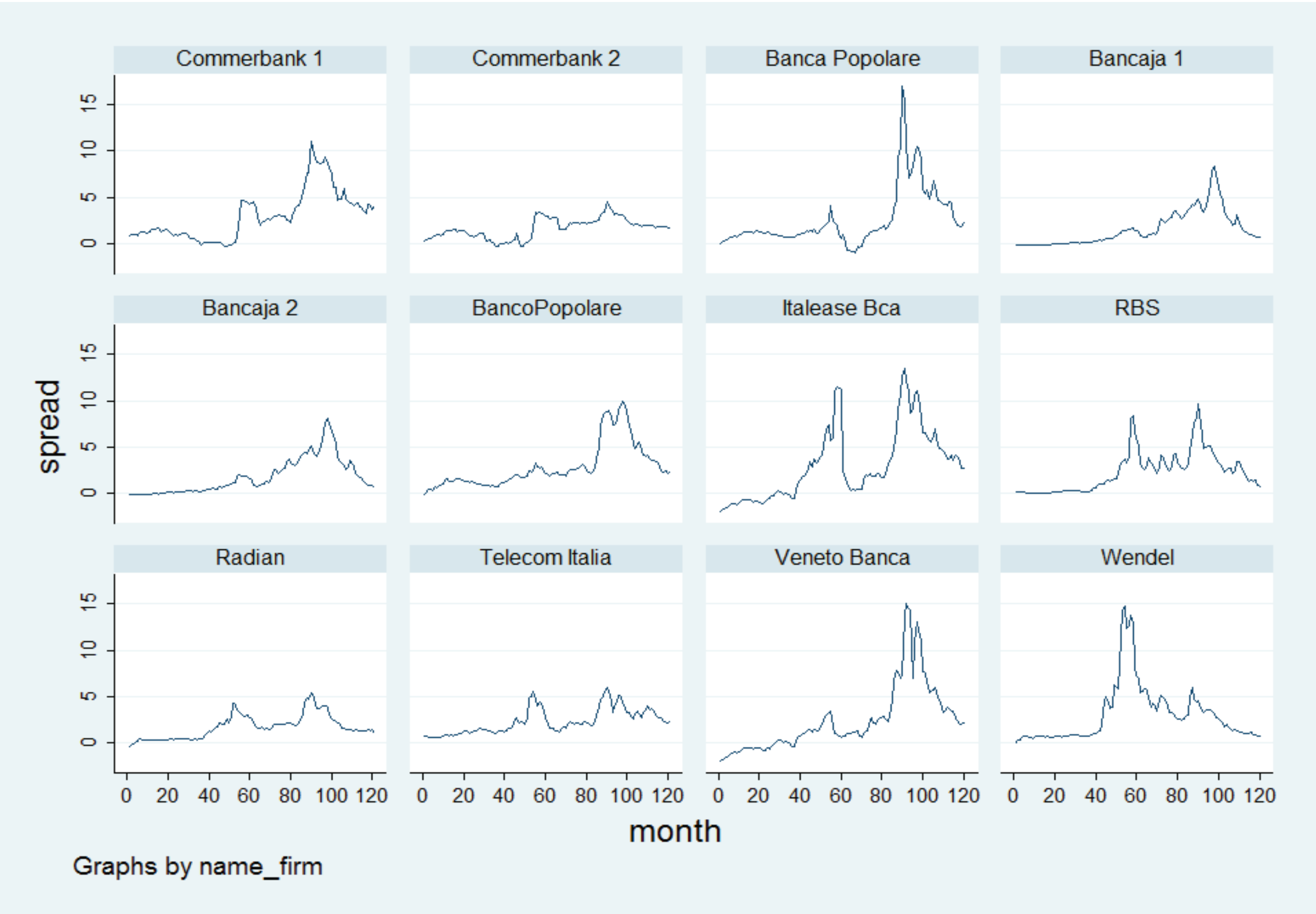

BBVA
CIBA
CIC 1
CIC 2
CIC 3
Citigroup
Cofinimmo
Cofiroute 1
Cofiroute 2
Credit Agricole 1
Credit Agricole 2
Credit du nord
spread
0
2
4
6
0 20 40 60 80 100 120
month
Graphs by name_firm


E.ON
EDF
GDF
GE Capital 1
RWE 1
RWE 2
RWE 3
Suez All.15
TERNA
Telstra
Unicredit
VW Intl
spread
month
Graphs by name_firm


Elia System
Finmeccanica
Fortis 1
Fortis 2
Fortis 3
Fortis 4
Fortis 5
GE Capital 2
HBOS 1
HBOS 2
Intesa Sanpa
Merrill Lynch
spread
month
Graphs by name_firm



Arcelor Fin 1
Arcelor Fin 2
Gr Edit
KBL
Lafarge
SG 1
SG 2
SG 3
SG 4
SG 5
SG 6
SG 7
spread
-2 0 2 4 6
0 20 40 60 80 100 120
month
Graphs by name_firm


Commerbank 1
Commerbank 2
Banca Popolare
Bancaja 1
Bancaja 2
BancoPopolare
Italease Bca
RBS
Radian
Telecom Italia
Veneto Banca
Wendel
spread
month
0 5 10 15
0 20 40 60 80 100 120
Graphs by name_firm

Appendix II.3. Descriptive Statistics – Full sample

N°	Spread	Range	Median	Mean	St.deviation	Variance	Skewness	Kurtosis
1	Acea	3,68568	1,07493	1,21368	0,84125	0,7077	1,26592	1,17865
2	Credit Agricole 1	3,38911	1,3457	1,36276	0,73505	0,54029	0,72004	0,21429
3	Airbus	3,30125	0,91007	0,98633	0,62044	0,38494	1,56131	2,9492
4	BNP Paribas	4,15574	1,71401	1,64924	1,12816	1,27273	0,45909	-0,64024
5	BNP 1	4,24154	1,66812	1,82654	1,22948	1,51161	0,35488	-1,14165
6	BNP 2	4,65716	1,98608	2,12654	1,48555	2,20686	0,12222	-1,4734
7	BPCE 1	5,37908	1,98371	1,91545	1,35398	1,83326	0,60799	-0,26988
8	BPCE 2	5,56397	1,75289	1,85321	1,3827	1,91185	0,69287	-0,22381
9	BPCE 3	5,41102	1,77339	1,8279	1,39518	1,94654	0,67819	-0,31763
10	BPCE 4	4,93061	1,42442	1,62347	1,29773	1,68411	0,79975	-0,19837
11	BPCE 5	5,76346	1,96828	1,93624	1,43835	2,06885	0,65397	-0,18036
12	CIBA	3,8015	0,98036	1,17017	0,80891	0,65433	1,6847	2,25969
13	CIC 1	4,64105	2,00691	1,93379	1,33541	1,78332	0,27095	-0,9336
14	Citigroup	6,37749	1,32434	1,61578	1,36105	1,85246	1,03637	0,83154
15	Cofinimmo	3,36257	1,42438	1,5763	0,97632	0,95319	0,26672	-1,30629
16	Cofiroute 1	3,72027	0,91836	1,10737	0,83747	0,70136	1,67695	2,95928
17	Cofiroute 2	3,81735	0,88218	1,09732	0,79098	0,62565	1,35575	1,74399
18	Credit Agri.	4,78935	1,92174	2,0338	1,39799	1,95437	0,21538	-1,26969
19	Commerbank 1	11,2863	2,59057	3,01415	2,66011	7,07618	0,99266	0,38527
20	Commerbank 2	4,84549	1,80699	1,68194	1,09297	1,19458	0,10433	-0,65158
21	E.ON	2,00045	0,65368	0,63193	0,39647	0,15719	0,50815	0,89053
22	EDF	1,88758	0,66673	0,65929	0,48699	0,23716	0,66319	-0,28566
23	Elia System	6,37749	1,32434	1,6158	1,36102	1,85239	1,03644	0,83167
24	Fortis 1	3,1468	0,5308	0,84061	0,79674	0,63479	0,77563	-0,38926
25	Fortis 2	4,65716	1,98608	2,13092	1,48019	2,19095	0,12795	-1,47447
26	Fortis 3	4,06256	1,5718	1,66818	1,28553	1,65258	0,4259	-1,21468
27	Fortis 4	5,52951	1,20209	1,73428	1,57345	2,47574	0,42585	-1,19554
28	Fortis 5	4,2817	1,1612	1,51525	1,21034	1,46493	0,58375	-0,93236
29	GDF	1,65782	0,49135	0,53412	0,40233	0,16187	0,54534	-0,20961
30	GE Capital 1	1,11088	0,12382	0,19731	0,26091	0,06807	1,00087	0,43524
31	GE Capital 2	9,66941	0,106	0,40387	1,84097	3,38918	2,09975	5,09084
32	HBOS 1	8,93763	2,16272	2,64905	2,37751	5,65253	0,81399	-0,13385
33	HBOS 2	10,33989	1,80713	2,06438	2,82734	7,99388	0,64512	-0,47382
34	Intesa Sanpa	8,46984	0,67834	1,13718	1,54561	2,38892	1,66568	2,59082
35	Merrill Lynch	10,92101	0,48449	1,40921	2,5559	6,53262	1,28093	0,94447
36	RWE 1	1,55037	0,44068	0,52962	0,35253	0,12428	0,98979	0,56961
37	RWE 2	1,78916	0,79457	0,7236	0,40146	0,16117	0,55306	-0,06782
38	RWE 3	1,53597	0,62111	0,61517	0,36148	0,13067	0,35893	-0,38668
39	SG 1	4,63651	1,66351	1,67438	1,2141	1,47403	0,60056	-0,34866
40	SG 2	5,12788	1,87107	1,78895	1,25695	1,57991	0,56364	-0,24475

41	SG 3	5,77509	1,22047	1,39305	1,33808	1,79047	1,3768	1,72658
42	Suez All.15	1,74234	0,72601	0,76139	0,42853	0,18364	0,64848	-0,4191
43	Telstra	3,12768	0,66015	0,80815	0,62722	0,3934	1,88715	3,71527
44	TERNA	3,01021	0,60224	0,68397	0,57994	0,33634	1,1397	1,32805
45	VW Intl	2,94251	0,72554	0,93457	0,52091	0,27135	2,21697	5,53364
46	BBVA	4,7639	0,66278	1,0433	1,10612	1,2235	1,17017	0,73561
47	Bank of stcotland	3,1206	0,32388	0,70867	0,73962	0,54704	0,70149	-0,59976
48	CIC 2	4,63104	1,85856	1,86033	1,29173	1,66856	0,36403	-0,89015
49	CIC 3	4,96631	1,98858	1,93153	1,36383	1,86004	0,52007	-0,58759
50	SG 4	5,21144	1,90664	1,84466	1,31325	1,72463	0,62578	-0,18483
51	SG 5	5,45681	1,87856	1,81536	1,30122	1,69317	0,65862	0,05337
52	SG 6	5,39746	1,94047	1,85379	1,32888	1,76593	0,64863	-0,00465
53	Credit du nord	4,82786	1,97294	1,8795	1,27413	1,62342	0,43987	-0,59229
54	SG 7	6,5642	1,90761	1,87452	1,43185	2,05018	0,55601	-0,02191
55	Finmeccanica	7,75839	1,53966	2,01164	1,41191	1,99349	1,56607	3,1273
56	Unicredit	1,18986	0,13217	0,22711	0,26608	0,0708	1,08843	0,43026
57	Veneto Banca	17,04081	1,29853	2,46067	3,68094	13,54931	1,67932	2,62601
58	Wendel	15,79634	1,95781	3,0368	3,21398	10,32968	2,0678	4,53053
59	RBS	9,63212	2,19024	2,3014	2,20706	4,87111	1,11218	0,98154
60	Telecom Italia	5,42661	2,03968	2,32638	1,36715	1,86909	0,7968	-0,27895
61	Gr Edit	3,8078	1,68947	1,65314	0,94248	0,88827	0,17915	-1,20077
62	Italease Bca	16,80138	2,06076	3,07634	3,937	15,49994	0,98737	0,24629
63	Lafarge	5,46681	1,51033	1,7238	1,22268	1,49494	1,24848	1,39595
64	Arcelor Fin 1	6,37758	1,20427	1,4273	1,01091	1,02195	1,36166	2,87541
65	Arcelor Fin 2	3,8078	1,68947	1,65547	0,94631	0,8955	0,1894	-1,18817
66	Bancaja 1	8,58102	0,99787	1,60332	1,87311	3,50853	1,41735	1,79931
67	Radian	5,93874	1,54219	1,70618	1,29687	1,68187	0,76526	0,06495
68	KBL	4,06062	2,16195	1,86587	1,17932	1,39079	0,11323	-1,34592
69	Bancaja 2	8,27332	1,06626	1,78468	1,93129	3,7299	1,23408	0,99281
70	Banca Popolare	18,05318	1,33984	2,59675	3,15583	9,95926	2,1494	5,12841
71	BancoPopolare	10,01397	2,15891	2,89556	2,42457	5,87853	1,49388	1,23375

Appendix II.4. Unit-root test – Augmented Dickey-Fuller (ADF):

H0 : The serie contain a unit root
Ha : The serie doesn't contain a unit root. The serie is stationary

"Unilateral p-value" present the risk of rejecting H0 while it is true:

N°	Spread	Tau (observed value)	Tau (critical value)	Unilateral p-value	Alpha
1	Acea	-2,12222	-0,82131	51,96%	0,05
2	Credit Agricole 1	-2,11197	-0,82131	52,59%	0,05
3	Airbus	-1,89531	-0,82131	64,39%	0,05
4	BNP Paribas	-1,59131	-0,82131	78,40%	0,05
5	BNP 1	-1,50418	-0,82131	81,51%	0,05
6	BNP 2	-1,93742	-0,82131	62,09%	0,05
7	BPCE 1	-1,67467	-0,82131	75,02%	0,05
8	BPCE 2	-1,61235	-0,82131	77,57%	0,05
9	BPCE 3	-1,91506	-0,82131	63,29%	0,05
10	BPCE 4	-1,5689	-0,82131	79,29%	0,05
11	BPCE 5	-1,2609	-0,82131	88,08%	0,05
12	CIBA	-2,03005	-0,82131	56,99%	0,05
13	CIC 1	-2,48554	-0,82131	32,52%	0,05
14	Citigroup	-1,61152	-0,82131	77,61%	0,05
15	Cofinimmo	-1,54543	-0,82131	80,14%	0,05
16	Cofiroute 1	-1,47639	-0,82131	82,45%	0,05
17	Cofiroute 2	-1,74726	-0,82131	71,75%	0,05
18	Credit Agri.	-1,68266	-0,82131	74,64%	0,05
19	Commerbank 1	-2,68615	-0,82131	23,19%	0,05
20	Commerbank 2	-2,17333	-0,82131	49,20%	0,05
21	E.ON	-2,46131	-0,82131	33,71%	0,05
22	EDF	-2,34417	-0,82131	39,82%	0,05
23	Elia System	-1,45114	-0,82131	83,22%	0,05
24	Fortis 1	-3,24884	-0,82131	7,39%	0,05
25	Fortis 2	-1,72447	-0,82131	72,82%	0,05
26	Fortis 3	-2,12578	-0,82131	51,78%	0,05
27	Fortis 4	-1,50589	-0,82131	81,46%	0,05
28	Fortis 5	-1,74725	-0,82131	71,75%	0,05
29	GDF	-2,71527	-0,82131	22,16%	0,05
30	GE Capital 1	-1,42237	-0,82131	84,02%	0,05
31	GE Capital 2	-1,49778	-0,82131	81,76%	0,05
32	HBOS 1	-1,96284	-0,82131	60,66%	0,05
33	HBOS 2	-1,59654	-0,82131	78,20%	0,05
34	Intesa Sanpa	-2,1301	-0,82131	51,52%	0,05

35	Merrill Lynch	-2,0802	-0,82131	54,34%	0,05
36	RWE 1	-2,71156	-0,82131	22,30%	0,05
37	RWE 2	-2,6752	-0,82131	23,68%	0,05
38	RWE 3	-1,08967	-0,82131	91,43%	0,05
39	SG 1	-2,03523	-0,82131	56,74%	0,05
40	SG 2	-2,58964	-0,82131	27,37%	0,05
41	SG 3	-2,66673	-0,82131	24,00%	0,05
42	Suez All.15	-2,63181	-0,82131	25,45%	0,05
43	Telstra	-2,36039	-0,82131	38,95%	0,05
44	TERNA	-1,62625	-0,82131	77,08%	0,05
45	VW Intl	-1,67724	-0,82131	74,91%	0,05
46	BBVA	-1,78505	-0,82131	69,89%	0,05
47	Bank of stcotland	-1,76897	-0,82131	70,69%	0,05
48	CIC 2	-1,67033	-0,82131	75,18%	0,05
49	CIC 3	-1,48613	-0,82131	82,10%	0,05
50	SG 4	-1,64104	-0,82131	76,41%	0,05
51	SG 5	-1,54058	-0,82131	80,30%	0,05
52	SG 6	-1,30721	-0,82131	87,00%	0,05
53	Credit du nord	-2,06936	-0,82131	54,94%	0,05
54	SG 7	-1,74727	-0,82131	71,75%	0,05
55	Finmeccanica	-3,15513	-0,82131	9,20%	0,05
56	Unicredit	-2,14443	-0,82131	50,79%	0,05
57	Veneto Banca	-2,36031	-0,82131	38,96%	0,05
58	Wendel	-2,70813	-0,82131	22,42%	0,05
59	RBS	-1,40033	-0,82131	84,61%	0,05
60	Telecom Italia	-1,26602	-0,82131	87,94%	0,05
61	Gr Edit	-2,02787	-0,82131	57,13%	0,05
62	Italease Bca	-1,79387	-0,82131	69,46%	0,05
63	Lafarge	-2,64656	-0,82131	24,87%	0,05
64	Arcelor Fin 1	-2,12849	-0,82131	51,61%	0,05
65	Arcelor Fin 2	-3,01288	-0,82131	12,38%	0,05
66	Bancaja 1	-3,06731	-0,82131	11,05%	0,05
67	Radian	-1,4784	-0,82131	82,38%	0,05
68	KBL	-1,71126	-0,82131	73,41%	0,05
69	Bancaja 2	-2,7137	-0,82131	22,21%	0,05
70	Banca Popolare	-0,94299	-0,82131	93,66%	0,05
71	BancoPopolare	-2,31941	-0,82131	41,11%	0,05

Appendix II.5. Normality test – summary:

N°	Variable\Test	Shapiro-Wilk	Jarque-Bera
1	(Acea)	< 0,0001	< 0,0001
2	(Airbus)	< 0,0001	< 0,0001
3	(BNP 1)	< 0,0001	0,042
4	(BNP 2)	< 0,0001	0,011
5	(BNP 3)	< 0,0001	0,004
6	(BPCE 1)	< 0,0001	0,020
7	(BPCE 2)	< 0,0001	0,007
8	(BPCE 3)	< 0,0001	0,008
9	(BPCE 4)	< 0,0001	0,001
10	(BPCE 5)	< 0,0001	0,012
11	(Bank of stcotland)	< 0,0001	0,003
12	(BBVA)	< 0,0001	< 0,0001
13	(CIBA)	< 0,0001	< 0,0001
14	(CIC 1)	< 0,0001	**0,054**
15	(CIC 2)	< 0,0001	0,036
16	(CIC 3)	< 0,0001	0,027
17	(Citigroup)	< 0,0001	< 0,0001
18	(Cofinimmo)	< 0,0001	0,007
19	(Cofiroute 1)	< 0,0001	< 0,0001
20	(Cofiroute 2)	< 0,0001	< 0,0001
21	(Commerbank 1)	< 0,0001	< 0,0001
22	(Commerbank 2)	**0,068**	**0,307**
23	(Credit Agricole 1)	< 0,0001	0,005
24	(Credit Agricole 2)	< 0,0001	0,009
25	(Credit du nord)	< 0,0001	**0,059**
26	(E.ON)	0,001	0,010
27	(EDF)	< 0,0001	0,010
28	(Elia System)	< 0,0001	< 0,0001
29	(Finmeccanica)	< 0,0001	< 0,0001
30	(Fortis 1)	< 0,0001	0,001
31	(Fortis 2)	< 0,0001	0,004
32	(Fortis 3)	< 0,0001	0,004
33	(Fortis 4)	< 0,0001	0,004
34	(Fortis 5)	< 0,0001	0,004
35	(GDF)	0,001	0,045
36	(GE Capital 1)	< 0,0001	< 0,0001
37	(GE Capital 2)	< 0,0001	< 0,0001
38	(HBOS 1)	< 0,0001	0,001
39	(HBOS 2)	< 0,0001	0,009
40	(Intesa Sanpa)	< 0,0001	< 0,0001

41	(Merrill Lynch)	< 0,0001	< 0,0001
42	(RWE 1)	< 0,0001	< 0,0001
43	(RWE 2)	0,000	0,045
44	(RWE 3)	0,010	0,187
45	(SG 1)	< 0,0001	0,019
46	(SG 2)	< 0,0001	0,035
47	(SG 3)	< 0,0001	< 0,0001
48	(SG 4)	< 0,0001	0,018
49	(SG 5)	< 0,0001	0,013
50	(SG 6)	< 0,0001	0,014
51	(SG 7)	0,000	0,044
52	(Suez All.15)	< 0,0001	0,009
53	(Telstra)	< 0,0001	< 0,0001
54	(TERNA)	< 0,0001	< 0,0001
55	(Unicredit)	< 0,0001	< 0,0001
56	(VW Intl)	< 0,0001	< 0,0001
57	(Arcelor Fin 1)	< 0,0001	< 0,0001
58	(Arcelor Fin 2)	< 0,0001	0,020
59	(Bancaja 1)	< 0,0001	< 0,0001
60	(Bancaja 2)	< 0,0001	< 0,0001
61	(Banca Popolare)	< 0,0001	< 0,0001
62	(BancoPopolare)	< 0,0001	< 0,0001
63	(Gr Edit)	< 0,0001	0,019
64	(Italease Bca)	< 0,0001	< 0,0001
65	(KBL)	< 0,0001	0,009
66	(Lafarge)	< 0,0001	< 0,0001
67	(Radian)	< 0,0001	0,003
68	(RBS)	< 0,0001	< 0,0001
69	(Telecom Italia)	< 0,0001	0,001
70	(Veneto Banca)	< 0,0001	< 0,0001
71	(Wendel)	< 0,0001	< 0,0001

Appendix II.6. Descriptive Statistics – Pre-crisis period:

N°	Spread	Range	Median	Mean	St.deviation	Variance	Skewness	Kurtosis
1	Acea	0,35280	0,40216	0,41988	0,01000	0,10002	0,16073	-1,12993
2	Credit Agricole 1	0,47347	0,44347	0,43239	0,01638	0,12798	0,04655	-0,89592
3	Airbus	0,21257	0,32190	0,33745	0,00392	0,06265	-0,04763	-1,20874
4	BNP Paribas	1,72424	0,57649	0,70811	0,20445	0,45216	1,04932	0,20987
5	BNP 1	1,90675	0,50280	0,64801	0,26540	0,51517	1,29674	0,60036
6	BNP 2	0,26430	0,39995	0,37552	0,00448	0,06697	-0,81844	-0,05805
7	BPCE 1	0,60189	0,34093	0,34581	0,01436	0,11982	0,53152	1,07871
8	BPCE 2	0,24274	0,28581	0,31609	0,00548	0,07406	-0,01301	-1,30054
9	BPCE 3	0,29786	0,23710	0,27207	0,00763	0,08738	0,15471	-1,31722
10	BPCE 4	0,26949	0,29771	0,31837	0,00678	0,08234	0,24577	-1,40586
11	BPCE 5	0,56529	-0,01039	-0,00275	0,01238	0,11128	-1,72198	4,64237
12	CIBA	0,30465	0,02321	0,03324	0,01070	0,10343	0,09441	-1,62879
13	CIC 1	1,42111	0,95332	0,84449	0,15975	0,39969	-0,08347	-1,14526
14	Citigroup	0,29021	0,32100	0,33647	0,00656	0,08101	0,46622	-0,54441
15	Cofinimmo	0,27155	0,34255	0,34620	0,00653	0,08078	0,05666	-1,27519
16	Cofiroute 1	0,29162	0,36998	0,37274	0,00677	0,08228	0,07050	-1,25506
17	Cofiroute 2	0,38209	0,25018	0,25922	0,01304	0,11419	0,04475	-1,50327
18	Credit Agri.	0,67526	0,53285	0,52334	0,01982	0,14078	-0,94511	1,36646
19	Commerbank 1	1,37418	0,37832	0,43970	0,11966	0,34592	1,92851	3,11524
20	Commerbank 2	0,71718	0,48801	0,42005	0,06773	0,26024	-0,10544	-1,70644
21	E.ON	1,71486	1,13255	1,07375	0,15993	0,39991	-0,86708	0,56078
22	EDF	1,81610	0,99211	0,90591	0,21321	0,46175	-0,64681	-0,33083
23	Elia System	0,36774	0,57530	0,56975	0,00669	0,08177	-0,13540	-0,09863
24	Fortis 1	0,56469	0,41161	0,40075	0,01877	0,13700	-0,26436	-0,50558
25	Fortis 2	0,20798	0,38366	0,38419	0,00356	0,05967	0,11619	-1,01012
26	Fortis 3	0,59256	0,23415	0,19277	0,03688	0,19205	0,02560	-1,40205
27	Fortis 4	0,21919	0,10577	0,12598	0,00446	0,06682	0,30484	-1,24370
28	Fortis 5	0,38209	0,25018	0,25930	0,01302	0,11409	0,04578	-1,50315
29	GDF	0,44493	0,78430	0,77241	0,01362	0,11670	-0,27722	-0,80019
30	GE Capital 1	0,27919	0,02927	0,06226	0,00662	0,08139	0,31990	-1,35423
31	GE Capital 2	1,90675	0,50280	0,64999	0,26360	0,51342	1,30728	0,61898
32	HBOS 1	0,73200	0,40548	0,41287	0,03125	0,17677	0,14887	-0,30377
33	HBOS 2	1,92560	0,27334	0,27914	0,19244	0,43868	-0,07212	-0,11912
34	Intesa Sanpa	1,44909	0,49474	0,50640	0,18838	0,43403	0,16953	-1,25831
35	Merrill Lynch	0,45734	0,16605	0,10962	0,02282	0,15107	-0,00196	-1,50348
36	RWE 1	0,25223	-0,03812	-0,03992	0,00713	0,08441	0,06790	-1,50624
37	RWE 2	2,18924	-1,02204	-1,02393	0,28660	0,53535	-0,05473	-0,35443
38	RWE 3	0,33240	0,22682	0,24687	0,00911	0,09545	0,02889	-1,07287
39	SG 1	2,33629	-0,97146	-0,98550	0,34173	0,58458	-0,20091	-0,52215

40	SG 2	2,09780	0,01996	-0,01109	0,26069	0,51058	-0,41812	-0,13961
41	SG 3	1,96444	-0,85160	-0,85751	0,22785	0,47733	-0,07273	-0,36822
42	Suez All.15	0,45283	0,22280	0,20557	0,01347	0,11607	0,17494	-0,87543
43	Telstra	0,39947	0,27443	0,27865	0,01251	0,11186	0,13235	-1,19369
44	TERNA	0,38640	0,19586	0,19861	0,01158	0,10759	-0,06017	-1,07155
45	VW Intl	0,25729	0,28718	0,31477	0,00525	0,07248	0,14032	-1,25810
46	BBVA	0,21267	0,32837	0,34201	0,00405	0,06360	0,04676	-1,15927
47	Bank of stcotland	0,17985	0,10614	0,11016	0,00181	0,04255	0,09950	-0,68982
48	CIC 2	0,22355	0,35635	0,36838	0,00379	0,06160	-0,15515	-0,93270
49	CIC 3	0,24797	0,29771	0,32814	0,00558	0,07470	0,22240	-1,34027
50	SG 4	0,22827	0,31016	0,33473	0,00461	0,06792	0,29295	-1,17440
51	SG 5	1,33628	0,35543	0,23822	0,11293	0,33606	-1,36914	0,71751
52	SG 6	0,26275	0,31666	0,31390	0,00497	0,07053	0,03733	-0,78925
53	Credit du nord	0,61319	0,46777	0,40978	0,04096	0,20240	-0,22360	-1,49678
54	SG 7	0,83898	0,14384	0,12017	0,03113	0,17644	-1,46063	2,63543
55	Finmeccanica	0,27105	-0,02024	-0,00583	0,00639	0,07993	0,13164	-1,41824
56	Unicredit	0,30990	0,59298	0,58530	0,00606	0,07786	-0,25545	-0,74923
57	Veneto Banca	2,05368	0,59933	0,53706	0,16322	0,40401	-1,84039	3,86581
58	Wendel	0,78390	0,64711	0,62536	0,02835	0,16837	-0,42474	-0,11974
59	RBS	0,28899	-0,05613	-0,02537	0,00813	0,09019	0,25706	-1,48179
60	Telecom Italia	0,41852	0,03921	0,05909	0,01840	0,13566	0,10709	-1,56371
61	Gr Edit	1,34954	0,94695	0,91925	0,10952	0,33094	-0,81518	0,21016
62	Italease Bca	1,68897	0,98979	0,99167	0,17243	0,41525	-0,56761	-0,10560
63	Lafarge	0,78390	0,64711	0,62536	0,02835	0,16837	-0,42474	-0,11974
64	Arcelor Fin 1	2,20334	-0,77042	-0,75938	0,29207	0,54043	0,01597	-0,49052
65	Arcelor Fin 2	0,44685	0,51072	0,47890	0,01033	0,10164	-1,02599	0,86512
66	Bancaja 1	0,55560	0,50934	0,54052	0,01760	0,13265	0,62563	0,00620
67	Radian	0,93574	0,36284	0,30121	0,03930	0,19824	-2,53489	5,95010
68	KBL	0,37714	0,12196	0,13760	0,01187	0,10893	0,15305	-1,20576
69	Bancaja 2	1,04356	0,96439	0,99988	0,10054	0,31708	0,21969	-1,22746
70	Banca Popolare	2,31095	-0,57831	-0,63465	0,32093	0,56651	-0,38096	-0,20278
71	BancoPopolare	0,80700	0,69721	0,65549	0,02505	0,15826	-2,24570	5,60895

Appendix II.7. Descriptive Statistics – Subprime crisis period:

N°	Spread	Range	Median	Mean	St.deviation	Variance	Skewness	Kurtosis
1	Acea	2,03368	1,08535	1,24546	0,31717	0,56318	0,94432	-0,23096
2	Credit Agricole 1	2,90568	1,36350	1,55380	0,54048	0,73517	1,06425	0,15559
3	Airbus	2,88102	1,77088	1,87241	0,51459	0,71735	0,38277	-0,42733
4	BNP Paribas	2,78775	1,41796	1,48039	0,90903	0,95343	0,18853	-1,54899
5	BNP 1	3,74416	2,12235	2,08205	2,16073	1,46994	-0,01290	-1,85571
6	BNP 2	4,78657	2,05259	2,24667	1,16516	1,07943	1,08248	1,05288
7	BPCE 1	4,50866	1,92065	2,18642	1,04852	1,02397	0,93599	0,38028
8	BPCE 2	4,68990	1,89220	2,20824	1,12020	1,05840	1,00786	0,62210
9	BPCE 3	4,00686	1,59347	1,90839	0,88513	0,94081	0,94917	0,36910
10	BPCE 4	4,70500	2,02927	2,27421	1,17025	1,08178	1,01142	0,61235
11	BPCE 5	2,52307	1,11840	1,26937	0,50482	0,71051	0,34300	-0,95515
12	CIBA	1,25864	0,62677	0,70871	0,12383	0,35189	0,72751	-0,64570
13	CIC 1	3,50742	1,75779	2,01132	1,09108	1,04455	0,18640	-1,25465
14	Citigroup	3,89900	2,00739	2,24967	0,93997	0,96952	0,68602	-0,15292
15	Cofinimmo	3,51728	1,90462	2,05330	0,74214	0,86148	0,69647	0,02355
16	Cofiroute 1	4,41753	2,03759	2,30924	1,31797	1,14803	0,98459	0,24939
17	Cofiroute 2	5,98551	2,23695	2,49049	2,47680	1,57378	0,76730	-0,15012
18	Credit Agri.	3,11896	2,04013	1,84546	0,82194	0,90661	-0,16189	-1,44825
19	Commerbank 1	3,32009	1,27423	1,75162	1,18675	1,08938	1,01193	-0,49530
20	Commerbank 2	3,20623	1,62332	1,77700	0,88703	0,94182	0,69976	-0,72293
21	E.ON	4,91756	0,50023	1,68510	3,45643	1,85915	0,45973	-1,42459
22	EDF	3,74219	1,36659	1,38201	1,83746	1,35553	0,22935	-1,59269
23	Elia System	3,12280	1,79714	1,87366	0,59704	0,77268	0,68531	-0,04554
24	Fortis 1	2,25612	1,89643	1,78330	0,37864	0,61533	-0,22236	-0,88876
25	Fortis 2	2,66228	2,00406	1,99859	0,43940	0,66287	-0,21931	-0,27974
26	Fortis 3	1,60675	0,74062	0,81278	0,13518	0,36767	1,66434	2,59316
27	Fortis 4	1,40919	0,79564	0,88417	0,16429	0,40533	0,59686	-0,64175
28	Fortis 5	5,98551	2,23695	2,49049	2,47680	1,57378	0,76730	-0,15012
29	GDF	2,57124	1,43823	1,60160	0,32692	0,57177	1,03313	0,66840
30	GE Capital 1	2,90659	1,19446	1,33173	0,62258	0,78904	0,53380	-0,79177
31	GE Capital 2	3,63952	2,12235	2,09553	2,11232	1,45338	0,00001	-1,87068
32	HBOS 1	4,02961	1,71422	1,88408	2,07042	1,43889	0,10340	-1,67836
33	HBOS 2	5,10110	3,45932	2,26255	3,31268	1,82008	-0,16220	-1,78005
34	Intesa Sanpa	3,93868	1,90217	1,93497	2,11757	1,45519	0,14971	-1,68025
35	Merrill Lynch	1,36331	0,54310	0,64299	0,14384	0,37926	0,90299	-0,35746
36	RWE 1	0,94057	0,21075	0,30779	0,06609	0,25707	1,15327	0,21468
37	RWE 2	8,33017	1,10934	1,74793	6,88686	2,62428	1,13247	-0,03126
38	RWE 3	7,92802	3,38774	3,46030	4,63949	2,15395	0,52530	-0,46825
39	SG 1	8,02725	2,19640	3,01175	4,65441	2,15741	0,70847	-0,51365

40	SG 2	4,55148	0,86137	1,20861	1,13677	1,06619	1,49851	1,93666
41	SG 3	9,80665	2,62396	3,20809	8,46197	2,90895	0,63837	-0,84454
42	Suez All.15	1,29664	0,61236	0,71775	0,15589	0,39484	1,00230	-0,35525
43	Telstra	1,59513	0,75434	0,84487	0,15432	0,39284	0,87874	-0,00993
44	TERNA	1,26189	0,68438	0,72746	0,07730	0,27803	0,79193	0,52683
45	VW Intl	2,58479	1,85115	1,87929	0,50472	0,71043	0,00924	-0,72407
46	BBVA	2,57646	2,03100	2,01266	0,47620	0,69007	-0,26477	-0,34098
47	Bank of stcotland	2,72253	1,44644	1,42913	0,43610	0,66038	0,38909	-0,43242
48	CIC 2	2,65853	2,01462	2,06084	0,50996	0,71412	-0,18718	-0,43094
49	CIC 3	2,51080	2,00156	1,97411	0,42584	0,65257	-0,24871	-0,32663
50	SG 4	2,55580	2,02834	2,01970	0,46715	0,68348	-0,22466	-0,42530
51	SG 5	2,53427	2,06344	2,03830	0,44598	0,66782	-0,27849	-0,30752
52	SG 6	1,58742	0,85238	0,94895	0,16686	0,40849	0,97731	0,04059
53	Credit du nord	2,59738	1,11412	1,41511	0,62847	0,79276	0,89975	-0,45467
54	SG 7	1,02600	0,63689	0,71540	0,07961	0,28215	0,60163	-0,62072
55	Finmeccanica	0,76260	0,20613	0,31604	0,05803	0,24089	0,71347	-0,92226
56	Unicredit	2,90075	1,02349	1,30044	0,56078	0,74885	1,16010	0,38102
57	Veneto Banca	4,76059	1,54541	2,07841	1,61858	1,27223	1,24003	0,30272
58	Wendel	3,03915	1,79599	1,79343	0,86062	0,92770	-0,07173	-1,36152
59	RBS	1,50942	0,85124	0,89065	0,21128	0,45965	0,09331	-1,21550
60	Telecom Italia	1,75055	0,93068	1,02175	0,25618	0,50614	0,50250	-0,80487
61	Gr Edit	5,19323	1,13419	0,99663	1,30956	1,14436	0,12468	0,26666
62	Italease Bca	2,46402	1,98430	1,96198	0,29591	0,54398	-0,01090	0,08430
63	Lafarge	3,03915	1,79599	1,79343	0,86062	0,92770	-0,07173	-1,36152
64	Arcelor Fin 1	12,09555	2,56445	3,55500	12,23513	3,49788	1,12785	0,24636
65	Arcelor Fin 2	2,31459	2,09579	1,80380	0,63027	0,79390	-0,17182	-1,65378
66	Bancaja 1	5,13660	1,77890	2,43359	2,14022	1,46295	1,13644	-0,01731
67	Radian	3,73158	1,96095	2,12276	0,80535	0,89741	0,56674	-0,23677
68	KBL	8,18129	2,54008	2,77882	4,28639	2,07036	1,18320	0,92854
69	Bancaja 2	4,28688	1,87201	2,41567	1,66921	1,29198	1,05082	-0,25118
70	Banca Popolare	3,78632	1,08611	1,27721	0,68533	0,82785	1,05439	1,13087
71	BancoPopolare	13,99888	5,18384	6,03077	17,46720	4,17938	0,77424	-0,43692

Appendix II.8. Descriptive Statistics – Eurozone crisis period:

N°	Spread	Range	Median	Mean	St.deviation	Variance	Skewness	Kurtosis
1	Acea	3,10263	1,40683	1,75283	0,73127	0,85514	1,13978	0,03653
2	Credit Agricole 1	1,32587	0,94522	0,99904	0,11561	0,34001	0,55755	-0,44051
3	Airbus	3,46509	2,07385	2,42643	0,82324	0,90733	0,65775	-0,82065
4	BNP Paribas	3,04015	2,91713	2,84678	0,84097	0,91705	-0,15102	-1,31889
5	BNP 1	3,03807	3,35301	3,19987	0,93421	0,96654	-0,07363	-1,36688
6	BNP 2	4,21557	2,27100	2,78164	1,08040	1,03942	0,99504	-0,15002
7	BPCE 1	4,81599	2,39710	2,69513	1,45185	1,20493	0,71740	-0,23754
8	BPCE 2	4,95125	2,33004	2,64150	1,50937	1,22856	0,55330	-0,36754
9	BPCE 3	4,27106	1,93070	2,29240	1,38723	1,17781	0,64803	-0,65715
10	BPCE 4	4,65455	2,39509	2,85294	1,36871	1,16992	0,96583	0,07562
11	BPCE 5	2,01244	1,03620	0,83704	0,37605	0,61323	0,22089	-1,40519
12	CIBA	4,18943	1,86266	1,97934	1,14280	1,06902	0,48838	-0,30301
13	CIC 1	0,94824	0,75518	0,83929	0,06929	0,26323	0,81731	-0,38908
14	Citigroup	3,18915	2,70089	2,93208	0,81343	0,90190	0,61472	-0,77049
15	Cofinimmo	3,54519	2,46406	2,80049	0,93259	0,96570	0,38061	-0,98953
16	Cofiroute 1	3,96386	2,26640	2,78004	1,00866	1,00432	0,71854	-0,61778
17	Cofiroute 2	3,11940	1,92633	1,99021	0,81383	0,90213	0,58128	-0,67027
18	Credit Agri.	2,82299	2,19218	2,11937	0,56223	0,74982	0,01473	-0,63921
19	Commerbank 1	1,96644	0,99681	1,14917	0,21126	0,45963	1,12625	0,60596
20	Commerbank 2	1,88991	0,98741	1,12227	0,22368	0,47295	1,15252	0,43662
21	E.ON	8,80916	4,35133	5,26988	5,48752	2,34255	0,82791	-0,52065
22	EDF	2,87011	2,21183	2,42968	0,43994	0,66328	1,30923	1,07246
23	Elia System	1,84544	1,66370	1,58195	0,21869	0,46764	-0,01008	-0,69703
24	Fortis 1	3,03730	3,65102	3,42537	0,58632	0,76571	-0,44889	-0,64674
25	Fortis 2	3,58554	2,39375	2,85562	1,01231	1,00614	0,61154	-1,00179
26	Fortis 3	1,13953	0,76992	0,82135	0,06451	0,25399	1,27910	1,24869
27	Fortis 4	1,59222	0,82798	0,88581	0,16612	0,40758	0,98044	0,24730
28	Fortis 5	3,11940	1,92633	1,99021	0,81383	0,90213	0,58128	-0,67027
29	GDF	6,79613	2,98082	3,15976	1,99451	1,41227	1,33179	2,45675
30	GE Capital 1	2,45641	1,15247	1,04620	0,45982	0,67810	0,43690	-0,71119
31	GE Capital 2	3,03807	3,35301	3,19987	0,93421	0,96654	-0,07363	-1,36688
32	HBOS 1	3,14741	2,34929	2,41035	0,84975	0,92182	0,34486	-0,86144
33	HBOS 2	4,29261	2,30864	2,40926	1,44167	1,20070	0,35778	-0,77502
34	Intesa Sanpa	3,27479	1,87869	1,94757	0,94314	0,97116	0,20615	-0,93907
35	Merrill Lynch	1,24449	0,70883	0,76119	0,08717	0,29524	0,98385	0,29572
36	RWE 1	0,91196	0,25621	0,29112	0,05697	0,23868	0,78977	-0,20225
37	RWE 2	3,59991	0,20084	0,51570	0,67913	0,82409	1,36690	1,32434
38	RWE 3	8,29525	3,59486	3,80388	4,53507	2,12957	0,80107	0,07054
39	SG 1	7,54935	2,63626	3,58566	6,20602	2,49119	0,76052	-0,97564

40	SG 2	7,00677	1,04337	1,90010	3,25417	1,80393	1,24109	0,34884
41	SG 3	7,86983	1,35750	1,81001	3,87021	1,96729	1,53314	1,51882
42	Suez All.15	1,06749	0,64064	0,63295	0,07538	0,27455	0,48408	-0,44801
43	Telstra	1,07202	0,85529	0,95684	0,06816	0,26107	1,53134	1,54602
44	TERNA	1,14968	0,78934	0,83436	0,07197	0,26828	0,80871	0,29523
45	VW Intl	3,82017	2,14871	2,49749	1,15033	1,07254	0,63126	-0,63432
46	BBVA	4,13537	2,22979	2,66117	1,15723	1,07575	0,81268	-0,42669
47	Bank of stcotland	5,15130	1,69855	2,27456	2,02957	1,42463	1,13128	0,04041
48	CIC 2	4,64200	2,40667	2,74261	1,37649	1,17324	0,68065	-0,43870
49	CIC 3	4,39291	2,22954	2,75933	1,26010	1,12254	0,95373	-0,20876
50	SG 4	4,20900	2,27662	2,81546	1,30324	1,14159	0,95007	-0,30523
51	SG 5	4,44317	2,36582	2,92038	1,48533	1,21874	0,86956	-0,57214
52	SG 6	1,45087	0,98124	0,95223	0,12188	0,34911	0,10736	-0,81384
53	Credit du nord	1,79660	0,74977	0,68471	0,12039	0,34697	1,00811	2,13966
54	SG 7	2,18835	0,81138	1,06099	0,35835	0,59862	1,07822	-0,20304
55	Finmeccanica	0,99112	0,23805	0,33224	0,07142	0,26724	1,07364	0,06012
56	Unicredit	1,20606	0,84859	0,93721	0,09802	0,31308	0,89173	-0,11689
57	Veneto Banca	2,46143	1,56480	1,62162	0,37274	0,61052	0,44189	-0,67311
58	Wendel	2,99574	2,23548	2,29064	0,37289	0,61065	0,27417	0,41993
59	RBS	7,83272	2,99684	3,22810	3,32737	1,82411	0,88948	0,71029
60	Telecom Italia	7,55766	3,21551	3,51138	3,18894	1,78576	0,68982	0,19355
61	Gr Edit	16,60161	4,30639	4,84761	14,02638	3,74518	1,26376	1,39062
62	Italease Bca	7,83050	3,67582	4,86188	6,64618	2,57802	0,63172	-1,14257
63	Lafarge	2,99574	2,23548	2,28511	0,36269	0,60224	0,24956	0,49246
64	Arcelor Fin 1	11,97012	4,47941	5,38637	11,15984	3,34064	0,83002	-0,40950
65	Arcelor Fin 2	2,52043	2,88877	2,88629	0,46494	0,68186	0,07071	-1,13252
66	Bancaja 1	2,90957	1,92257	2,08587	0,67856	0,82375	0,61361	-0,63830
67	Radian	4,51923	2,03195	2,42020	1,41820	1,19088	1,03264	-0,10054
68	KBL	8,90607	3,01135	3,51051	3,83611	1,95860	1,24399	1,51073
69	Bancaja 2	4,15433	3,06084	3,20320	1,25722	1,12126	0,75822	-0,37517
70	Banca Popolare	14,08030	3,91513	5,43457	14,96969	3,86907	1,14436	0,27356
71	BancoPopolare	5,24968	2,60188	2,68254	1,99533	1,41256	0,29044	-0,93605

Appendix II.9.a Correlation Matrix – Part 1

Variables	Acea	Airbus	BNP 1	BNP 2	BNP 3	BPCE 1	BPCE 2	BPCE 3	BPCE 4	BPCE 5	BOS	BBVA	CIBA	CIC 1	CIC 2	CIC 3	Citi group
Acea	1																
Airbus	0,619	1															
BNP 1	0,942	0,667	1														
BNP 2	0,738	0,306	0,738	1													
BNP 3	0,671	0,432	0,691	0,945	1												
BPCE 1	0,936	0,701	0,970	0,679	0,633	1											
BPCE 2	0,950	0,718	0,972	0,706	0,667	0,974	1										
BPCE 3	0,944	0,729	0,971	0,696	0,659	0,972	0,996	1									
BPCE 4	0,954	0,701	0,960	0,673	0,625	0,968	0,984	0,985	1								
BPCE 5	0,923	0,707	0,968	0,689	0,654	0,971	0,978	0,979	0,961	1							
Bank of stcotland	0,685	0,874	0,704	0,510	0,626	0,731	0,772	0,774	0,754	0,728	1						
BBVA	0,898	0,413	0,858	0,791	0,699	0,832	0,860	0,847	0,857	0,845	0,539	1					
CIBA	0,253	0,730	0,305	-0,254	-0,163	0,343	0,349	0,364	0,365	0,330	0,545	0,040	1				
CIC 1	0,906	0,670	0,966	0,702	0,672	0,962	0,946	0,945	0,929	0,963	0,677	0,818	0,282	1			
CIC 2	0,915	0,635	0,969	0,721	0,671	0,960	0,948	0,947	0,932	0,958	0,651	0,822	0,248	0,976	1		
CIC 3	0,934	0,737	0,971	0,683	0,667	0,973	0,970	0,972	0,959	0,972	0,735	0,817	0,352	0,974	0,970	1	
Citigroup	0,767	0,834	0,784	0,596	0,688	0,785	0,817	0,816	0,805	0,790	0,928	0,617	0,433	0,774	0,750	0,805	1
Cofinimmo	0,815	0,573	0,815	0,866	0,883	0,773	0,810	0,809	0,797	0,779	0,722	0,779	0,056	0,791	0,791	0,799	0,820
Cofiroute 1	0,667	0,853	0,664	0,385	0,498	0,686	0,704	0,708	0,699	0,682	0,841	0,439	0,555	0,675	0,646	0,731	0,900
Cofiroute 2	0,701	0,934	0,710	0,291	0,375	0,749	0,752	0,762	0,755	0,741	0,851	0,460	0,734	0,722	0,689	0,783	0,861
Commerbank 1	0,807	0,189	0,754	0,809	0,699	0,708	0,711	0,696	0,705	0,708	0,326	0,813	-0,234	0,755	0,774	0,720	0,539
Commerbank 2	0,737	0,369	0,675	0,806	0,810	0,638	0,663	0,650	0,644	0,649	0,535	0,698	-0,148	0,684	0,684	0,675	0,697
Credit Agricole 1	0,735	0,928	0,786	0,585	0,698	0,798	0,826	0,831	0,796	0,808	0,935	0,588	0,493	0,784	0,757	0,832	0,915
Credit Agricole 2	0,789	0,383	0,860	0,754	0,698	0,835	0,788	0,776	0,764	0,825	0,435	0,793	-0,021	0,890	0,890	0,834	0,561
Credit du nord	0,935	0,586	0,974	0,777	0,721	0,947	0,944	0,942	0,929	0,945	0,630	0,867	0,199	0,968	0,973	0,959	0,744

E.ON	0,767	0,792	0,834	0,456	0,465	0,866	0,858	0,865	0,847	0,858	0,764	0,661	0,526	0,830	0,817	0,853	0,714
EDF	0,892	0,824	0,902	0,673	0,703	0,909	0,939	0,937	0,928	0,911	0,896	0,753	0,410	0,885	0,872	0,921	0,922
Elia System	0,767	0,834	0,784	0,596	0,688	0,785	0,817	0,816	0,805	0,790	0,928	0,617	0,433	0,774	0,750	0,805	1,000
Finmeccanica	0,879	0,373	0,871	0,701	0,578	0,849	0,834	0,824	0,820	0,849	0,402	0,817	0,047	0,865	0,883	0,841	0,538
Fortis 1	0,796	0,848	0,798	0,570	0,641	0,826	0,861	0,861	0,854	0,816	0,969	0,652	0,497	0,763	0,745	0,818	0,942
Fortis 2	0,671	0,433	0,691	0,945	1,000	0,633	0,667	0,659	0,625	0,654	0,626	0,700	-0,163	0,672	0,671	0,667	0,688
Fortis 3	0,852	0,629	0,854	0,796	0,801	0,830	0,846	0,850	0,832	0,846	0,702	0,728	0,083	0,864	0,867	0,873	0,842
Fortis 4	0,776	0,634	0,766	0,795	0,835	0,738	0,779	0,778	0,765	0,754	0,766	0,683	0,110	0,745	0,744	0,772	0,836
Fortis 5	0,782	0,665	0,755	0,725	0,761	0,750	0,790	0,792	0,779	0,762	0,773	0,663	0,146	0,748	0,737	0,783	0,856
GDF	0,882	0,806	0,898	0,599	0,598	0,902	0,910	0,910	0,895	0,908	0,773	0,772	0,471	0,892	0,881	0,917	0,817
GE Capital 1	0,853	0,805	0,808	0,524	0,559	0,832	0,851	0,844	0,858	0,807	0,885	0,699	0,519	0,779	0,758	0,832	0,880
GE Capital 2	0,646	0,887	0,677	0,189	0,261	0,733	0,721	0,726	0,719	0,716	0,762	0,405	0,706	0,692	0,660	0,750	0,755
HBOS 1	0,892	0,716	0,885	0,754	0,765	0,876	0,916	0,913	0,901	0,884	0,872	0,786	0,288	0,851	0,852	0,880	0,936
HBOS 2	0,943	0,711	0,953	0,687	0,657	0,934	0,942	0,941	0,938	0,929	0,741	0,810	0,352	0,937	0,934	0,952	0,859
Intesa Sanpa	0,906	0,564	0,865	0,547	0,424	0,870	0,880	0,875	0,888	0,868	0,545	0,798	0,330	0,830	0,838	0,849	0,618
Merrill Lynch	0,776	0,879	0,800	0,355	0,391	0,831	0,843	0,844	0,842	0,815	0,853	0,561	0,703	0,776	0,754	0,829	0,845
RWE 1	0,776	0,845	0,763	0,403	0,461	0,815	0,812	0,808	0,826	0,781	0,830	0,632	0,568	0,751	0,717	0,801	0,817
RWE 2	0,841	0,793	0,878	0,570	0,583	0,888	0,882	0,878	0,863	0,884	0,765	0,714	0,470	0,884	0,871	0,894	0,817
RWE 3	0,863	0,782	0,899	0,660	0,675	0,895	0,911	0,909	0,891	0,899	0,816	0,783	0,421	0,883	0,870	0,908	0,820
SG 1	0,954	0,649	0,978	0,748	0,696	0,952	0,972	0,972	0,961	0,960	0,696	0,873	0,292	0,952	0,956	0,962	0,782
SG 2	0,953	0,637	0,977	0,771	0,720	0,956	0,967	0,965	0,956	0,956	0,699	0,871	0,263	0,953	0,962	0,963	0,787
SG 3	0,959	0,576	0,938	0,748	0,665	0,915	0,942	0,933	0,939	0,918	0,675	0,889	0,227	0,894	0,903	0,907	0,769
SG 4	0,951	0,635	0,973	0,781	0,731	0,948	0,967	0,965	0,955	0,950	0,711	0,877	0,258	0,944	0,949	0,954	0,796
SG 5	0,954	0,600	0,977	0,768	0,706	0,953	0,959	0,955	0,947	0,952	0,662	0,883	0,237	0,956	0,963	0,956	0,758
SG 6	0,954	0,600	0,977	0,765	0,705	0,952	0,957	0,953	0,947	0,951	0,658	0,881	0,236	0,957	0,964	0,956	0,760
SG 7	0,942	0,579	0,966	0,745	0,681	0,935	0,938	0,935	0,930	0,938	0,634	0,885	0,235	0,947	0,953	0,941	0,744
Suez All.15	0,888	0,845	0,886	0,648	0,683	0,906	0,931	0,933	0,918	0,897	0,881	0,753	0,442	0,866	0,854	0,919	0,884
Telstra	0,483	0,892	0,481	0,029	0,171	0,547	0,545	0,552	0,565	0,518	0,768	0,253	0,813	0,487	0,436	0,565	0,702
TERNA	0,971	0,588	0,932	0,733	0,656	0,916	0,935	0,927	0,936	0,909	0,694	0,890	0,255	0,889	0,898	0,904	0,771

Unicredit	0,865	0,705	0,819	0,445	0,419	0,858	0,854	0,843	0,875	0,809	0,762	0,704	0,517	0,791	0,775	0,825	0,761
VW Intl	0,640	0,926	0,657	0,284	0,368	0,718	0,729	0,739	0,724	0,708	0,822	0,401	0,639	0,656	0,632	0,732	0,807
Arcelor Fin 1	0,744	0,899	0,772	0,419	0,495	0,801	0,809	0,821	0,799	0,809	0,824	0,548	0,563	0,782	0,754	0,840	0,854
Arcelor Fin 2	0,716	0,529	0,765	0,770	0,810	0,735	0,712	0,714	0,686	0,752	0,592	0,652	0,034	0,803	0,780	0,772	0,716
Bancaja 1	0,819	0,303	0,814	0,801	0,694	0,768	0,789	0,785	0,783	0,800	0,398	0,937	-0,081	0,785	0,804	0,774	0,521
Bancaja 2	0,814	0,295	0,820	0,794	0,685	0,770	0,788	0,784	0,780	0,802	0,378	0,922	-0,086	0,801	0,821	0,783	0,515
Banca Popolare	0,814	0,181	0,743	0,580	0,410	0,717	0,723	0,713	0,723	0,725	0,224	0,766	-0,024	0,722	0,753	0,713	0,366
BancoPopolare	0,863	0,267	0,843	0,750	0,598	0,795	0,801	0,796	0,801	0,805	0,321	0,871	-0,058	0,819	0,845	0,799	0,493
Gr Edit	0,718	0,533	0,769	0,774	0,814	0,739	0,716	0,718	0,689	0,756	0,596	0,652	0,036	0,806	0,784	0,776	0,720
Italease Bca	0,899	0,572	0,895	0,608	0,552	0,890	0,881	0,875	0,878	0,870	0,612	0,772	0,287	0,898	0,907	0,899	0,758
KBL	0,791	0,427	0,849	0,810	0,782	0,816	0,781	0,774	0,755	0,812	0,520	0,739	-0,050	0,888	0,883	0,831	0,673
Lafarge	0,802	0,906	0,829	0,510	0,587	0,844	0,864	0,865	0,852	0,840	0,887	0,635	0,555	0,816	0,784	0,867	0,905
Radian	0,953	0,723	0,958	0,684	0,647	0,966	0,980	0,977	0,976	0,955	0,800	0,839	0,387	0,929	0,927	0,955	0,839
RBS	0,870	0,635	0,859	0,766	0,765	0,835	0,876	0,870	0,855	0,852	0,807	0,766	0,200	0,829	0,838	0,842	0,902
Telecom Italia	0,907	0,659	0,914	0,589	0,538	0,919	0,907	0,903	0,897	0,927	0,624	0,775	0,326	0,934	0,927	0,927	0,739
Veneto Banca	0,854	0,273	0,830	0,703	0,555	0,790	0,789	0,783	0,795	0,765	0,327	0,836	-0,009	0,805	0,834	0,792	0,461
Wendel	0,545	0,941	0,585	0,266	0,423	0,626	0,641	0,654	0,633	0,625	0,879	0,318	0,665	0,591	0,550	0,664	0,856

Appendix II.9.b Correlation Matrix – Part 2

Variables	Cofi route 1	Cofi route 2	Commerz bank 1	Commerz bank 2	CA 1	CA 2	C.du nord	E.ON	EDF	Elia System	Finmec canica	Fortis 1
Cofiroute 1	**1**											
Cofiroute 2	0,913	**1**										
Commerbank 1	0,389	0,326	**1**									
Commerbank 2	0,544	0,443	0,871	**1**								
Credit Agricole 1	0,852	0,860	0,405	0,584	**1**							
Credit Agricole 2	0,406	0,429	0,819	0,684	0,558	**1**						
Credit du nord	0,622	0,652	0,835	0,733	0,730	0,902	**1**					
E.ON	0,611	0,775	0,411	0,422	0,814	0,667	0,772	**1**				
EDF	0,820	0,842	0,617	0,693	0,925	0,691	0,866	0,869	**1**			
Elia System	0,900	0,861	0,539	0,697	0,915	0,561	0,744	0,714	0,922	**1**		
Finmeccanica	0,442	0,479	0,867	0,694	0,501	0,869	0,906	0,645	0,713	0,538	**1**	
Fortis 1	0,844	0,850	0,460	0,599	0,918	0,537	0,728	0,802	0,938	0,942	0,531	**1**
Fortis 2	0,498	0,376	0,699	0,808	0,698	0,698	0,720	0,465	0,703	0,688	0,577	0,642
Fortis 3	0,732	0,679	0,784	0,849	0,800	0,755	0,874	0,666	0,874	0,842	0,750	0,767
Fortis 4	0,674	0,635	0,685	0,834	0,822	0,631	0,770	0,622	0,855	0,836	0,605	0,789
Fortis 5	0,733	0,699	0,666	0,815	0,817	0,569	0,752	0,619	0,852	0,856	0,587	0,806
GDF	0,730	0,836	0,630	0,654	0,837	0,741	0,877	0,895	0,920	0,817	0,782	0,831
GE Capital 1	0,832	0,869	0,527	0,621	0,849	0,579	0,753	0,818	0,930	0,880	0,632	0,922
GE Capital 2	0,802	0,896	0,221	0,302	0,799	0,435	0,589	0,782	0,770	0,755	0,452	0,781
HBOS 1	0,797	0,771	0,709	0,771	0,858	0,686	0,866	0,743	0,947	0,936	0,717	0,924
HBOS 2	0,767	0,797	0,758	0,722	0,805	0,789	0,944	0,784	0,915	0,859	0,814	0,830
Intesa Sanpa	0,535	0,651	0,686	0,550	0,609	0,691	0,837	0,772	0,795	0,618	0,860	0,668
Merrill Lynch	0,838	0,914	0,368	0,420	0,841	0,515	0,715	0,827	0,879	0,845	0,582	0,887
RWE 1	0,797	0,843	0,385	0,453	0,834	0,536	0,685	0,825	0,862	0,817	0,536	0,881
RWE 2	0,732	0,822	0,611	0,653	0,824	0,747	0,858	0,879	0,903	0,817	0,772	0,813

RWE 3	0,716	0,776	0,599	0,635	0,878	0,750	0,874	0,904	0,945	0,820	0,736	0,856
SG 1	0,670	0,708	0,782	0,705	0,771	0,829	0,978	0,803	0,903	0,782	0,876	0,787
SG 2	0,666	0,698	0,800	0,728	0,772	0,846	0,985	0,799	0,906	0,787	0,878	0,790
SG 3	0,642	0,666	0,820	0,747	0,708	0,777	0,934	0,763	0,897	0,769	0,884	0,783
SG 4	0,670	0,697	0,798	0,734	0,778	0,823	0,977	0,793	0,910	0,796	0,866	0,798
SG 5	0,637	0,672	0,817	0,721	0,737	0,865	0,987	0,789	0,885	0,758	0,902	0,760
SG 6	0,641	0,674	0,821	0,725	0,734	0,867	0,988	0,782	0,883	0,760	0,902	0,756
SG 7	0,604	0,660	0,822	0,724	0,711	0,869	0,980	0,782	0,861	0,744	0,885	0,730
Suez All.15	0,813	0,846	0,575	0,653	0,929	0,651	0,849	0,859	0,961	0,884	0,679	0,924
Telstra	0,779	0,872	0,007	0,182	0,750	0,199	0,381	0,661	0,662	0,702	0,193	0,750
TERNA	0,629	0,689	0,805	0,743	0,714	0,777	0,924	0,791	0,894	0,771	0,868	0,791
Unicredit	0,714	0,795	0,533	0,508	0,718	0,628	0,761	0,821	0,864	0,761	0,704	0,846
VW Intl	0,819	0,892	0,248	0,399	0,853	0,366	0,570	0,756	0,801	0,807	0,422	0,845
Arcelor Fin 1	0,823	0,904	0,406	0,529	0,892	0,533	0,704	0,807	0,860	0,854	0,534	0,841
Arcelor Fin 2	0,569	0,527	0,709	0,772	0,699	0,814	0,801	0,590	0,735	0,716	0,697	0,641
Bancaja 1	0,344	0,350	0,835	0,685	0,501	0,790	0,853	0,544	0,641	0,521	0,787	0,513
Bancaja 2	0,348	0,352	0,851	0,695	0,495	0,813	0,868	0,547	0,640	0,515	0,810	0,493
Banca Popolare	0,298	0,338	0,845	0,608	0,292	0,721	0,788	0,471	0,552	0,366	0,926	0,378
BancoPopolare	0,346	0,372	0,915	0,717	0,431	0,833	0,895	0,546	0,644	0,493	0,907	0,469
Gr Edit	0,574	0,531	0,711	0,776	0,704	0,814	0,805	0,593	0,740	0,720	0,700	0,644
Italease Bca	0,706	0,719	0,788	0,680	0,655	0,801	0,916	0,685	0,814	0,758	0,854	0,709
KBL	0,528	0,495	0,846	0,793	0,636	0,927	0,900	0,616	0,741	0,673	0,837	0,596
Lafarge	0,871	0,896	0,456	0,570	0,935	0,580	0,754	0,821	0,920	0,905	0,586	0,916
Radian	0,720	0,788	0,706	0,676	0,821	0,764	0,928	0,860	0,945	0,839	0,809	0,882
RBS	0,760	0,706	0,752	0,808	0,797	0,700	0,855	0,684	0,913	0,902	0,754	0,860
Telecom Italia	0,679	0,740	0,726	0,650	0,725	0,819	0,906	0,800	0,851	0,739	0,885	0,720
Veneto Banca	0,389	0,859	0,646	0,427	0,817	0,884	0,582	0,637	0,461	0,869	0,467	0,555
Wendel	0,894	0,153	0,378	0,900	0,300	0,501	0,663	0,773	0,856	0,260	0,844	0,423

Appendix III

Credit spread sample and statistics

This part regroups all the appendices of chapter III.

Appendix III.1. The corporate bond sample:

N	ISIN	Bond issuer	Sector	Maturity	Rating
1	XS0196712086,XX,186	Acea	Industry - cars	2014	Investment grade
2	XS0168193364,XX,47	AIG	Financial	2015	Investment grade
3	XS0176914579,XX,186	Airbus	Industy -aircraft	2018	Investment grade
4	XS0201674594,XX,186	Bank of stcotland	Financial	2014	Investment grade
5	ES0413211055,XX,186	BBVA	Financial	2014	Investment grade
6	FR0000189219,XX,25	BNP Paribas 1	Financial	2015	Investment grade
7	XS0099950213,XX,47	BNP Paribas 2	Financial	2019	Investment grade
8	XS0124269506,XX,186	BNP Parisbas 3	Financial	2016	Investment grade
9	FR0000188948,XX,25	BPCE	Financial	2015	Investment grade
10	XS0201674594,XX,186	Bank of Scotland	Financial	2014	Investment grade
11	XS0197646218,XX,186	Citigroup	Financial	2019	Investment grade
12	FR0010054031,XX,47	BPCE	Financial	2020	Investment grade
13	XS0193197505,XX,186	Cofinimmo	Real estate	2014	Investment grade
14	FR0000487217,XX,186	Cofiroute-Vinci 1	Industry-services	2016	Investment grade
15	XS0148579153,XX,186	E.ON	Industry - energy	2017	Investment grade
16	XS0107242520,XX,47	Commerzbank 1	Financial	2020	Investment grade
17	DE0008029513,XX,13	Commerzbank 2	Financial	2018	Investment grade
18	XS0183046431,XX,47	Credit Agricole 1	Financial	2015	Investment grade
19	XS0170386998,XX,186	Credit Agricole 2	Financial	2018	Investment grade
20	XS0195963623,XX,47	Credit Agricole 3	Financial	2019	Investment grade
21	FR0010082933,XX,25	Credit du nord	Financial	2016	Investment grade
22	XS0106975492,XX,47	CSFB	Financial	2015	Investment grade
23	XS0161774665,XX,47	DFS	Industry	2018	Investment grade
24	XS0125172972,XX,186	DZ Bank 1	Financial	2016	Investment grade
25	XS0114128829,XX,47	DZ Bank 2	Financial	2020	Investment grade
26	XS0195980551,XX,47	EBS	Financial	2014	Investment grade
27	FR0000487258,XX,186	EDF	Industry - energy	2016	Investment grade

28	BE0119550466,XX,186	Elia System	Industry - energy	2019	Investment grade
29	XS0201775946,XX,47	Erste 1	Financial	2019	Investment grade
30	XS0196891153,XX,47	Erste 2	Financial	2016	Investment grade
31	XS0192847860,XX,47	Erste 3	Financial	2016	Investment grade
32	XS0175316628,XX,47	Erste 4	Financial	2018	Investment grade
33	XS0122720732,XX,186	Fortis	Financial	2016	Investment grade
34	FR0000472334,XX,186	GDF	Industry - energy	2018	Investment grade
35	XS0197508764,XX,186	GE Capital	Financial	2014	Investment grade
36	XS0165449736,XX,186	HBOS 1	Financial	2015	Investment grade
37	XS0192560653,XX,186	HBOS 2	Financial	2016	Investment grade
38	XS0201271045,XX,186	Intesa Sanpa 1	Financial	2014	Investment grade
39	XS0197688053,XX,47	Intesa Sanpa 2	Financial	2014	Investment grade
40	XS0197079972,XX,186	Merrill Lynch	Financial	2014	Investment grade
41	XS0196302425,XX,186	RWE 1	Industry - energy	2014	Investment grade
42	XS0172851650,XX,186	RWE 2	Industry - energy	2018	Investment grade
43	XS0158197821,XX,186	Salliemae 1	Financial	2021	Investment grade
44	XS0168279080,XX,186	Salliemae 2	Financial	2024	Investment grade
45	XS0187454706,XX,186	Salliemae 3	Financial	2024	Investment grade
46	XS0112998223,XX,186	Scor	Financial	2020	Investment grade
47	FR0010154906,XX,25	SG 1	Financial	2017	Investment grade
48	FR0000189110,XX,25	SG 2	Financial	2015	Investment grade
49	XS0110673950,XX,186	SG 3	Financial	2015	Investment grade
50	FR0000487886,XX,186	SG 4	Financial	2016	Investment grade
51	XS0200388451,XX,47	SG 5	Financial	2014	Investment grade
52	FR0010016790,XX,25	SG 6	Financial	2015	Investment grade
53	FR0010042226,XX,25	SG 7	Financial	2016	Investment grade
54	FR0010071027,XX,25	SG 8	Financial	2016	Investment grade
55	XS0191075588,XX,47	SG 9	Financial	2016	Investment grade
56	XS0196578255,XX,186	Telstra	Telecomunication	2014	Investment grade
57	XS0203714802,XX,186	TERNA	Industry - energy	2014	Investment grade
58	XS0168881760,XX,186	VW Intl	Industry - cars	2018	Investment grade
59	XS0204395213,XX,186	Arcelor Finance 1	Financial	2014	Speculative grade
60	XS0215451559,XX,186	Banco Popolare	Financial	2015	Speculative grade
61	XS0112532535,XX,47	Bank of Austria 1	Financial	2015	Speculative grade
62	AT0000541719,XX,50	Bank of Austria 2	Financial	2020	Speculative grade
63	XS0203156798,XX,186	Italease Bca	Financial	2014	Speculative grade
64	XS0136805404,XX,186	Dexia	Financial	2016	Speculative grade
65	XS0182242247,XX,186	Finmeccanica	Industry - aircraft	2018	Speculative grade
66	XS0196630270,XX,186	Lafarge	Indus - construction	2014	Speculative grade
67	XS0167127447,XX,186	RBS	Financial	2015	Speculative grade
68	XS0184373925,XX,186	Telecom Italia	Telecomunication	2019	Speculative grade
69	DE0002516564	Unicredit	Financial	2015	Speculative grade
70	XS0110196093,XX,47	Unicredit	Financial	2015	Speculative grade

Appendix III.2. Descriptive statistics (changes data):

N	Variable	Observt°	Mean	Std.dev	Min	Max
1	Credit spread	8400	.0153792	.3295783	-3.618723	4.284408
2	Leverage	8400	-.0599128	.3612648	-2.255833	2.174167
3	Equity Return	8400	-.004644	.1116548	-2.859987	2.876735
4	Historic volatility 180	8400	.0000282	.0029181	-.0532627	.052981
5	10yrs treasury rate	8400	-.0248545	.1491221	-.4156894	.4054314
6	Dividend yield	8400	-.0063149	1.687383	-0.51107	0.436213
7	EUROSTOXX50 idx	8400	.0013025	.0471258	-.1952399	.1236053
8	VSTOXX Index	8400	-.028446	4.771173	-12.14335	32.35719
9	Term slope 30-10y	8400	-.0001305	.0757772	-.2796121	.252674
10	Business Climate	8400	-.00325	.2481349	-.93	.66
11	LTROs	8400	81.93426	124070.9	-540387.7	556582.2
12	Bid-Ask spread	8400	.0010589	1.637426	-63.46774	77.64516
13	Market liquidity	8400	.0007794	.1279889	-.3507805	.9217194
14	Lag spread	8400	.0170552	.3229103	-3.618723	4.284408
15	Lag equity return	8400	-.0042631	.1114596	-2.859987	2.876735
16	Lag Market return	8400	.0013207	.0471162	-.1952399	.1236053
17	Lag 10 yrs rate	8400	-.0243212	.1486752	-.4156894	.4054314
18	Lag Market liquidity	8400	.0010855	.1279524	-.3507805	.9217194
19	Market value	8400	14.18293	3442.74	-58205.22	45820.54
20	Number of employees	8400	189.7446	4383.973	-60100	187093
21	Confidence Index	8400	-.0533333	2.109112	-6.6	5.4
22	Historic volatility 24	8400	.0003495	.1583445	-2.97095	2.662373
23	S&P Europe 350 idx	8400	.0029411	.0416258	-.1913196	.1108446
24	Term slope 5-2y	8400	-.003661	.105009	-.3171485	.4172895
25	OIS rate	8400	-.0166961	.1613529	-.8931761	.2318333

Appendix III.3.1. Correlation Matrix (Part 1):

	Credit spread	Leverage	Equity Return	His.Vol 180	10yrs rate	Dividend yield	E.STOXX 50 idx	VSTOXX Index	Term slope 30-10y	Business Climate
Credit spread	1.0000									
Leverage	0.0161	1.0000								
Equity Return	-0.2512	0.0354	1.0000							
Historic volatility 180	-0.0332	-0.0255	0.0674	1.0000						
10yrs treasury rate	-0.3134	0.0385	0.1446	0.1466	1.0000					
Dividend yield	0.0952	-0.0143	-0.2444	0.0028	-0.0442	1.0000				
EUROSTOXX50 idx	-0.3574	0.0275	0.5561	0.0430	0.2684	-0.1742	1.0000			
VSTOXX Index	0.2679	-0.0018	-0.3606	-0.0259	-0.1772	0.1621	-0.7382	1.0000		
Term slope 30-10y	-0.0568	-0.0390	0.0662	0.0383	-0.2725	-0.0161	0.0318	-0.0012	1.0000	
Business Climate	-0.2185	0.0699	0.2989	0.1042	0.1774	-0.1087	0.4236	-0.1534	0.1298	1.0000
Bid-Ask spread	0.0486	0.0020	-0.0132	0.0030	-0.0164	0.0038	-0.0219	0.0243	0.0025	-0.0222
Market liquidity	0.2747	0.0383	-0.2185	-0.0617	-0.0744	0.1310	-0.3779	0.5635	-0.1547	-0.1423
Lag spread	0.3413	0.0149	-0.0643	-0.0829	-0.1202	0.0476	-0.0476	-0.0204	-0.0265	-0.1994
Lag equity return	-0.2176	0.0388	0.1889	0.0902	0.1648	-0.0574	0.1650	0.0460	0.0010	0.2530
Lag Market return	-0.2868	0.0244	0.1860	0.1064	0.2933	-0.0477	0.2504	0.0569	-0.0371	0.3725
Lag 10 yrs rate	-0.0984	0.0123	-0.0330	0.1344	0.2985	0.0057	-0.0970	0.1043	-0.0950	0.1050
Lag Market liquidity	0.1850	0.0190	-0.0719	-0.0936	-0.1166	0.0818	-0.0395	-0.0101	-0.0921	-0.2631
Market value	-0.2292	0.0348	0.5514	0.0063	0.1364	-0.1397	0.4401	-0.3016	0.0168	0.2193
Number of employees	0.0190	0.0060	-0.0214	0.0126	0.0088	0.0162	-0.0192	0.0344	0.0163	-0.0290
Confidence Index	-0.2746	0.0481	0.3029	0.0974	0.2634	-0.0755	0.4592	-0.2062	0.0694	0.6308
LTROs	-0.0028	-0.0039	-0.0010	0.0078	0.0006	-0.0009	-0.0018	-0.0007	-0.0007	-0.0009

Historic volatility 24	0.0428	-0.0042	-0.0771	0.3333	0.0244	-0.0107	-0.1023	0.1709	0.0743	-0.0386
S&P Europe 350 idx	-0.3542	0.0386	0.5419	0.0375	0.2423	-0.1723	0.9620	-0.7238	0.0268	0.4559
Term slope 5-2y	-0.0341	-0.0318	-0.0647	-0.0699	0.1992	0.0493	-0.1107	0.0355	0.1325	-0.0999
OIS rate	-0.2273	0.0861	0.3071	0.3305	0.2902	-0.0988	0.4356	-0.2172	-0.0439	0.4867

Appendix III.3.2. Correlation Matrix (Part 2):

	Bid-Ask spread	Market liquidity	Lag spread	Lag equity return	Lag Mket return	Lag 10yrs rate	Lag Mket liquidity	Market value	Number of employees	Confidence Index
Bid-Ask spread	1.0000									
Market liquidity	0.0155	1.0000								
Lag spread	0.0196	0.1215	1.0000							
Lag equity return	-0.0070	-0.0823	-0.2667	1.0000						
Lag Market return	-0.0052	-0.1735	-0.3678	0.5553	1.0000					
Lag 10 yrs rate	-0.0095	-0.0091	-0.3258	0.1415	0.2671	1.0000				
Lag Market liquidity	0.0172	0.2625	0.2796	-0.2200	-0.3794	-0.0771	1.0000			
Market value	0.0022	-0.1472	-0.0563	0.1486	0.1241	-0.0271	-0.0611	1.0000		
Number of employees	0.0100	-0.0424	-0.0037	0.0042	0.0076	0.0070	0.0122	0.0083	1.0000	
Confidence Index	-0.0147	-0.1504	-0.1881	0.2806	0.3885	0.0660	-0.1521	0.2362	-0.0016	1.0000
LTROs	-0.0032	0.0005	0.0009	0.0030	-0.0029	-0.0020	-0.0026	-0.0011	0.0050	-0.0022
Historic volatility 24	0.0055	-0.0061	-0.0185	0.0439	0.0826	-0.0339	-0.0917	-0.0816	0.0534	-0.0020
S&P Europe 350 idx	-0.0257	-0.3751	-0.0602	0.1751	0.2581	-0.0893	-0.0804	0.4378	-0.0211	0.4837
Term slope 5-2y	-0.0016	0.0532	0.0489	-0.0607	-0.0740	0.0471	-0.0179	-0.0293	-0.0116	-0.0708
OIS rate	-0.0106	-0.2536	-0.2062	0.2636	0.3799	0.1899	-0.2802	0.2067	0.0053	0.4193

	LTROs	Hist Vol 24	S&P 350 idx	T.slope 5-2y	OIS rate
LTROs	1.0000				
Historic volatility 24	-0.0008	1.0000			
S&P Europe 350 idx	-0.0011	-0.0870	1.0000		
Term slope 5-2y	0.0045	0.0394	-0.1177	1.0000	
OIS rate	-0.0053	0.0884	0.4391	-0.3610	1.0000

Appendix III.4. The CDS sample:

N	CDS Entity	Maturity	Description
1	LAFARGE	SNR 10Y	CR CDS PREM. MID
2	ACEA	SNR 10Y	CR CDS PREM. MID
3	AIRBUS GROUP N.V.	SNR 10Y	CR CDS PREM. MID
4	BANCA ITALEASE SPA	SNR 10Y	MM CDS PREM. MID
5	BBV ARGENTARIA SA	SNR 10Y	CR CDS PREM. MID
6	BK OF SCOTLAND PLC	SNR 10Y	CR CDS PREM. MID
7	COMMERZBANK AG	SNR 10Y	CR CDS PREM. MID
8	CREDIT AGRICOLE SA	SNR 10Y	CR CDS PREM. MID
9	DEXIA CREDIT LOCAL	SNR 10Y	CR CDS PREM. MID
10	E.ON SE	SNR 10Y	CR CDS PREM. MID
11	ERSTE GROUP BANK AG	SNR 10Y	CR CDS PREM. MID
12	FINMECCANICA S.P.A.	SNR 10Y	CR CDS PREM. MID
13	FORTIS BANK	SNR 10Y	CR CDS PREM. MID
14	GDF SUEZ SA	SNR 10Y	CR CDS PREM. MID
15	INTESA SANPAOLO SPA	SNR 10Y	CR CDS PREM. MID
16	SCOR SE	SNR 10Y	CR CDS PREM. MID
17	SOCIETE GENERALE	SNR 10Y	CR CDS PREM. MID
18	TELECOM ITALIA SPA	SNR 10Y	CR CDS PREM. MID
19	THE RBS GROUP PLC	SNR 10Y	CR CDS PREM. MID
20	VINCI-COFIROUTE	SNR 10Y	MM CDS PREM. MID

Appendix IV

Proofs of the proposed model

This part regroups all the appendices of chapter IV.

Appendix IV.1. Ito calculus for the firm value in T_1 and T_2:

In the benchmark setup, the dynamics of the firm value is assumed to be given by the following stochastic differential equation (SDE):

$$dV_t = (r-\kappa)V_t\ dt + \sigma_v V_t\ d\widetilde{\mathbb{W}}_t \tag{1}$$

This SDE can be written in its integral form as follows:

$$V_t = V_0 + (r-\kappa)\int_0^t V_s ds + \sigma_v \int_0^t V_s\, d\widetilde{\mathbb{W}}_s \quad ; \quad t \in \mathbb{R}_+$$

Applying Ito's formula to $f(V_t) = \ln(V_t)$ we get:

$$\begin{aligned} d\ln(V_t) &= (r-\kappa)V_t f'(V_t)dt + \sigma_v V_t f'(V_t) d\widetilde{\mathbb{W}}_t + \frac{1}{2}\sigma_v^2 V_t^2 f''(V_t)dt \\ &= (r-\kappa)dt + \sigma_v d\widetilde{\mathbb{W}}_t - \frac{1}{2}\sigma_v^2 dt \\ &= \left(r-\kappa-\frac{\sigma^2}{2}\right)dt + \sigma_v d\widetilde{\mathbb{W}}_t \end{aligned}$$

Hence, using this previous result gives:

$$\begin{aligned} \ln(V_t) - \ln(V_0) &= \int_0^t d\ln(V_s) \\ &= \int_0^t \left(r-\kappa-\frac{\sigma^2}{2}\right)ds + \int_0^t \sigma_v d\widetilde{\mathbb{W}}_S \\ \ln(V_t) &= \ln(V_0) + \left(r-\kappa-\frac{\sigma^2}{2}\right)t + \sigma_v d\widetilde{\mathbb{W}}_t \quad ; \quad t \in \mathbb{R}_+ \end{aligned}$$

Going back to V_t by using $V_t = \exp(\ln(V_t))$ gives:

$$V_t = V_0 \exp\left(\left(r - \kappa - \frac{\sigma^2}{2}\right) t + \sigma_v \widetilde{\mathbb{W}}_t\right) \tag{1}$$

This is a well-known result commonly designed as the unique solution of the stochastic differential equation given in (1). Using the independent increments property of the Brownian motion, we have similarly for two dates T_1 and T_2:

$$V_{T_2} = V_{T_1} \exp\left(\left(r - \kappa - \frac{\sigma^2}{2}\right)(T_2 - T_1) + \sigma_v \widetilde{\mathbb{W}}_{T2} - \widetilde{\mathbb{W}}_{T1}\right) \tag{2}$$

This result will be used in the subsequent formulations.

Appendix IV.2. Proof of equation (2):

The price of the corporate bond in our setup is a function of the independent random variables R, V_{T1} and V_{T2}. That is:

$$P(0,T) = e^{-r(T_2)}\, \mathbb{E}\left(f\big(R, V_{T1}, V_{T2}\big)\right)$$

With:

$$\begin{aligned} f\big(R, V_{T1}, V_{T2}\big) = e^{-r(T_2)} \Big\{ & D\ \mathbf{1}_{\{V_{T1} \geq b\ ;\ V_{T2} \geq D\}} +\ \alpha_1\ \mathbf{1}_{\{V_{T1} \geq b\ ;\ V_{T2} < D\}} \\ & + \mathbf{1}_{\{R=\delta\}}\Big(D\ \mathbf{1}_{\{V_{T1} < b\ ;\ V_{T2} \geq D+\delta\}} + \alpha_2\ \mathbf{1}_{\{V_{T1} < b\ ;\ V_{T2} < D+\delta\}}\Big) \\ & + \mathbf{1}_{\{R=0\}}\ \big(\alpha_3 \mathbf{1}_{\{V_{T1} < b\}}\big) \Big\} \end{aligned} \tag{3}$$

Obtained with regard to the payoffs that we presented in Table IV-1. Next, from the conditional expectations properties we have:

$$\begin{aligned} P(0,T) &= \mathbb{E}\left(f\big(R, V_{T1}, V_{T2}\big)\right) \\ &= \mathbb{E}\left(\mathbb{E}\Big(f\big(R, V_{T1}, V_{T2}\big)\Big| V_{T1}, V_{T2}\Big)\right) \\ &= \mathbb{E}\Big(\varphi\big(V_{T1}, V_{T2}\big)\Big) \end{aligned} \tag{4}$$

With:

$$\begin{aligned} \varphi(v_1, v_2) &= \mathbb{E}\Big(f\big(R, v_1, v_2\big)\Big) \\ &= \mathbb{P}\big(R = \delta\big) f\big(\delta, v_1, v_2\big) +\ \mathbb{P}\big(R = 0\big) f\big(0, v_1, v_2\big) \qquad ; \quad v_1, v_2 \in \mathbb{R} \end{aligned}$$

Replacing in (4) we obtain:

$$
\begin{aligned}
P(0,T) &= \mathbb{E}\Big(\mathbb{P}(R=\delta)\ f(\delta, V_{T1}, V_{T2}) + \mathbb{P}(R=0)\ f(0, V_{T1}, V_{T2})\Big) \\
&= \mathbb{P}\big(R=\delta\big)\,\mathbb{E}\Big(f(\delta, V_{T1}, V_{T2})\Big) + \mathbb{P}\big(R=0\big)\,\mathbb{E}\Big(f(0, V_{T1}, V_{T2})\Big) \qquad (5)
\end{aligned}
$$

Hence with regard to the results in equations (3) and (5) we have:

$$
\begin{aligned}
P(0,T) = e^{-r(T_2)} \Bigg\{ & \mathbb{E}^{\mathbb{Q}}\big(D\ \mathbf{1}_{\{V_{T1}\geq b\ ;\ V_{T2}\geq D\}} + \alpha_1\ \mathbf{1}_{\{V_{T1}\geq b\ ;\ V_{T2}< D\}}\big) \\
& + \ \mathbb{P}(R=\delta)\ \Big(\mathbb{E}^{\mathbb{Q}}\big(D\ \mathbf{1}_{\{V_{T1}< b\ ;\ V_{T2}\geq D+\delta\}} + \alpha_2\ \mathbf{1}_{\{V_{T1}< b\ ;\ V_{T2}< D+\delta\}}\big)\Big) \\
& + \ \mathbb{P}(R=0)\ \Big(\mathbb{E}^{\mathbb{Q}}\big(\alpha_2 \mathbf{1}_{\{V_{T1}< b\}}\big)\Big)\Bigg\}
\end{aligned}
$$

Which yields to the result in equation (2):

$$
\begin{aligned}
P(0,T) = e^{-r(T_2)} \Bigg\{ & \underbrace{\mathbb{E}^{\mathbb{Q}}\big(D\ \mathbf{1}_{\{V_{T1}\geq b\ ;\ V_{T2}\geq D\}}\big)}_{(i)} + \underbrace{\mathbb{E}^{\mathbb{Q}}\big(\alpha_1\ \mathbf{1}_{\{V_{T1}\geq b\ ;\ V_{T2}< D\}}\big)}_{(ii)} \\
& + \mathbb{P}(R=0)\ \underbrace{\mathbb{E}^{\mathbb{Q}}\big(\alpha_3\ \mathbf{1}_{\{V_{T1}< b\}}\big)}_{(iii)} + \mathbb{P}(R=\delta)\ \underbrace{\mathbb{E}^{\mathbb{Q}}\big(D\ \mathbf{1}_{\{V_{T1}< b\ ;\ V_{T2}\geq D+\delta\}}\big)}_{(iv)} \\
& + \mathbb{P}(R=\delta)\ \underbrace{\mathbb{E}^{\mathbb{Q}}\big(\alpha_2\ \mathbf{1}_{\{V_{T1}< b\ ;\ V_{T2}< D+\delta\}}\big)}_{(v)} \Bigg\} \qquad (2)
\end{aligned}
$$

Appendix IV.3. Proof of equation (3)

The price of the corporate bond proposed in equation (2) is as follows:

$$P(0,T) = e^{-r(T_2)} \Bigg\{ \underbrace{\mathbb{E}^{\mathbb{Q}}\big(D\ \mathbf{1}_{\{V_{T1}\geq b\ ;\ V_{T2}\geq D\}}\big)}_{(i)} + \underbrace{\mathbb{E}^{\mathbb{Q}}\big(\alpha_1\ \mathbf{1}_{\{V_{T1}\geq b\ ;\ V_{T2}<D\}}\big)}_{(ii)}$$

$$+ \mathbb{P}(R=0)\ \underbrace{\mathbb{E}^{\mathbb{Q}}\big(\alpha_3\ \mathbf{1}_{\{V_{T1}<b\}}\big)}_{(iii)} + \mathbb{P}(R=\delta)\ \underbrace{\mathbb{E}^{\mathbb{Q}}\big(D\ \mathbf{1}_{\{V_{T1}<b\ ;\ V_{T2}\geq D+\delta\}}\big)}_{(iv)}$$

$$+ \mathbb{P}(R=\delta)\ \underbrace{\mathbb{E}^{\mathbb{Q}}\big(\alpha_2\ \mathbf{1}_{\{V_{T1}<b\ ;\ V_{T2}<D+\delta\}}\big)}_{(v)} \Bigg\} \quad (2)$$

The solution for the entities (i) to (v) is as follows:

1. **Entity (i):**

$$(i) = \mathbb{E}^{\mathbb{Q}}\big(D\ \mathbf{1}_{\{V_{T1}\geq b\ ;\ V_{T2}\geq D\}}\big)$$
$$= D\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{V_{T1}\geq b\ ;\ \frac{V_{T2}}{V_{T1}}\geq \frac{D}{V_{T1}}\right\}}\right)$$

Noticing from the properties of the Brownian motion that $V_{T1} \perp\!\!\!\perp \frac{V_{T2}}{V_{T1}}$, then (i) rewrites:

$$= D\ \mathbb{E}^{\mathbb{Q}}\left(\mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{V_{T1}\geq b\ ;\ \frac{V_{T2}}{V_{T1}}\geq \frac{D}{V_{T1}}\right\}}|V_{T1}\right)\right)$$
$$= D\ \mathbb{E}^{\mathbb{Q}}\big(\phi(V_{T1})\big) \quad (6)$$

With:

$$\phi(x) = \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{x\geq b\ ;\ \frac{V_{T2}}{V_{T1}}\geq \frac{D}{x}\right\}}\right)$$

$$= \mathbf{1}_{\{x\geq b\}}\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{\frac{V_{T2}}{V_{T1}}\geq \frac{D}{x}\right\}}\right) \quad (7)$$

From the solution of the SDE given in equation (2) we have:

$$\frac{V_{T2}}{V_{T1}} = \exp\left(\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1) + \sigma\sqrt{T_2-T_1}\ G_1\right)$$

Hence replacing in (7) we get:

$$
\begin{aligned}
\phi(x) &= \mathbf{1}_{\{x \geq b\}}\ \mathbb{Q}\left(\exp\left(\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)+\sigma\sqrt{T_2-T_1}\ G_1\right) \geq \frac{D}{x}\right) \\
&= \mathbf{1}_{\{x \geq b\}}\ \mathbb{Q}\left(G_1 \geq \frac{\ln\left(\frac{D}{x}\right)-\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)}{\sigma\sqrt{T_2-T_1}}\right) \\
&= \mathbf{1}_{\{x \geq b\}}\ \mathbb{Q}\left(G_1 < \frac{\ln\left(\frac{x}{D}\right)+\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)}{\sigma\sqrt{T_2-T_1}}\right) \\
\phi(x) &= \mathbf{1}_{\{x \geq b\}}\ N\big(d_1(x)\big) \qquad ; \qquad x \in \mathbb{R}
\end{aligned}
$$

Where $N(\ )$ denotes the standard Gaussian cumulative distribution function given by:

$$
N(x) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{x} e^{-\frac{t^2}{2}}\ dt \qquad \forall\ x \in \mathbb{R} \tag{8}
$$

And:

$$
d_1(x) = \frac{\ln\left(\frac{x}{D}\right)+\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)}{\sigma\sqrt{T_2-T_1}}
$$

Then, according to (6) we obtain:

$$
(i) = D\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\{V_{T1} \geq b\}}\ N\big(d_1(V_{T1})\big)\right)
$$

Where:

$$
d_1(V_{T1}) = \frac{\ln\left(\frac{V_{T1}}{D}\right)+\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)}{\sigma\sqrt{T_2-T_1}}
$$

2. **Entity $(\boldsymbol{ii})$:**

$$
\begin{aligned}
(ii) &= \mathbb{E}^{\mathbb{Q}}(\alpha_1\ \mathbf{1}_{\{V_{T1} \geq b\ ;\ V_{T2} < D\}}) \\
&= \alpha_1 \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{V_{T1} \geq b\ ;\ \frac{V_{T2}}{V_{T1}} < \frac{D}{V_{T1}}\right\}}\right)
\end{aligned}
$$

Again, since $V_{T1} \perp\!\!\!\perp \frac{V_{T2}}{V_{T1}}$, (ii) rewrites:

$$
\begin{aligned}
(ii) &= \alpha_1 \mathbb{E}^{\mathbb{Q}}\left(\mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{V_{T1} \geq b\ ;\ \frac{V_{T2}}{V_{T1}} < \frac{D}{V_{T1}}\right\}} | V_{T1}\right)\right) \\
&= \alpha_1 \mathbb{E}^{\mathbb{Q}}\big(\phi(V_{T1})\big)
\end{aligned} \tag{9}
$$

With:

$$\begin{aligned}\phi(x) &= \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{x\geq b\,;\,\frac{V_{T2}}{V_{T1}}<\frac{D}{x}\right\}}\right)\\ &= \mathbf{1}_{\{x\geq b\}}\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{\frac{V_{T2}}{V_{T1}}<\frac{D}{x}\right\}}\right)\\ &= \mathbf{1}_{\{x\geq b\}}\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{\frac{V_{T2}}{V_{T1}}<\frac{D}{x}\right\}}\right)\end{aligned} \tag{10}$$

Doing similar calculus as previously in entity (i) we find:

$$(ii) = (1-w_1)D\ \mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1}\geq b\}}\ N\big(d_2(V_{T1})\big)\Big)$$

Where $N(\ )$ denotes the standard Gaussian cumulative distribution function and:

$$d_2(V_{T1}) = \frac{\ln\left(\frac{D}{V_{T1}}\right) - \left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)}{\sigma\sqrt{T_2-T_1}}$$

3. Entity (iii)**:**

$$\begin{aligned}(iii) &= \mathbb{E}^{\mathbb{Q}}(\alpha_3\ 1_{\{V_{T1}<b\}})\\ &= \alpha_3\ \mathbb{Q}(V_{T1}<b)\end{aligned} \tag{11}$$

From the solution of the SDE in equation (2) we have:

$$V_{T1} = V_0\exp\Big((r-\kappa-\tfrac{\sigma^2}{2})(T_1)+\sigma\sqrt{T_1}\ G_2\Big).$$

Replacing in (11):

$$\begin{aligned}(iii) &= \alpha_3\ \mathbb{Q}\left(V_0\exp\left(\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_1)+\sigma\sqrt{T_1}\ G_2\right)<b\right)\\ &= \alpha_3\ \mathbb{Q}\left(\mathrm{G}_2 < \frac{\ln\left(\frac{b}{V_0}\right)\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_1)}{\sigma\sqrt{T_1}}\right)\\ &= \alpha_3\ \mathbb{Q}\Big(\mathrm{G}_2 < d_3(V_0)\Big)\\ &= \alpha_3\ N\big(d_3(V_0)\big)\\ (iii) &= (1-w_3)D\ N\big(d_3(V_0)\big)\end{aligned}$$

Where $N(\ )$ denotes the standard Gaussian cumulative distribution function and:

$$d_3(V_0) = \frac{\ln\left(\frac{b}{V_0}\right)\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_1)}{\sigma\sqrt{T_1}}$$

4. **Entity (*iv*):**

$$\begin{aligned}(iv) = \ & \mathbb{E}^{\mathbb{Q}}\big(D\ \mathbf{1}_{\{V_{T1}<b\ ;\ V_{T2}\geq D+\delta\}}\big)\\ = \ & D\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{V_{T1}<b\ ;\ \frac{V_{T2}}{V_{T1}}\geq\frac{D+\delta}{V_{T1}}\right\}}\right)\end{aligned}$$

Again, since $V_{T1} \perp\!\!\!\perp \frac{V_{T2}}{V_{T1}}$, (iv) rewrites:

$$\begin{aligned}&= D\ \mathbb{E}^{\mathbb{Q}}\left(\mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{V_{T1}<b\ ;\ \frac{V_{T2}}{V_{T1}}\geq\frac{D+\delta}{V_{T1}}\right\}}|V_{T1}\right)\right)\\ &= D\ \mathbb{E}^{\mathbb{Q}}\big(\phi(V_{T1})\big) \qquad (12)\end{aligned}$$

With:

$$\begin{aligned}\phi(x) &= \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{x<b\ ;\ \frac{V_{T2}}{V_{T1}}\geq\frac{D+\delta}{x}\right\}}\right)\\ &= \mathbf{1}_{\{x<b\}}\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{\frac{V_{T2}}{V_{T1}}\geq\frac{D+\delta}{x}\right\}}\right)\\ &= \mathbf{1}_{\{x<b\}}\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{\frac{V_{T2}}{V_{T1}}\geq\frac{D+\delta}{x}\right\}}\right) \qquad (13)\end{aligned}$$

Again, from the solution of the SDE in (2) we have:

$$\frac{V_{T2}}{V_{T1}} = \exp\left(\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)+\sigma\sqrt{T_2-T_1}\ G_3\right)$$

Replacing in (13) we get:

$$\begin{aligned}\phi(x) &= \mathbf{1}_{\{x<b\}}\ \mathbb{Q}\left(\exp\left(\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)+\sigma\sqrt{T_2-T_1}G_3\right)\geq\frac{D+\delta}{x}\right)\\ &= \mathbf{1}_{\{x<b\}}\ \mathbb{Q}\left(G_3\geq\frac{\ln\left(\frac{D+\delta}{x}\right)-\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)}{\sigma\sqrt{T_2-T_1}}\right)\\ &= \mathbf{1}_{\{x<b\}}\ \mathbb{Q}\left(G_3<\frac{\ln\left(\frac{x}{D+\delta}\right)+\left(r-\kappa-\frac{\sigma^2}{2}\right)(T_2-T_1)}{\sigma\sqrt{T_2-T_1}}\right)\\ \phi(x) &= \mathbf{1}_{\{x\geq b\}}\ N\big(d_4(x)\big) \qquad ; \qquad x\in\mathbb{R}\end{aligned}$$

Where $N(\ )$ denotes the standard Gaussian cumulative and:

$$d_4(x) = \frac{\ln\left(\frac{x}{D+\delta}\right) + \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_2 - T_1)}{\sigma\sqrt{T_2 - T_1}}$$

Then, according to (12) we obtain:

$$(iv) = D\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\{V_{T1}<b\}}\ N\big(d_4(V_{T1})\big)\right)$$

Where:

$$d_4(V_{T1}) = \frac{\ln\left(\frac{V_{T1}}{D+\delta}\right) + \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_2 - T_1)}{\sigma\sqrt{T_2 - T_1}}$$

5. **Entity ($\boldsymbol{v}$):**

$$\begin{aligned}(v) &= \mathbb{E}^{\mathbb{Q}}(\alpha_2\ \mathbf{1}_{\{V_{T1}<b\ ;\ V_{T2}<D+\delta\}})\\ &= \alpha_2\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{V_{T1}<b\ ;\ \frac{V_{T2}}{V_{T1}}<\frac{D+\delta}{V_{T1}}\right\}}\right)\end{aligned}$$

Using again $V_{T1} \perp\!\!\!\perp \frac{V_{T2}}{V_{T1}}$, (v) rewrites:

$$\begin{aligned}&= \alpha_2\ \mathbb{E}^{\mathbb{Q}}\underbrace{\left(\mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{V_{T1}<b\ ;\ \frac{V_{T2}}{V_{T1}}<\frac{D+\delta}{V_{T1}}\right\}}\right)|V_{T1}\right)}_{\phi(V_{T1})}\\ &= \alpha_2\ \mathbb{E}^{\mathbb{Q}}\big(\phi(V_{T1})\big) \qquad (14)\end{aligned}$$

With:

$$\begin{aligned}\phi(x) &= \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{x<b\ ;\ \frac{V_{T2}}{V_{T1}}<\frac{D+\delta}{x}\right\}}\right)\\ &= \mathbf{1}_{\{x<b\}}\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{\frac{V_{T2}}{V_{T1}}<\frac{D+\delta}{x}\right\}}\right)\\ &= \mathbf{1}_{\{x<b\}}\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\left\{\frac{V_{T2}}{V_{T1}}<\frac{D+\delta}{x}\right\}}\right) \qquad (15)\end{aligned}$$

Doing as previously for entity (iv) we find:

$$(v) = (1 - w_2)D\ \mathbb{E}^{\mathbb{Q}}\left(\mathbf{1}_{\{V_{T1}<b\}}\ N\big(d_5(V_{T1})\big)\right)$$

Where $N(\ )$ denotes the standard Gaussian cumulative distribution function and:

$$d_2(V_{T1}) = \frac{\ln\left(\frac{D+\delta}{V_{T1}}\right) - \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_2 - T_1)}{\sigma\sqrt{T_2 - T_1}}$$

Finally, summarizing the results of the entities (i) to (v) yields to the result in equation (3):

$$\begin{aligned} P(0,T) = e^{-r(T_2)} \Bigg\{ & D\ \mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1} \geq b\}} N\big(d_1(V_{T1})\big)\Big) + \alpha_1 \mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1} \geq b\}} N\big(d_2(V_{T1})\big)\Big) \\ & + \mathbb{P}(R=0)\Big(\alpha_3\ N\big(d_3(V_0)\big)\Big) + \mathbb{P}(R=\delta)\Big(D\ \mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1}<b\}}\ N\big(d_4(V_{T1})\big)\Big)\Big) \\ & + \mathbb{P}(R=\delta)\Big(\alpha_2\ \mathbb{E}^{\mathbb{Q}}\Big(\mathbf{1}_{\{V_{T1}<b\}}\ N\big(d_5(V_{T1})\big)\Big)\Big)\Bigg\} \end{aligned} \quad (3)$$

Where:

$$d_1(V_{T1}) = \frac{\ln\left(\frac{V_{T1}}{D}\right) + \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_2 - T_1)}{\sigma\sqrt{T_2 - T_1}}$$

$$d_2(V_{T1}) = \frac{\ln\left(\frac{D}{V_{T1}}\right) - \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_2 - T_1)}{\sigma\sqrt{T_2 - T_1}}$$

$$d_3(V_0) = \frac{\ln\left(\frac{b}{V_0}\right) - \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_1)}{\sigma\sqrt{T_1}}$$

$$d_4(V_{T1}) = \frac{\ln\left(\frac{V_{T1}}{D+\delta}\right) + \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_2 - T_1)}{\sigma\sqrt{T_2 - T_1}}$$

$$d_5(V_{T1}) = \frac{\ln\left(\frac{D+\delta}{V_{T1}}\right) - \left(r - \kappa - \frac{\sigma^2}{2}\right)(T_2 - T_1)}{\sigma\sqrt{T_2 - T_1}}$$

Valorisation des obligations d'entreprise et spreads de crédit : les leçons de la crise financière

Résumé

L'objectif de cette thèse est de contribuer à améliorer le calcul de la valorisation des obligations d'entreprise, notamment en essayant de tirer des leçons de la récente crise économique et financière. Afin d'atteindre cet objectif, nous proposons une approche basée sur les spreads de crédit. Nous commençons, dans un premier chapitre, par une analyse des principaux modèles de valorisation existants, que nous reformulons du point de vue des spreads et que nous simulons numériquement. Nous montrons que, malgré les caractéristiques attrayantes des modèles de type structurel, ceux-ci comportent plusieurs lacunes qui peuvent être trompeuses surtout en contexte de crise. Dans les deuxième et troisième chapitres, nous mettons l'accent sur les spreads empiriques, que nous analysons pendant les crises des subprimes et de la zone euro. Par l'intermédiaire: (i) d'une analyse descriptive, (ii) d'analyses en composantes principales, ainsi que (iii) d'analyses par régressions statistiques, nous parvenons à mettre la lumière sur plusieurs facteurs qui affectent les mouvements des spreads et que ne sont pas pris en compte par les modèles existants. Parmi ces facteurs, nous montrons: (i) que la vague de sauvetage des banques pendant la crise a eu un effet considérable sur les spreads de crédit, et (ii) que la taille d'une firme a également un effet sur ses spreads. Sur la base de ces résultats empiriques, nous proposons dans un quatrième chapitre une contribution à la modélisation structurelle des obligations d'entreprise, qui prend en compte la possibilité des firmes de négocier un sauvetage en cas de détresse. À l'aide de ce modèle, nous parvenons, d'une part, à reproduire les observations empiriques de spreads plus faibles pour des probabilités de sauvetage plus élevées (comme c'est le cas pour les grandes banques), et d'autre part, à combler plusieurs lacunes des modèles existants, tels que les simples mécanismes de faillite, ou les faibles spreads de crédit pour les courtes maturités.

Mots clés : Obligations d'entreprise, Spread de crédit, Risque de crédit, Modélisation des risques, Crise financière.

Corporate bond valuation and credit spreads: Lessons from the financial crisis

Abstract

The aim of this thesis is to contribute to the improvement of the valuation of corporate bonds, particularly by drawing some lessons from the recent economic and financial crisis. In order to achieve this goal, we propose an approach based on corporate bonds' credit spreads. We start, in the first chapter, by analyzing the main existing valuation models, which we reformulate from the standpoint of credit spreads and which we simulate numerically. We show that, despite the attractive features that the structural models have, the latter exert contain several shortcomings which may be misleading especially in a crisis context. In the second and third chapters, we focus on the empirical credit spreads, which we analyze during the subprime crisis and the Eurozone crisis periods. By the means of: (i) a descriptive analysis, (ii) principal component analyses, and (iii) statistical regression analyses, we manage to shed light on a number of factors which affect the movements of the spreads and have not been addressed by the existing models. Among these factors, we show that: (i) the wave of bailouts that occurred during the crisis has had an important effect on the spreads, and (ii) the size of a firm is connected with its spreads. Based on these empirical results, we propose in the fourth chapter a contribution to the modeling of corporate bonds which accounts for the possibility of firms to negotiate a rescue plan in case of distress. This model allows us, on the one hand, to reproduce the empirical observations of lower credit spreads for higher probabilities of receiving a bailout (as it is the case for large banks), and on the other hand, to tackle several drawbacks of the existing models, such as the simple bankruptcy mechanisms or the low credit spreads for short maturities.

Keywords: Corporate bonds, Credit spread, Credit risk, Risk modeling, Financial crisis.

Discipline : Sciences Économiques (05)

Intitulé et adresse du laboratoire : CEPN Centre d'Economie de Paris Nord, 99 Avenue Jean-Baptiste Clément, 93340 Villetaneuse – France