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Is there a positive effect of uncertainty on economic activity ?

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Introduction Générale

"There is the potential for continued volatility and unevenness of global growth as countries continue to grapple with the pandemic. Russia's unprovoked invasion of Ukraine has further increased economic uncertainty"
— Janet Yellen, *Secrétaire au Trésor des Etats-Unis*

Depuis la crise de 2007-2008, les chercheurs en économie se sont de plus en plus interéssés au sujet de l'impact de l'incertitude sur l'activité économique. Cet interêt pour l'incertitude s'est fortement amplifié dans le contexte actuel, porté à la fois par la pandémie du COVID-19 et par la guerre en Ukraine. Au cours des débats, les décideurs de politiques économiques se sont penchés sur ces différentes questions: qu'est-ce qu'un choc d'incertitude ? quelle est l'ampleur et la persistance des effets de ces chocs sur l'activité économique ? Ces questions sont au centre des débats des politiques économiques depuis la crise de 2007-2008. En effet, selon certains auteurs, la faible reprise observée après la crise aurait été principalement due au fort niveau d'incertitude qui subsistait à ce moment-là (Blanchard, 2009; Stock and Watson, 2012; Bloom et al., 2013). Désormais, il est recommandé aux décideurs de politiques économiques de prendre en considération le niveau d'incertitude au moment d'établir leurs politiques. Cependant, nous constatons que ce débat ne se base que sur une dimension négative de l'incertitude:

> *Uncertainty over the pace, breadth and scale of these changes could weigh on our economic prospects for some time... At times of great uncertainty, households, businesses and investors ask basic economic questions. Will inflation remain under control? Will the financial system do its job? Will I keep mine ?* (Carney, 2016).

En se focalisant exclusivement sur l'effet négatif de l'incertitude, les opinions politiques écartent de fait la possibilité que certaines formes d'incertitude pourraient avoir un effet positif. Il n'y a aucune raison de penser que toutes les situations incertaines soient néfastes. Par exemple, est-ce qu'une incertitude autour d'une innovation technologique permettant d'accroître les capacités de production freinerait la croissance ? Cette thèse traitera la question de l'effet des chocs d'incertitude et plus précisement, cette thèse s'interrogera sur l'existence d'un éventuel effet positif des chocs d'incertitude sur l'activité économique.

Même si le sujet de l'incertitude a ressurgi dans les débats économiques depuis la crise de 2007-2008, cela fait tout de même longtemps que cette question intéresse les économistes. Il faut distinguer l'aspect théorique de l'aspect empirique. L'aspect théorique porte sur la notion d'incertitude ainsi que sur ses effets théoriques attendus. La crise de 2007-2008 a apporté la dimension empirique suite au travail fondateur de Bloom (2009) où une importante littérature empirique s'est développée par la suite.

Evolution de la notion d'incertitude

Concernant l'aspect théorique, l'année 1921 est considérée comme étant le point d'ancrage où Frank Knight a établi la définition moderne de l'incertitude en économie, développant une distinction entre la notion de risque et la notion d'incertitude:

> *"Uncertainty must be taken in a sense radically distinct from the familiar notion of Risk, from which it has never been properly separated....*

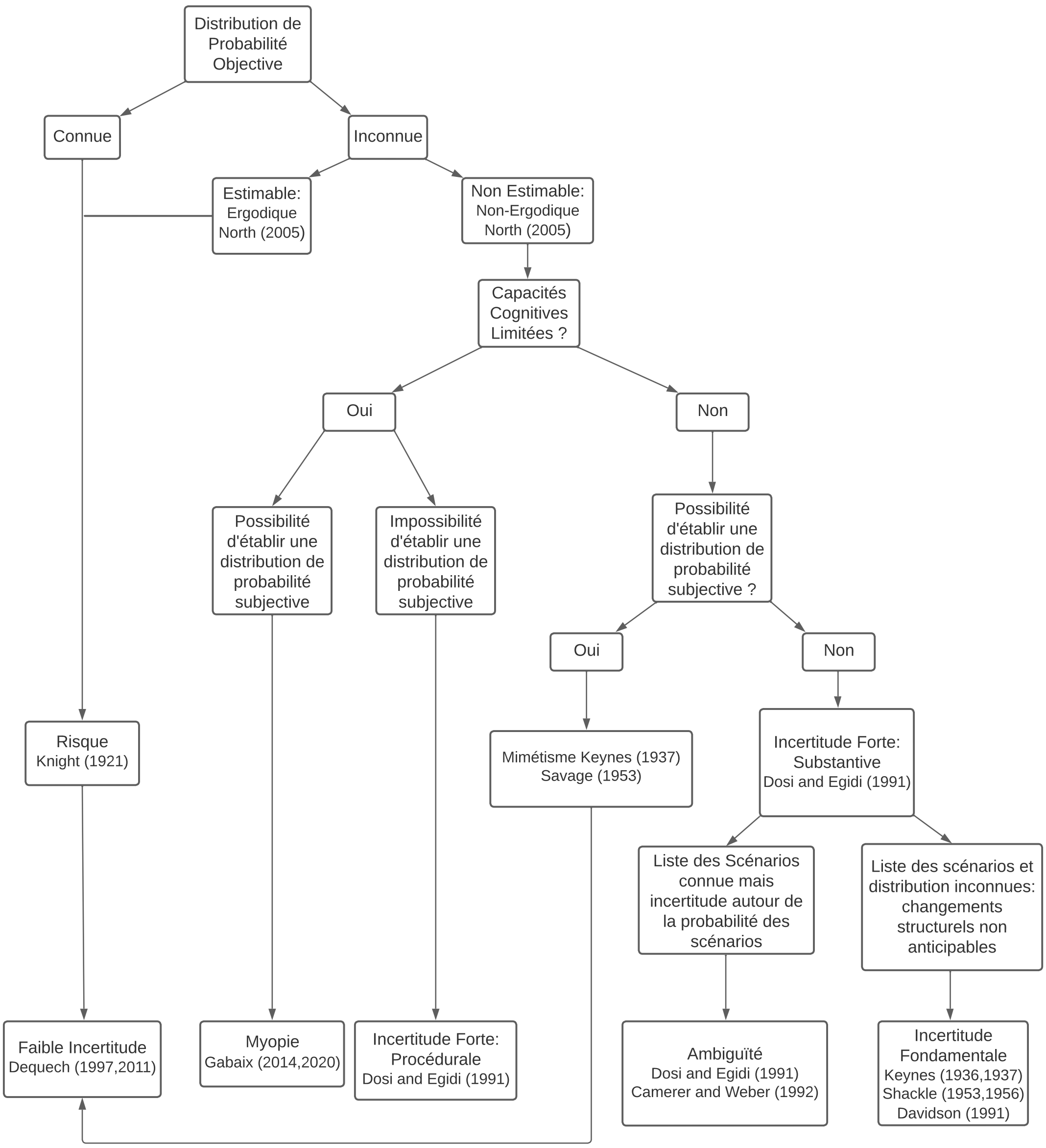
The essential fact is that 'risk' means in some cases a quantity susceptible of measurement, while at other times it is something distinctly not of this character; and there are far-reaching and crucial differences in the bearings of the phenomena depending on which of the two really present and operating.... It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an uncertainty at all." (Knight, 1921)

D'après la distinction de Knight (1921), le risque est décrit comme étant une situation incertaine où tous les états de la nature sont objectivement connus à l'avance ainsi que leur probabilité d'occurrence. Le lancer de dé non truqué à six faces illustre parfaitement cette notion de risque où nous connaissons l'ensemble des résultats de ce lancer (1 à 6) ainsi que la probabilité associée à chacun des résultats: 1/6. Contrairement au risque, l'incertitude correspond à la situation où nous ne pouvons pas connaître l'ensemble des scénarios possibles et/ou nous ne pouvons pas déterminer les probabilités d'occurence de ces scénarios d'une façon objective. Cette distinction est extrêmement connue dans le monde académique mais est aussi très large. Depuis Knight (1921), la littérature a défini plusieurs notions et formes d'incertitude comme l'llustre la Figure 1.

La distinction de Knight (1921) porte sur l'existence d'une distribution de probabilité objective. S'il existe une telle distribution, nous sommes dans une situation de risque qui est qualifiée par Dequech (1997) comme étant une situation de faible incertitude.[2] Même si nous connaissons la distribution de probabilité d'une façon objective du lancer de dé par exemple, il n'y a aucune raison objective de déterminer quel sera le résultat final de ce lancer. Ce raisonnement s'applique également dans des situations où la distribution n'est pas uniforme. Ainsi, même si un scénario a une probabilité de 95% de se

[2]La notion de "faible" incertitude ne reflète pas le niveau d'incertitude au sein de l'économie. Il s'agit d'une autre manière de désigner ces situations de risque, quelque soit le niveau de l'incertitude dans l'économie à ce moment-là.

Figure 1: Différentes Notions d’Incertitude



produire dans le futur, nous n'avons aucune raison objective de penser que ce scénario va forcément se réaliser par la suite.

Si la distribution de probabilité objective n'est pas connue, Davidson (1991) met en avant le fait que les perspectives dominantes impliquant l'incertitude se basent sur une analyse statistique des données passées afin d'estimer cette distribution. Du côté des institutionnalistes, North (2005) se base sur la distinction de Knight (1921) et emploie le concept d'ergodicité pour désigner l'estimation d'une distribution de probabilité objective en s'inspirant également de Davidson (1991). Le terme ergodique se rapporte à la probabilité qu'un état de la nature se reproduise et à la probabilité qu'un autre état de la nature ne se produise jamais. Ce processus stochastique ergodique signifie que les moyennes calculées d'après les observations passées ne peuvent être durablement différentes de la moyenne à long terme des observations futures (Davidson, 1991). Pour North, un monde non-ergodique correspond à celui où le futur n'est pas probabilisable en projetant les connaissances antérieures, c'est-à-dire à partir des données statistiques des années antérieures. L'incertitude constituerait *la condition sous-jacente qui est responsable de la structure de l'organisation humaine tout au long de l'histoire et de la préhistoire*. Les efforts déployés par l'Homme afin de rendre l'environnement plus prévisible seraient à l'origine de nos institutions. Ces institutions ont pour but de réduire l'incertitude *en diminuant le nombre de choix possibles*, permettant à l'agent d'améliorer sa capacité à maîtriser son environnement très complexe (North, 2005).

Certains auteurs rejettent l'idée des probabilités objectives: "*it is hard to think of an important natural decision for which probabilities are objectively known*" (Camerer and Weber, 1992). Keynes (1937) énonce le fait que de telles probabilités ne peuvent pas être connues à l'avance mais que cela n'empêche pas les agents économiques de faire des prévisions sur les scénarios ainsi que sur la distribution de probabilité. Dans ce cas-là, cette distribution ne peut être déterminée que d'une manière subjective. Il s'agit également de la notion d'incertitude de Savage (1954) développée au sein de la théorie de l'espérance d'utilité subjective. La prise de décision dans l'incertain se fait sur la base des probabilités dites subjectives. Orléan (1987) souligne également que ces probabilités subjectives ne constitueraient pas une base fiable pour une prise de décision dans l'incertain même si les agents peuvent les estimer. Keynes insiste sur le fait que cette prise de décision dans l'incertain dépend de ces probabilités subjectives mais également du degré de confiance que les agents attribueraient à ces probabilités. Un agent n'investira pas s'il a peu confiance dans l'estimation des probabilités même si le gain est élevé.

Dequech (2011) associe également cette distribution de probabilité subjective à la faible incertitude, faisant opposition à la forte incertitude qui se rapproche plus de la notion de Keynes (1921, 1936, 1937) avec l'absence d'une distribution de probabilité, qu'elle soit objective ou subjective. Cette absence de l'estimation d'une distribution de probabilité subjective peut être due a une forme d'incertitude qui est liée aux capacités cognitives limitées des agents (Dosi and Egidi, 1991). Dans les théories mainstream, les agents font le meilleur usage possible de toute l'information disponible ce qui leur permet de résoudre des problèmes d'optimisation. Dosi and Egidi (1991) pointe le fait qu'il n'y a aucune raison de supposer que les agents sont naturellement dotés de compétences cognitives suffisantes pour identifier les solutions d'un problème d'optimisation particulier. Il est également impossible de présumer que ces compétences soient uniformément réparties entre les différents agents. Dosi and Egidi (1991) qualifient cette incertitude comme une incertitude "procédurale' correspondant à l'ensemble des situations où les agents sont contraints par leurs capacités mentales et computationnelles limitées rendant le problème de décision dans l'incertain complexe. Cette incertitude peut varier d'un agent à un autre selon la complexité du problème. Le fait que le concept d'incertitude procédurale lie la complexité aux capacités des agents implique que ce qui est une incertitude faible pour certains agents peut être une incertitude procédurale pour d'autres agents. Si la situation était complexe mais que les capacités cognitives des agents étaient illimitées, l'incertitude procédurale n'existerait pas. Cette notion est en lien avec celle de Williamson (1985) où l'incertitude correspond à une situation où la complexité de l'environnement de décision est trop large par rapport aux capacités cognitives des agents.

Même si les agents ont des capacités cognitives limitées, il peuvent tout de même essayer de déterminer une distribution. Ce cas de figure est en lien avec les récents travaux de Gabaix (2014, 2020) qui a développé un modèle théorique Nouveau Keynésien où les agents sont considérés comme étant en partie "myopes". Cette myopie correspond à une situation où les agents ont une capacité limitée à pouvoir analyser parfaitement l'ensemble des informations disponibles et doivent allouer une partie de leur attention à certaines informations. De ce fait, les agents ne peuvent analyser que partiellement l'ensemble des informations disponibles. Cette myopie rend les agents incapables d'anticiper avec perfection le futur et l'évolution future des variables économiques.

Contrairement aux situations précédentes où les agents disposent de toute l'information disponible, l'incertitude "substantive" est l'incertitude vis-à-vis du futur à cause d'un manque d'informations dont ont besoin les agents au moment de la prise de décision (Dosi and Egidi, 1991). Le futur est incertain pour les agents parce qu'ils ne disposent pas de toutes les informations disponibles. Cette incertitude substantive peut être divisée en deux sous-catégories: l'ambigüité et l'incertitude fondamentale (Dosi and Egidi, 1991; Dequech, 2011).

Dans une situation d'ambiguïté, l'agent prenant une décision ne peut associer une probabilité à chacun des évènements parce que des informations essentielles sont manquantes au moment de la prise de décision mais la liste des scénarios est déjà prédéterminée (Camerer and Weber, 1992). L'ambiguïté correspond à l'incertitude autour de la probabilité d'un ou de plusieurs scénarios. L'illustration la plus connue est tirée du paradoxe d'Ellsberg. Un agent est confronté à deux urnes contenant 100 boules chacune. Les deux urnes contiennent des boules rouges et des boules noires mais les proportions sont inconnues dans la première alors que la seconde contient exactement 50 boules rouges et 50 boules noires. Pour chaque urne, l'agent doit parier sur la couleur d'une boule tirée au sort de façon aléatoire et montre son indifférence entre parier sur la couleur rouge ou noire. Si on demande à l'agent quelle urne préferera t-il utiliser pour parier, il préfèrera utiliser l'urne où la distribution est connue au lieu d'utiliser la seconde. Sous ambiguïté, l'agent peut refuser de parier parce qu'il attend de disposer de plus d'informations ou parce qu'il a peur que quelqu'un d'autre puisse avoir l'information manquante (Frisch and Baron, 1988; Camerer and Weber, 1992).

Contrairement à l'ambiguïté, l'incertitude fondamentale est caractérisée par le fait qu'il n'existe pas une liste de scénarios prédéterminée à l'avance:

> "*By "uncertain" knowledge, let me explain, I do not mean merely to distinguish what is known for certain from what is only probable. The game of roulette is not subject, in this sense, to uncertainty ... The sense in which I am using the term is that in which the prospect of a European war is uncertain, or the price of copper and the rate of interest twenty years hence, or the obsolescence of a new invention, or the position of private wealth-owners in the social system in 1970. About these matters there is no scientific basis on which to form any calculable probability whatever.*" (Keynes, 1937)

Selon la définition de Keynes, le futur est imprévisible et ne suit pas des lois de probabilités prédéterminées. Lors d'une prise de décision sur un montant de l'investissement par un entrepreneur, énoncer tous les états de la nature possibles qui résulteraient de cet investissement ainsi que les probabilités associées ne serait pas possible. Il en va de même pour les contreparties que l'entrepreneur pourrait solliciter afin d'obtenir le montant du financement de cet investissement. La notion d'"incertitude" utilisée par de nombreux auteurs fait référence à cette notion d'incertitude fondamentale dont Shackle (1953, 1956) qui a inspiré de nombreux économistes hétérodoxes comme les Posts-Keynésiens. L'avenir est imprévisible et ne suit pas une distribution de probabilité prédéterminée contrairement aux perspectives dominantes impliquant l'incertitude qui sont basées sur une analyse statistique des données passées (Davidson, 1991). L'incertitude fondamentale peut être caractérisée aussi par le fait que la réalité est sujette à des changements structurels qui ne peuvent pas être connus ou anticipés à l'avance même si les agents disposent de toute l'information disponible. Ces changements structurels peuvent provenir de la créativité des individus qui ont la capacité d'acquérir au fil du temps de nouvelles compétences et de nouveaux savoirs. Orléan (1987) souligne que la nouveauté est au centre de la notion d'incertitude: c'est la présence du nouveau qui rend la quantification probabiliste caduque. Ces nouvelles compétences ou ces nouveaux savoirs ne peuvent pas être anticipés à l'avance étant donné qu'on ne sait pas quel est le domaine qui sera touché, ni dans combien de temps. L'exemple le plus donné par le courant post-keynésien est l'introduction des innovations technologiques dans un processus de destruction créatrice de Schumpeter (Davidson, 1991; Lavoie, 1992; Dow, 1996). Dans un système capitaliste, la recherche de profits constituerait une source de stimulation pour les entrepreneurs à innover constituant une pression endogène pour une innovation technologique qui constituera une forte forme d'incertitude (Kregel, 1990; Dequech, 2000). Etant donné qu'il s'agit d'innovations technologiques pour lesquelles il n'y a aucun recul, il sera très difficile de donner les résultats, profits et avantages que ces innovations généreront dans le futur au moment de prendre la décision. Un changement structurel de nature politique, institutionnelle, sociale ou culturelle pouvant influencer les décisions gouvernementales pourrait également être lié à la notion d'incertitude. Nous pouvons prendre le cas du Brexit en 2016 où le Royaume-Uni fut le premier pays à quitter l'Union Européenne. Etant donné qu'il n'existait aucun précédent, il était impossible de produire ex-ante une liste de scénarios sur la trajectoire future de l'économie britannique à cause de ce manque de connaissance. Un exemple plus récent qui illustre cette notion d'incertitude fondamentale est la pandémie du COVID-19 qui a affecté la plupart des pays de la planète et par conséquent, l'ensemble de l'économie mondiale. Cette situation inédite, de par son ampleur et sa nature, a amené les gouvernements des différents pays à prendre des décisions stoppant l'activité productive, boulversant le fonctionnement de nombreuses institutions comme l'école où un système d'enseignement à distance a dû être mis en place suite aux différentes mesures de confinement. Là encore, étant donné qu'il n'existait aucun précédent, prédire quelles seront les conséquences à long terme de ces mesures sur le plan économique mais également sur le plan psychologique des individus (travailleurs, étudiants, ...) paraît très difficile. En matière de changement structurel, la pandémie a fortement influencé le développement massif du télétravail qui était jusque-là peu adopté par les entreprises (Aksoy et al., 2022; Bloom et al., 2022).

Effets des chocs d'incertitude

Si la définition théorique de l'incertitude semble faire débat au sein des différents courants de pensées, il semblerait qu'un consensus aurait été atteint concernant son effet sur l'activité économique: l'incertitude serait purement nuisible pour l'activité économique. Il est évident que la littérature théorique présente de nombreux arguments sur un effet négatif. Cependant, nous verrons également que des arguments théoriques quant à un effet positif de l'incertitude sont aussi présents dans la littérature.

Effets Négatifs

Au sein de la littérature théorique, il a été montré que l'incertitude peut effectivement avoir des effets néfastes sur l'activité économique à travers trois principaux canaux: les options réelles, l'épargne de précaution et les frictions financières.

Les deux premiers canaux font références à des comportements attentistes que les agents adopteraient en présence d'incertitude (Bernanke, 1983; Pindyck, 1991). Le canal des options réelles se base sur le caractère irréversible des projets d'investissement, c'est-à-dire, qu'ils ne peuvent être annulés ou modifiés sans générer des coûts supplémentaires qui pourraient être élevés (Ramey and Shapiro, 2001; Cooper and Haltiwanger, 2006). "*Given the uncertainty, why build a new plant, or introduce a new product now? Better to pause until the smoke clears.*" (Blanchard, 2009) Les investisseurs ont la possibilité d'opérer un arbitrage entre les bénéfices supplémentaires provenant du lancement immédiat de ce projet d'investissement et les bénéfices retirés s'ils décident d'attendre afin de rassembler plus d'informations concernant le futur. Par conséquent, une accentuation de l'incertitude inciterait les entreprises et les investisseurs à adopter un comportement attentiste. Cette possibilité de retarder ou de stopper les décisions d'investissement et d'embauche permettrait d'obtenir plus d'informations concernant le futur, permettant ainsi d'accroître la probabilité de prendre les bonnes décisions. Dans un modèle théorique avec agents hétérogènes incluant le canal d'option réelle, Alfaro et al. (2018) montrent qu'une incertitude plus forte provoque un effet négatif sur la demande de capital, la demande de travail et conduit les entreprises à thésauriser les liquidités, à baisser leur niveau d'endettement pour se prémunir contre les chocs futurs ce qui, contracterait encore plus l'investissement. Bloom (2014) souligne également que le comportement attentiste des entreprises pourrait freiner une réallocation des ressources qui amélioreraient la productivité des entreprises.

L'épargne de précaution constitue également un autre canal (Bansal and Yaron, 2004; Fernández-Villaverde et al., 2011; Bloom, 2014). Elle est définie par Leland (1968) comme étant "*l'épargne supplémentaire due au fait que le revenu futur est aléatoire plutôt que déterminé*". Il a été montré que la montée de l'incertitude durant la Grande récession s'est accompagnée d'une forte hausse des taux d'épargne. Ce résultat suggère que l'incertitude peut avoir une influence sur les décisions de consommation des ménages (Blanchard, 1993). Lorsque les ménages font face à une situation incertaine vis-à-vis de leur situation financière ou concernant leur emploi, ces derniers chercheront à se protéger en augmentant leur épargne. Cette épargne de précaution entraîne une réduction de la consommation et donc, de la demande agrégée :"*Uncertainty is largely* *behind the dramatic collapse in demand*" (Blanchard, 2009). Ce canal a été mis en évidence dans des modèles macro-dynamiques de type DSGE (Basu and Bundick, 2017; Challe et al., 2017).

Le canal des frictions financières correspond à la prime de risque plus élevée pour financer les projets en présence d'incertitude. La montée de l'incertitude conduit les investisseurs à vouloir exiger ces primes de risque plus élevées afin d'être indemnisés (Christiano et al., 2014; Gilchrist et al., 2014). Par conséquent, l'incertitude pourrait également entraîner une hausse du coût du financement par l'emprunt. Les banques sont susceptibles d'appliquer des taux d'intérêt plus élevés car l'incertitude augmente la probabilité de défaillance. Cette augmentation du coût du financement aurait un effet négatif sur l'économie par son impact sur l'investissement.

Ces différents canaux constituent des arguments permettant d'expliquer la faible reprise économique après la crise de 2007-2008. Par exemple, le canal des options réelles pourrait expliquer la faible reprise de l'investissement après la crise de 2007-2008 malgré des taux d'intérêt qui avaient atteints des niveaux historiquement bas. Ce constat suggère également que l'incertitude pourrait affaiblir l'éfficacité des politiques économiques. Bloom et al. (2018) ont montré que l'effcacité d'une politique de relance de type subvention salariale à la production est réduite de plus de deux tiers quand le niveau d'incertitude est haut. Aastveit et al. (2017) ont montré que les effets de la politique monétaire sur l'activité économique aux Etats-Unis sont diminués de moitié lors des périodes de forte incertitude. Vavra (2014) montre qu'une plus grande volatilité provoquait une hausse de la flexibilité des prix. Pendant les périodes de forte volatilité, le désir des entreprises à vouloir changer leurs prix est plus important, conduisant le niveau global des prix à être plus sensible à la relance nominale et la production à être moins sensible à cette relance. Cela signifie que pour obtenir une augmentation donnée de la production réelle, il faut une augmentation plus importante de l'inflation en période de forte volatilité. Dans ce contexte de grande volatilité, la relance nominale génèrerait une hausse de l'inflation plutôt qu'une croissance de la production.

Effets positifs

Les arguments théoriques évoqués précédemment quant à l'effet négatif ont souvent été mis en avant au sein des débats économiques. En revanche, d'autres arguments mettant en avant que certaines formes d'incertitude pourraient avoir un effet positif sur l'activité sont également présents dans la littérature. L'un de ces arguments est lié à la théorie des *growth options* (Segal et al., 2015). Ces arguments se placent dans un cadre où une entreprise fait face à une situation incertaine mais la seule incertitude concernerait le potentiel profit que pourrait faire l'entreprise dans le futur au moment de prendre la décision. Les exemples donnés sont liés à des innovations technologiques telles que l'intelligence artificielle. Les réalisations industrielles de ces innovations technologiques seront difficiles à prévoir mais il n'y a aucun doute sur le fait qu'il y a aura des profits qui seront générés par de telles innovations. Cependant, quel sera le montant du profit futur et quelles entreprises pourront en bénéficier ? Cette incertitude autour du futur profit pousserait les entreprises à investir, à effectuer des dépenses en R&D, boostant ainsi l'activité économique. La *growth option* a été souvent liée à l'effet Oi-Hartman-Abel (Oi, 1961; Hartman, 1972; Tisdell, 1978; Abel, 1983) se basant sur une littérature théorique moins récente. Cet effet met en évidence le fait que les entreprises ont à la capacité à s'étendre pour exploiter les bons résultats ou des conditions favorables (hausse de la demande, hausse des prix) et à se contracter pour s'assurer contre des conditions moins favorables. Par conséquent, les entreprises ne seraient plus averses au risque car les grandes situations incertaines génèrent de plus grands profits espérés. Cependant, cet effet repose sur de fortes hypothèses comme une situation de concurrence pure et parfaite. Caballero (1991) montre que si les hypothèses de concurrence pure et parfaite sont relachées, les investissements des entreprises peuvent baisser lorsque l'incertitude augmente mais cette relation pourrait également rester positive si les entreprises ont des rendements d'échelle croissants dans une situation de concurrence imparfaite.

De récents arguments s'inspirent du modèle théorique de Gabaix (2014, 2020) où les agents sont considérés comme étant en partie "myopes", les rendant incapables d'anticiper avec perfection le futur. Par conséquent, Gabaix (2014, 2020) montrent qu'ils ne peuvent pas anticiper qu'une relance mise en place engendrera par la suite une hausse des taxes dans le futur supprimant ainsi l'équivalence ricardienne. Un corollaire de ces résultats serait que cette myopie est exacerbée quand l'incertitude est grande. Plus les agents sont myopes, moins les agents sont en capacité d'anticiper avec perfection le futur, l'évolution future des variables économiques et par conséquent, plus le futur est incertain, générant une relance d'autant plus efficace.

Etant donné qu'il n'existe pas de consensus quant à l'effet de l'incertitude sur l'activité économique dans la littérature théorique, étudier l'effet des chocs d'incertitude à un niveau empirique apparaît comme étant une importante question. Nous verrons également qu'il n'y a pas de consensus quant à un effet négatif de l'incertitude dans les études empiriques.

Evaluations Empiriques

Etudier les effets de l'incertitude à un niveau empirique suppose que nous ayons une variable ou une mesure reflétant ce phénomène non observable qu'est l'incertitude. Comment peut-on mesurer l'incertitude ? Cette a question a été abordée depuis l'article fondateur de Bloom (2009) où une littérature empirique fleurissante a emergé sur ce sujet. Cette litterature a developpé de nombreuses méthodologies permettant de mesurer l'incertitude.[3] Il est important de préciser que, contrairement à la littérature théorique faisant la distinction entre la notion de risque et d'incertitude, la littérature empirique

[3]Dans le chapitre 1 de cette thèse, une revue détaillée des méthologies mesurant l'incertitude sera menée.

ne peut faire une telle distinction. Les mesures développées se réfèrent à un mix entre ces deux notions (Bloom, 2014). Ainsi, le terme "mesure d'incertitude" désigne en réalité des mesures qui cherchent à approximer l'incertitude, à donner une estimation du niveau d'incertitude. Les premières mesures ont été basées sur la volatilité des marchés financiers (Bloom, 2009; Gilchrist et al., 2014; Caldara et al., 2016). D'autres mesures sont basées sur la dispersion des prévisions des prévisionnistes, sur des sondages auprès des consommateurs, entreprises concernant la perception des conditions économiques futures (Bloom, 2009; Bachmann et al., 2013; Leduc and Liu, 2016). Les erreurs de prévisions peuvent aussi représenter une alternative comme mesure d'incertitude (Jurado et al., 2015; Scotti, 2016; Ludvigson et al., 2021). Des mesures plus récentes se basent sur une analyse textuelle en comptant la fréquence d'apparition de mots-clés liés à l'incertitude dans la presse (Baker et al., 2016; Davis, 2016; Caldara and Iacoviello, 2022). En appliquant les mesures développées dans des modèles économétriques comme les modèles VAR, ces travaux empiriques soulignent également le comportement attentiste des agents en trouvant un effet négatif des mesures d'incertitude, stoppant les décisions d'investissement et d'embauche dans le cas des entreprises et les décisions de dépenses de consommation dans le cas des ménages. Cependant, cette branche de la littérature comporte une pricipale limite: elle se base sur des modèles linéaires et ne prend pas en compte le fait que les effets de l'incertitude puissent être différents selon l'état de l'économie comme stipulée par Greenspan (2003): "*An assumption of linearity may be adequate for estimating average relationships, but few expect that an economy will respond linearly to every aberration*".

Une autre branche de cette littérature empirique s'est developpée en appliquant des modèles économétriques non-linéaires. Ces études empiriques ont examiné les effets de l'incertitude dans différents régimes de l'économie comme expansion et récession. En adaptant le modèle VAR de l'article de Bloom (2009) à un modèle STVAR (Smooth Transition VAR) pour prendre en compte la non-linéarité, Caggiano et al. (2020) montrent que les chocs d'incertitude ont un effet récessif plus important dans les phases de récession. Caggiano et al. (2014), Caggiano et al. (2017a) et Colombo and Paccagnini (2020) montrent que la hausse du chômage générée par les chocs d'incertitude est également plus forte en phase de récession aux Etats-Unis. En utilisant un modèle IVAR (Interacted VAR), Caggiano et al. (2021) estiment que la contraction de l'activité économique après un choc d'incertitude est plus forte et plus persistante pendant la grande récession. Les récentes études empiriques citées précedemment semblent également converger vers un consensus avec un effet négatif des chocs d'incertitude sur les variables macroéconomiques qui seraient plus forts en période de récession. D'autres spécifications ont également été appliquées en utlisant d'autres variables seuils. Avec un modèle VAR à seuil, Alessandri and Mumtaz (2019) estiment des effets récessifs plus importants dans un régime de stress financier que dans un régime financier dit tranquille ou plus calme. En appliquant une approche alternative avec un modèle VAR à changements de régimes markoviens (MSVAR), Lhuissier and Tripier (2021) constatent également un effet négatif plus fort des chocs d'incertitude en régime de tensions économiques. En utilisant un modèle IVAR, Caggiano et al. (2017b) étudient les effets sous une spécification différente qui est liée à l'état de la politique monétaire. Les auteurs montrent que le déclin de l'activité économique causé par un choc d'incertitude est plus élevé quand la borne inférieure zéro est proche qu'en période de politique monétaire non contrainte.

Effets Positifs: Rôle de la nature des chocs

De récents travaux empiriques ont brisé cet apparent consensus quant à cet effet négatif. L'hypothèse de base de certains travaux est que l'incertitude peut être décomposée selon deux natures: une "bonne" incertitude et une "mauvaise" incertitude. La bonne incertitude porte sur le niveau des futurs profits ou de la croissance future mais sachant qu'ils évolueront positivement. A l'inverse, la mauvaise incertitude porte sur le montant de la baisse des profits et sur la baisse de la croissance future. Segal et al. (2015) décomposent l'incertitude entre "bonne" et "mauvaise" à partir de mesures de semi-variances. L'idée de la décomposition de l'incertitude de Segal et al. (2015), entre bonne et mauvaise, a été reprise par Forni et al. (2021) avec une décomposition entre "incertitude à la baisse" et "incertitude à la hausse". L'incertitude à la baisse est définie comme étant la différence entre la prédiction de la médiane (situation normale) de la croissance future et la prédiction du 5ème quantile inférieur de la croissance future (pire scénario de croissance). L'incertitude à la hausse est définie comme étant la différence entre la prédiction du 5ème quantile supérieur de la croissance future (meilleur scénario de croissance) et de la médiane (situation normale). L'incertitude à la baisse concerne le niveau de baisse de la croissance future et est considérée comme étant une "mauvaise" incertitude. A l'inverse, l'incertitude à la hausse porte sur le niveau de la croissance dans le futur mais tout en sachant qu'elle evoluera positivement. Ces deux composantes sont estimées par Forni et al. (2021) en appliquant la méthodologie de Adrian et al. (2019), se basant sur la regression quantile, afin de prédire la distribution de la croissance future. Les résultats de ces auteurs mettent en évidence que ces deux types d'incertitude ont des effets opposés. La mauvaise incertitude a des effets récessifs tandis que la bonne incertitude a des effets légèrement expansionnistes. Il convient de noter que ces chocs ont des effets positifs de façon structurelle. Ils sont empiriquement positifs puisqu'ils sont définis comme étant des chocs positifs sur la production industrielle. Forni et al. (2021) soulignent que les mouvements de la mauvaise incertitude dominent les mouvements de la bonne dans les mesures developpées dans la littérature, expliquant le fait que la plupart des travaux trouvent un effet négatif. Ferrara et al. (2022a) ont également appliqué cette idée d'une décomposition entre bonne et mauvaise incertitude dans le cas des matières premières. L'incertitude liée aux prix des matières premières pourrait avoir un effet différent selon ses composantes. La mauvaise incertitude, ayant un effet négatif, viendrait de la composante d'incertitude mondiale ancrée dans l'incertitude des prix du pétrole et commune avec les prix des autres matières premières. La bonne incertitude proviendrait de l'incertitude liée au marché pétrolier qui a un effet positif à court terme sur l'investissement. L'idée sous-jacente est que, face à d'éventuelles hausses des prix du pétrole dans le futur, les entreprises décident d'augmenter leur consommation d'énergie à l'instant présent. Cezar et al. (2020) montrent qu les flux transfrontaliers seraient freinés par un choc d'incertitude mais qu'une forte hétérogénéité se cache également derrière cet effet négatif. Les entreprises dont les performances sont faibles avant le choc auraient tendance à réduire durablement leurs investissements à l'étranger alors que les entreprises plus performantes les augmenteraient, constituant une preuve d'un effet assainissant des chocs parmi les firmes multinationales en présence de frictions financières.

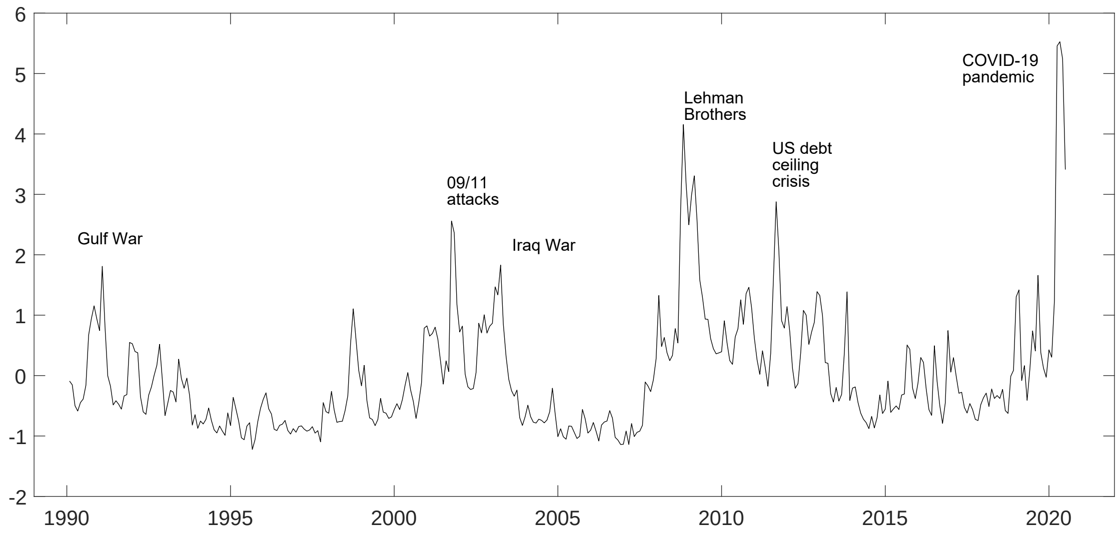
Dans le cas de la Norvège, Larsen (2021) décompose les chocs d'incertitude en developpant un large éventail de mesures d'incertitude à partir des techniques d'analyse textuelle et de machine learning: macroéconomie, finance, santé, prix du pétrole, politique, énergies, sports... A partir d'un modèle SVAR où la méthode d'identification des chocs d'incertitude repose sur des contraintes narratives, Larsen (2021) montre que l'incertitude macroéconomique a un effet récessif comme dans la plupart des travaux. En revanche, il constate aussi que l'incertitude liée à une fusion et acquisition a un effet expansionniste boostant l'investissement et la croissance. Dans le cas américain, Ludvigson et al. (2021) décomposent les chocs d'incertitude d'une façon moins détaillée que Larsen (2021) entre incertitude macroéconomique et incertitude financière en utilisant les erreurs de prévisions de plusieurs séries macroéconomiques et financières. En utilisant une nouvelle méthode d'identification des chocs dans un SVAR, reposant sur les contraintes narratives mais en restreignant les chocs à être d'une taille suffisamment importante à des dates spécifiques, ces auteurs estiment que les chocs d'incertitude liés à la finance ont un effet récessif comme dans les précédents travaux. En revanche, le résultat le plus suprenant est que le choc d'incertitude macroéconomique a des effets positifs sur la production industrielle, brisant le consensus concernant l'effet d'un tel choc qui est plus large (ou moins spécifique) que le choc lié à la fusion-acquisition de Larsen (2021). Pour expliquer ces résultats quant à cet effet positif, l'explication théorique donnée par Larsen (2021) et Ludvigson et al. (2021) repose sur les *growth options*. Ludvigson et al. (2021) se réfèrent aux innovations technologiques tandis que Larsen (2021) considère la fusion-acquisition comme étant une source de "bonne" incertitude pour les entreprises.

Objectifs et Plan de la Thèse

Cette brève revue des différents travaux empiriques montre que, contrairement aux idées reçues au sein des débats politiques, l'incertitude n'a pas que des effets néfastes sur l'activité économique et que les décideurs de politiques économiques ont encore une connaissance assez restreinte de l'incertitude. Les travaux de Larsen (2021) mettent en avant l'effet positif d'une incertitude très spécifique: l'incertitude liée à la fusion-acquisition. Les travaux de Ludvigson et al. (2021) soulignent l'effet positif d'une incertitude plus large telle que l'incertitude macroéconomique. Cette thèse s'inscrit dans la littérature de la recherche de l'effet positif d'un choc d'incertitude. Les chapitres de cette thèse vont révéler quelques limites dans cette littérature. Plus spécifiquement, les deux premiers chapitres vont révéler les limites des travaux de Ludvigson et al. (2021) concernant leur décompostion entre incertitude macroéconomique et incertitude financière, mais aussi concernant leur estimation d'un effet positif de l'incertitude macroéconomique sur la production industrielle à cause de problèmes méthodologiques. Les autres chapitres trouveront un effet positif plus robuste que ces auteurs et établiront un cadre plus général dans lequel cet effet positif puisse se produire, contrairement aux travaux de Larsen (2021) où l'effet positif porte sur une incertitude qui est spécifiquement liée à la fusion et acquisition.

Le chapitre 1 de cette thèse s'intéresse aux différentes méthodes qui ont été proposées afin de mesurer ou d'approximer l'incertitude. Depuis l'article fondateur de Bloom (2009), de nombreuses méthodes ont été proposées: volatilité des marchés financiers, l'analyse textuelle de la presse, la variance des erreurs de prévisions, la dispersion des prévisionnistes, les spread de taux d'interêt. Ce chapitre va contribuer à cette littérature empirique en s'inscrivant dans la lignée des indices composites. Ces indices composites ont pour but de synthétiser les mesures d'incertitude proposées dans la littérature en un indice agrégé. En effet, comme ces mesures sont developpées à partir de différentes méthodes, elles peuvent fournir des informations qui sont différentes. Par exemple, un indice de risque géopolitique ne fournira pas les même informations qu'une mesure liée à l'incertitude financière. A partir d'une analyse en composantes principales (ACP) et en appliquant diverses mesures d'incertitude développées dans la littérature, ce chapitre développe une mesure d'incertitude générale pour les Etats-Unis identifiant de nombreux évènements comme l'illustre la Figure 2: 09/11, guerre d'Irak, Lehman Brothers, Shutdown, COVID-19... Cette méthode de l'ACP permet également

Figure 2: Indice d'incertitude générale américain (1990-2020)



Note: Ce graphique est extrait du chapitre 1 de mener une profonde analyse permettant d'identifier d'autres facteurs expliquant les fluctuations dans l'incertitude. La méthode des modèles à facteurs dynamiques (DFM) permet de trouver des résultats similaires à ceux de l'ACP mais leur interprétation est plus difficile, voire impossible. Ces principaux facteurs que nous avons identifiés sont liés au risque pandémique, au risque géopolitique et à la perception publique. Par ailleurs, le second facteur de l'ACP permet d'établir la distinction entre deux types de choc d'incertitude: financier et non-financier. Par conséquent, ce second facteur permettrait de différencier les chocs d'incertitude selon leur véritable nature. Aucune variable de ce type n'a été developpée dans la littérature. Cette distinction est en lien avec la décomposition préconisée par Ludvigson et al. (2021) entre incertitude macroéconomique et incertitude financière. Cependant, les résultats de ce chapitre montrent que la mesure d'incertitude macroéconomique développée par ces auteurs s'avère être plus liée à la finance qu'elle ne devrait l'être. Par conséquent, ce chapitre révèle les limites de la décomposition de Ludvigson et al. (2021). Il faut préciser que les deux mesures d'incertitude de Ludvigson et al. (2021) sont utilisées dans le modèle économétrique où ces auteurs estiment leur effet positif de l'incertitude macroéoconomique sur la production industrielle. Par conséquent, nous pouvons nous interroger quant à la fiabilité de leur effet positif. Cette discussion est approfondie dans le second chapitre de cette thèse.

Le chapitre 2 examine en profondeur le modèle SVAR de Ludvigson et al. (2021) où l'effet positif des chocs d'incertitude macroéconomique sur la production industrielle est mis en avant. Contrairement à la plupart des modèles SVAR utilisant la décomposition de Cholesky pour identifier les chocs structurels d'incertitude, Ludvigson et al. (2021) ont proposé une nouvelle méthode d'identification des chocs d'incertitude en les restreignant à être d'une taille suffisamment importante lors de certaines dates. En utilisant une telle méthode de contraintes narratives, il convient de s'assurer que les contraintes selectionnées soient clairement justifiées. Parmi les contraintes de Ludvigson et al. (2021), la présence d'une contrainte au mois de décembre 1970 peut faire l'objet d'une discussion. Cette contrainte requiert qu'un choc d'incertitude macroéconomique soit suffisamment important lors du mois de décembre 1970 qui serait liée à la fin du système de Bretton Woods selon les auteurs. Les résultats de ce chapitre montrent que l'effet positif dépend uniquement de cette contrainte. En effet, en supprimant cette contrainte, l'effet des chocs d'incertitude macroéoconomique sur la production industrielle n'est plus interprétable.[4] De plus, en rajoutant des contraintes liées à des chocs qui n'ont pas été pris en compte tels que les attentats du 11 septembre ou encore la crise financière russe en 1998, les chocs d'incertitude macroéconomique ont désormais des effets récessifs, soulignant le manque de robustesse des résultats de ces auteurs suite à l'ajout de contraintes moins controversées. Nous montrons aussi que l'effet positif de la contrainte lié au choc de Bretton Woods en décembre 1970 proviendrait d'un biais dans la construction de la mesure d'incertitude de ces auteurs. En effet, leur mesure d'incertitude macroéconomique est basée sur l'agrégation de la variance des erreurs de prévisions de 132 séries macroéconomiques et financières. L'analyse désagrégée menée dans ce chapitre montre que les séries liées à la production industrielle affichent un important pic justement en décembre 1970. Ce mois de décembre 1970 correspond à un point de retournement du cycle économique suivant la période de récession entre 1969 et novembre 1970 et est considéré comme étant une forte erreur de prévision. Le simple fait d'associer un pic d'incertitude très grand à ce mois spécifique de croissance aurait pu générer de façon artificielle cet effet positif dans le modèle économétrique et par conséquent, expliquerait ce problème de dépendance. Ce chapitre recommande de mener une rigoureuse procédure de test de robustesse si les chercheurs souhaitent appliquer cette méthode d'identification des chocs. Ces deux premiers chapitres révè-

[4]Contrairement aux SVAR classiques estimant une seule fonction de réponse impulsionnelle, le SVAR de Ludvigson et al. (2021) estime un ensemble de fonctions de réponse. L'interprétation de cet ensemble est que la fonction de réponse peut osciller entre la plus petite valeur de cet ensemble et la plus grande valeur. En retirant la contrainte de décembre 1970, la fonction de réponse impulsionnelle de la production industrielle suite à un choc d'incertitude macroéconomique est comprise entre une valeur négative et une valeur positive. Par conséquent, l'effet estimé ne peut pas être considéré comme un effet négatif ou un effet positif.

lent les limites des travaux de Ludvigson et al. (2021) malgré les méthodes très intéressantes et novatrices que ces auteurs proposent. Il faudrait arriver à développer une meilleure méthodologie de décomposition des chocs d'incertitude entre macroéconomie et finance. Il faudrait aussi pouvoir arriver à trouver un effet positif qui soit plus robuste que celui estimé par ces auteurs. Les deux chapitres suivants vont se pencher sur ce deuxième problème en étudiant les éffets non-linéaires de l'incertitude.

Le chapitre 3 étudie l'effet non-linéaire de l'incertitude en appliquant la méthode des regressions quantiles. Ce chapitre s'inspire de la méthodologie de Adrian et al. (2022) qui ont examiné l'effet d'un assouplissement des conditions de financement sur les percentiles de la croissance future. Dans le contexte de l'étude de l'effet de l'incertitude, nous pouvons répondre à la question suivante: est-ce que les effets de l'incertitude sont les mêmes selon les différents percentiles de la croissance future ? Nous montrons que l'incertitude générale a un effet négatif sur l'ensemble des percentiles. Cependant, cet effet négatif est plus important sur les percentiles inférieurs correspondant aux pires scénarios de croissance (périodes de forte récession). Ce résultat est en lien avec les principaux travaux portant sur l'effet non-linéaire des chocs d'incertitude sur l'activité économique, ayant un effet négatif plus important sur la croissance et sur l'emploi lors des périodes de recession. La contribution la plus importante de ce chapitre consiste à étudier l'effet non-linéaire de l'incertitude selon sa nature: financière et non-financière. Un point crucial est de réussir à bien décomposer les chocs d'incertitude selon les deux natures susmentionnées. La méthode récente proposée par Kang et al. (2021) pourrait s'y prêter en permettant de désaggréger un indice d'incertitude générale en différentes composantes. Ainsi, les dates où le niveau d'incertitude générale dépasse un certain niveau sont retenues afin d'isoler les pics d'incertitude les plus importants. Puis, ces dates sont classées entre "finance" et "non-finance" selon l'évènement associé. Par exemple, la date associée à Lehman Brothers est classée comme un choc lié à la finance. L'inconvénient de cette méthode est de parvenir à bien identifier la véritable nature de ces pics. Le cas de Lehman Brothers aurait très bien pu être classé "non-finance" en examinant certaines mesures d'incertitude qui ne sont pas liées à la finance. L'originalité de ce chapitre est de revisiter la méthode de décomposition de Kang et al. (2021) en utilisant le second facteur de l'ACP du chapitre 1, associant les chocs à leur véritable nature, comme le critère de différenciation des chocs. Au final, les résultats de ce chapitre montrent que l'incertitude non-financière aurait un effet positif à plus long terme sur les quantiles inférieurs de la croissance future, rendant les pires scénarios de croissance moins pires.

Le chapitre 4 va prolonger le précédent chapitre en examinant l'effet des chocs d'incertitude à partir de la méthode des projections locales de Jordá (2005) dans un cadre non-linéaire. La variable d'incertitude générale du chapitre 1 est considérée comme étant la variable seuil ce qui permet d'étudier l'effet des chocs dans trois régimes d'incertitude générale: faible, modéré et fort. L'originalité de ce chapitre est d'examiner l'effet de la nature des chocs d'incertitude et notamment ceux de l'incertitude non-financière dans ces trois régimes différents. Les résultats de ce chapitre montrent que ces types de choc d'incertitude auraient un effet positif sur la production industrielle ainsi que sur l'emploi en réduisant le chômage dans un régime de forte incertitude et d'incertitude plus modérée. Ces résultats peuvent être reliés aux resultats du chapitre 3 à partir de l'hypothèse contra-cyclique de Bloom (2009) où l'incertitude est plus grande dans des périodes de recession. Les pires scénarios de croissance, c'est-à-dire les périodes de fortes recessions, peuvent être associés à des périodes de forte incertitude. Afin d'expliquer cet effet positif, nous pouvons nous référer aux arguments s'inspirant du modèle théorique de Gabaix (2020). Une relance mise en place serait efficace si les agents sont myopes, c'est-à-dire qu'ils sont dans l'incapacité de prédire le futur avec perfection. Plus cette myopie est grande, moins les agents sont en capacité d'anticiper avec perfection le futur et, par conséquent, plus le futur est incertain et plus la relance génère un effet positif. L'argument de la *growth option* lié aux innovations technologiques n'est pas remis en cause mais ne serait pas vraiment adéquat pour expliquer les résultats des deux derniers chapitres. Le caractère non-linéaire est absent dans cette explication théorique, contrairement à l'argument lié à Gabaix (2020) qui fonctionne si et seulement si la myopie est suffisamment importante.

Ces quatre chapitres sont basés sur une récente littérature empirique dont les travaux font l'objet de publications dans les plus prestigieuses revues du champ. Les deux premiers chapitres identifient des faiblesses dans cette littérature. Les deux autres tentent de pallier à ces limites en trouvant un effet positif de l'incertitude plus robuste et en y apportant une nouvelle explication théorique. A l'instar des précédents travaux tels que ceux Ludvigson et al. (2021) et de Larsen (2021), ces chapitres montrent que les chocs d'incertitude peuvent avoir un effet positif. De plus, les résultats de cette thèse contribuent à cette littérature en établissant un cadre plus général dans lequel cet positif puisse se produire. Le choc d'incertitude doit être d'une nature non-financière et il faut que ce choc impacte l'économie dans une période de forte incertitude, d'incertitude modérée ou dans une période de recession.

Chapter 1

Searching the Nature of Uncertainty: Macroeconomic and Financial Risks VS Geopolitical and Pandemic Risks*

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Introduction

The effects of uncertainty on macroeconomic environment have become an important topic in both economic policy and academic research in recent years. However, the topic of uncertainty is not recent. Indeed, a hundred years ago, Knight (1921) established the modern definition of this concept in economy by distinguishing the concept of risk from that of uncertainty: *"It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an uncertainty at all"*. Risk is associated with situations where all outcomes are identified and their probabilities of occurrences are known. Uncertainty is defined as situations where the possible outcomes of a choice like an investment decision or the probability distribution associated are unknown for the agents. Keynes (1921, 1936, 1937) defined uncertainty as the case where the risk in the decision is not objectively measurable in advance because of a lack of knowledge about the future. The future is unpredictable and does not follow a predetermined probability distribution unlike mainstream perspectives involving uncertainty which are based on a statistical analysis of past data (Davidson, 1991). The idea of unpredictable future is also put forward by Shackle (1953, 1956) referring to the situation where individuals can't produce *ex-ante* an exhaustive list of all possible outcomes of a choice because of a lack of knowledge about the future.[1]

From these very large definitions and concepts, a quite "old " theoretical literature has investigated the effects of uncertainty on the macroeconomic environment through the behavior of households, firms and investors (See, among many others, Leland,

[1]The Brexit could be a perfect example of an uncertainty shock according to these definitions. The future economic path of the UK is difficult to forecast. We can't objectively compute probabilities of potential scenarios using past observations given that there is no previous case since the United-Kingdom has been the first country to leave the European Union. We will not discuss the different definitions on the concept of uncertainty in this chapter. There are other definitions, concepts of uncertainty in the literature. See, among many others, Savage (1954), Davidson (1991), Ferrari-Filho and Conceição (2005), Dequech (1997, 2000, 2011).

1968; Bernanke, 1983; Dixit, 1989; Pindyck, 1991). The 2007-2008 financial crisis has sparked a renewed interest in the effects of uncertainty on the economy as uncertainty has been one of the main explanations for the weak global recovery through agents' behavior (Blanchard, 2009; Stock and Watson, 2012; Bloom et al., 2013). Kozlowski et al. (2020) argued that extreme rare events such as the Great Recession could have a macroeconomic impact over the long term affecting the beliefs of economic agents. This financial crisis has bring a new path on this topic that has been widely used: the empirical dimension. To better understand what are the effects of uncertainty, one variable reflecting or approximating uncertainty is necessary. Since uncertainty is an intrinsically unobservable phenomenon, a booming economic research has emerged on how to quantify uncertainty in recent years. However, there is no consensus leading to a single measure. This recent literature can't make the distinction between risk and uncertainty as highlighted by Knight (1921) but refers to a mixture of risk and uncertainty (Bloom, 2014). Many methodologies have been developed and the resulting indexes have been applied to investigate empirically the effects of uncertainty on macroeconomic environment. It is worth nothing that different effects are estimated depending on the measure applied (Rossi and Sekhposyan, 2015). In this chapter, we review different approaches measuring uncertainty. Recently, the literature has evolved from the level of uncertainty to its nature. Mainly, two uncertainty types are identified: macroeconomic and financial. Some economists have quantified financial uncertainty through the volatility on financial markets (See, among many others, Bloom, 2009; Gilchrist et al., 2014; Caldara et al., 2016). Then, other works have focused on macroeconomic uncertainty applying the notion of variance to develop survey-based measures (Bloom, 2009; Bachmann et al., 2013; Leduc and Liu, 2016). Recent papers have tried to decompose uncertainty shocks between macroeconomic and financial uncertainty shocks by applying econometric models (Jurado et al., 2015; Ludvigson et al., 2021). Finally, a last branch of empirical papers have applied textual analysis techniques and big data frameworks to develop news-based uncertainty measures (See, among many others, Baker et al., 2016; Davis, 2016; Caldara and Iacoviello, 2022). In front of the diversity of either the methods proposed or the data applied, the resulting measures differ from each other providing different information regarding uncertainty. Therefore, composite indexes have been developed to get a synthetic index of uncertainty. Two methods have been applied: a dynamic factor model (Charles et al., 2018) and a principal component analysis (Haddow et al., 2013; Larsen, 2017).

This chapter contributes to this growing empirical literature in two different ways. Firstly, a US global uncertainty index is computed on monthly data for the time period 1990M1:2020M6 combining different uncertainty indexes based on different categories. We provide an analysis in order to identify the nature (or determinants) of uncertainty shocks (financial, macroeconomics, news, geopolitical risk, ...). This chapter stands out from the other works applying the composite index approach with the estimation of a US global index including more recent measures as a measure related to pandemic risk. We also conduct an analysis in order to interpret the factors of the principal component analysis (PCA) that will not only explain the fluctuations of uncertainty but also the nature of uncertainty shocks (financial, macroeconomic policy, news, geopolitical risk, pandemic risk,...). The first factor of the PCA can be interpreted as a measure of the global level of uncertainty for the United States. It is worth nothing that the COVID-19 pandemic corresponds to the highest uncertainty peak. Interestingly, the second factor establishes the distinction between non-financial uncertainty shocks and financial uncertainty shocks underlying the importance of this distinction. As some uncertainty peaks are represented both in a macroeconomic (or non-financial) uncertainty measure and in a financial uncertainty index like the Gulf War and the collapse of Lehman Brothers, this second factor allows to determine what is the real nature of the shock associated with the peak in level of uncertainty. Is the nature of the uncertainty shock related to finance or macroeconomics ? To the best of our knowledge, there are no studies that have developed a single variable establishing this distinction.[2]

Secondly, we investigate the effect of the overall level of uncertainty from a structural VAR model (SVAR). Our identification strategy of shocks relies on the novel methodology proposed by Ludvigson et al. (2021) with *event constraints* imposing some uncertainty shocks on specific dates to exceed a threshold.[3] We find that general uncertainty has a negative effect inducing a decline in the US industrial production. This result is in line with a *wait and see* behavior where uncertainty leads firms to delay investment and hiring decisions (Bernanke, 1983; Pindyck, 1991) and can also lead consumers to rise their savings for precautionary reasons (Leland, 1968).

Two additional lessons can be drawn from this chapter and its results. The first lesson concerns the method used to get a synthetic index. We find many similarities between indexes computed from PCA and DFM in robustness checks. Both indexes have a strong correlation as in Charles et al. (2018). Thus, applying a less complex mathematical procedure, *i.e.* , applying a PCA rather than a DFM, we get a satisfactory general index of uncertainty. The second lesson concerns the macroeconomic uncertainty index developed by Jurado et al. (2015). In addition to our general uncertainty index, we have identified an index switching between macroeconomic uncertainty shocks and financial uncertainty shocks in the second PCA factor. Examining the variables factor map concerning the second factor, we get another result. The measure of macroeconomic uncertainty proposed by Jurado et al. (2015) belongs to a group made up of financial uncertainty variables showing that this index seems more linked to financial uncertainty than macroeconomic uncertainty.

The rest of this chapter is organized as follows. Section 1 reviews the different mea-

[2] Jurado et al. (2015) and Ludvigson et al. (2021) decomposed uncertainty shocks separately using two indexes.

[3] We adopt a macroeconomic approach as a wide range of empirical studies investigating the effects of uncertainty shocks on macroeconomic variables (See, among many others, Bloom, 2009; Jurado et al., 2015; Baker et al., 2016; Ludvigson et al., 2021; Larsen, 2021). Another branch of empirical studies adopt a financial approach exploring the links between uncertainty and financial markets (See, among many others, Białkowski et al., 2021; Dew-Becker et al., 2021).

sures of uncertainty proposing a new classification to analyze these measures according to their nature. Section 2 computes the general uncertainty index and presents the results of the PCA for the United States. Section 3 presents the SVAR model and its results. Section 4 presents robustness checks. The last section concludes.

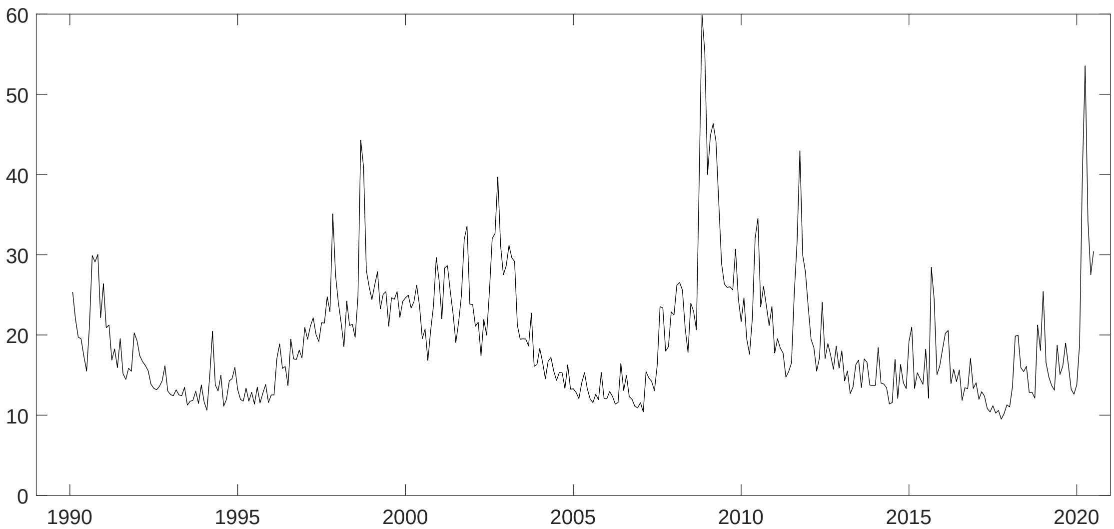
1.1 Measuring Uncertainty: literature review

There are no consensual and objective methodologies measuring uncertainty. A recent literature has emerged proposing different uncertainty proxies. Ferrara et al. (2017) have classified these measures into different categories: uncertainty on financial markets, macroeconomic uncertainty, micro-level and economic policy uncertainty. New uncertainty measures have been developed since then applying new methodologies. This section aims at extending the review of literature by including these new measures and approaches. Moreover, this literature review will also allow us to select the uncertainty proxies that we are going to apply to develop our global uncertainty index in the next section. In order to get a large set of measures, we will select monthly measures of uncertainty which can span over the time period January 1990 to June 2020. Some other uncertainty measures have been proposed but they are available on a shorter period or with a different frequency or data are not available on authors website.

1.1.1 Financial Uncertainty

The first measure of uncertainty developed in the empirical literature was based on financial market fluctuations and more precisely, on volatility. For example, Bloom (2009) applied the Volatility Index (VIX) as a measure of uncertainty. The VIX, developed by the Chicago Board Options Exchange (CBOE) since 1990, is a measure of 30-day option-implied volatility in the S&P 500 index. Using historical data, a high level of this index means a high volatility in financial markets which corresponds to periods of crisis. This “fear index” (Whaley, 2000, 2009) could reflect agents’ expectations in the equity market. A rise of this index is interpreted as a sign of a growing uncertainty. Figure 1.1 plots the VIX index showing that the greatest uncertainty peaks are related to the COVID-19 pandemic, the collapse of Lehman Brothers in 2008 and the 1998 Russian financial crisis. We can find other peaks which are related to periods of geopolitical tensions like the Gulf War, the Iraq War or the 09/11 attack.

Figure 1.1: VIX Index



Note: The measure spans the time period 1990:M1-2020:M6.
Source: Yahoo Finance

The VIX has been applied to build other measures as the variance risk premium in Zhou (2018) defined as the difference between an *ex-ante* risk-neutral expectations and the *ex-post* observation of the return variance represented by the realized variance. The risk-neutral expectation of variance (or the implied variance) is measured by the VIX as it could proxy stock market expectations.[4] The realized variance is the volatil-

[4]The implied variance corresponds to the estimate of the underlying future volatility of assets derived from option prices which can be approximated by the VIX reflecting the stock market’s expectation of volatility based on S&P 500 index options (Bollerslev et al., 2009; Whaley, 2009).

ity of the S&P 500 index using high-frequency returns (Bollerslev et al., 2009).[5] The difference between both variables is high during crisis periods and recessions (see Figure A1). On the one hand, when the implied variance exceeds the realized variance, traders have increased the price of options as a hedge against a potential transition to a riskier economic environment. Market participants are willing to pay more in order to hedge against unexpected market volatility (Carr and Wu, 2009; Feunou et al., 2018) and hence, reflecting a growing future uncertainty. The variance risk premium is high and positive with the Gulf War in 1990, the 1997 Asian financial crisis, the 1998 Russian financial crisis, the Iraq War (see Figure A1). On the other hand, when the realized variance exceeds the implied volatility, the interpretation is more difficult and the literature does not really explain what happens when there is a negative level. Considering the implied variance as an *ex-ante* uncertainty and the realized as an *ex-post* uncertainty, the interpretation that we can put forward is that the hedge has been insufficient against risks that have already occurred. For example, the highest negative peak of this variable represents the collapse of Lehman Brothers (see Figure A1), so either market participants have underestimated the importance of occurrence of the bankruptcy, or they could not predict that a bankruptcy could occur. Therefore, researchers should be very careful when applying this index. Indeed, if the variance risk premium is equal to 0, it does not mean necessary that the level of uncertainty remains unchanged or is low but just that both variances are equal. We could misinterpret the fact that there is no uncertainty at time t. It is worth nothing that some authors don't consider the variance risk premium as a measure of uncertainty but they interpret it as solely as a measure of the agents' risk-aversion (Rosenberg and Engle, 2002; Beckaert and Hoerova, 2016). Another shortcoming of VIX based uncertainty measures relies on the limited time span. Manela and Moreira (2017) tried to solve this issue applying machine learning tech-

[5]The academic literature has demonstrated that the realized variance measure computed from high-frequency data provided a more accurate ex-post observation of the return variance than a variance computed from daily returns (Barndorff-Nielsen and Shephard, 2002; Meddahi, 2002).

niques. They applied front of articles from the Wall-Street journal to develop a new VIX measure covering a very large time period to extend options implied measures of uncertainty back to the end of the 19^{th} century. The variation in the topics in the business press could reflect the evolution of investors' concerns about these topics. They have estimated a measure based on the co-movement between the front-page title of the journal and the VIX capturing the fear of the investors over history: the News Implied Volatility (NVIX) . We can consider the NVIX as an extension of the VIX combined with information from words of the business press. The NVIX is high for the 1929 crisis, the 1998 Russian financial crisis and Long Term Capital Management, the Iraq War in 2003 and the collapse of Lehman Brothers in 2008 (see Figure A2). This methodology is very interesting to have data on a very large period with a variable that can replace the VIX until the end of the 19^{th} century.[6]

Some measures of uncertainty directly are related to firm-level stock market returns following the idea of volatility indexes to measure uncertainty. More specifically, a standard deviation of returns is computed for specific companies. Bloom (2009) has proposed to compute the cross-sectional standard deviation of US firm-level stock returns. Gilchrist et al. (2014) have constructed a measure of idiosyncratic uncertainty ($IVOL$) using daily stock returns data from a panel of 11303 nonfinancial corporations.[7] They propose a three step approach. Firstly, the authors remove the forecastable variation in daily excess returns by estimating the four-factor model advocated by Carhart (1997). Secondly, they compute a quarterly firm-specific standard deviation of daily returns with the OLS residuals of the previous regression. This standard deviation provides a firm-specific measure of uncertainty. And finally, to construct their measure at the aggregate level, the authors use a dynamic panel data model including time fixed effects which capture common shocks in the idiosyncratic volatility. Figure A4 plots the monthly

[6]Unsurprisingly, we find many similarities between the VIX and the NVIX with a correlation equal to 0.80 (see Figure A3) over the time period 1990-2016.

[7]The authors have chosen firms with at least 1250 trading days of data. However, there is no justification about the choice of the number of trading days.

version of this measure developed by Caldara et al. (2016). The collapse of Lehman Brothers corresponds to the highest peak. Other peaks are related to financial crises as the 1997 Asian financial crisis, the 1998 Russian crisis are also observed. As in the case of the VIX measure, the IVOL index displays other peaks which are related to geopolitical tensions like the Gulf War and the Iraq war.

Corporate bond spreads have also been used as an indicator of tension on financial markets (Bachmann et al., 2013). This measure is defined as the difference between the yield of Baa-rated corporate bonds and the 30-year Treasury yield. A rise is assumed to reflect a greater tension in the financial markets as investors demand a higher yield because of uncertainty about the financial health of corporates.[8] Corporate bond spreads exhibit spikes during financial crises (see Figure 1.2) with the 2000 dot-com bubble, the collapse of Lehman Brothers where there was a real doubt about the financial health of each company, bank, financial institution, etc...

1.1.2 Macroeconomic Uncertainty

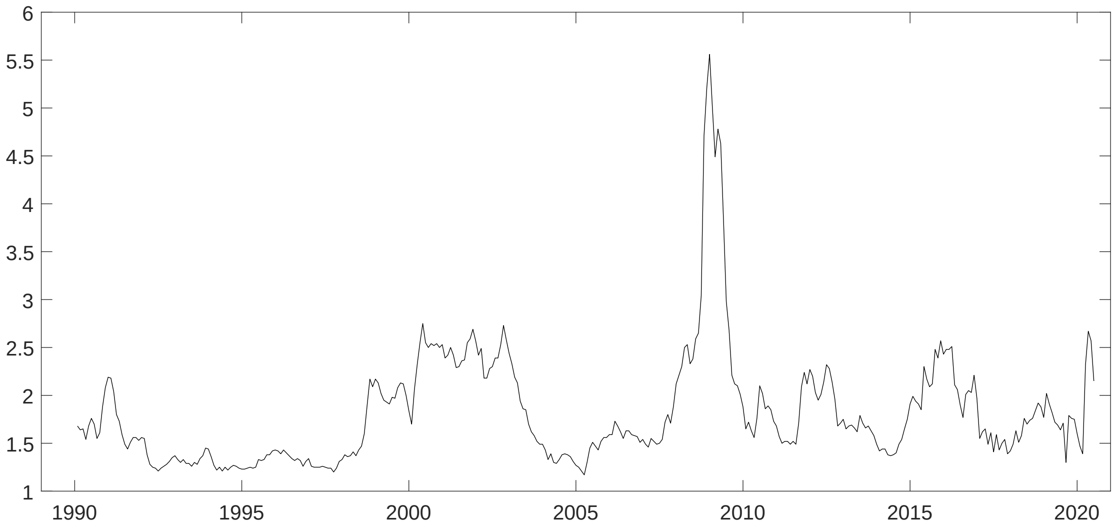
As financial uncertainty, the development of a macroeconomic uncertainty index has been the subject of recent researches. Various methodologies have been proposed: dispersion among forecasters, confidence indexes, yield spread and forecast errors.

Dispersion among forecasters

As in the case of financial uncertainty indexes, measures of dispersion have been proposed to represent macroeconomic uncertainty such as the forecast disagreement. Professional forecasters are asked about the future evolution of a macroeconomic variable. Even if these forecasters may apply the same data set, they may, however, have their own interpretation and thus produce different forecasts. Therefore, no consensus about

[8]The 30-year Treasury bond is missing between March 2002 and January 2006. Following Bachmann et al. (2013), we complete data applying the difference between the yield of Baa-rated corporate bonds and the 20-year Treasury yield.

Figure 1.2: Corporate Bond Spread



Note: The measure spans the time period 1990:M1-2020:M6.
Source: FRED Saint-Louis Database

the future value of the macroeconomic variable will be reached. Zarnowitz and Lambros (1987) define the consensus as the degree of agreement among corresponding point predictions by different individuals. If there is a strong disagreement among forecasters on the future evolution of a macroeconomic variable, the evolution of this variable could be more uncertain in the future. It is assumed that there is a positive relationship between uncertainty about the future and forecast disagreements (Bomberger, 1996; Giordani and Soderlind, 2003).

Bloom (2009) has proposed the standard deviation of GDP forecasts about the one-year-ahead using the survey of professional forecasters at the Federal Reserve Bank of Philadelphia.[9] Istrefi and Mouabbi (2018) have developed a subjective measure of interest rate uncertainty based on the Consensus Economics survey for some advanced

[9]At a micro-level, Bloom (2009) proposed to compute the cross-sectional standard deviation of firm profit growth from Compustat quarterly accounts and the annual standard deviation of the five-factor total-factor productivity (TFP) growth rates from the National Bureau of Economic Research (NBER).

economies.[10] Their measure is defined as the sum of the variance of disagreement among professional forecasters and the conditional variance of mean forecast errors exploiting the difference between expected and observed interest rates.[11]

Survey-based measures and Confidence Indexes

Other survey-based measures have been proposed like confidence indexes which can represent an alternative measure to proxy uncertainty (Haddow et al., 2013; Leduc and Liu, 2016; Nowzohour and Stracca, 2020). Bachmann et al. (2013) construct a measure of forecast dispersion using the Philadelphia Fed's Business Outlook Survey giving qualitative information on the current state of firms' business conditions and their expectations about future business conditions. They apply the following answers by firms to the questions "What is your evaluation of the level of general business activity six months from now vs [current month]: decrease; no change; increase?" However, this question is too general and large. In the business confidence index of the Organisation for Economic Co-operation and Development (OECD), questions are more specific. This index is based on firms' assessment of production, orders and stocks, the current situation and their short-term expectations. The questions concern job prospects, production, sales prices and order books. An index above 100 signals a boost in the confidence towards the future economic situation. Inversely, an index below 100 translates a pessimistic attitude and a growing uncertainty (see Figure 1.3). The index is low during the Gulf War, the 09/11 attack, the 2007-2008 financial crisis and during the current COVID-19 pandemic with lockdown measures stopping economic activities.

Similarly, a consumer confidence has been developed. On the one hand, a consumer may be optimistic if there is no uncertainty about a favorable change in his future income. On the other hand, if there exists a doubt about an adverse change, this confidence will decline and therefore, the consumer will prefer to save rather than to consume. The

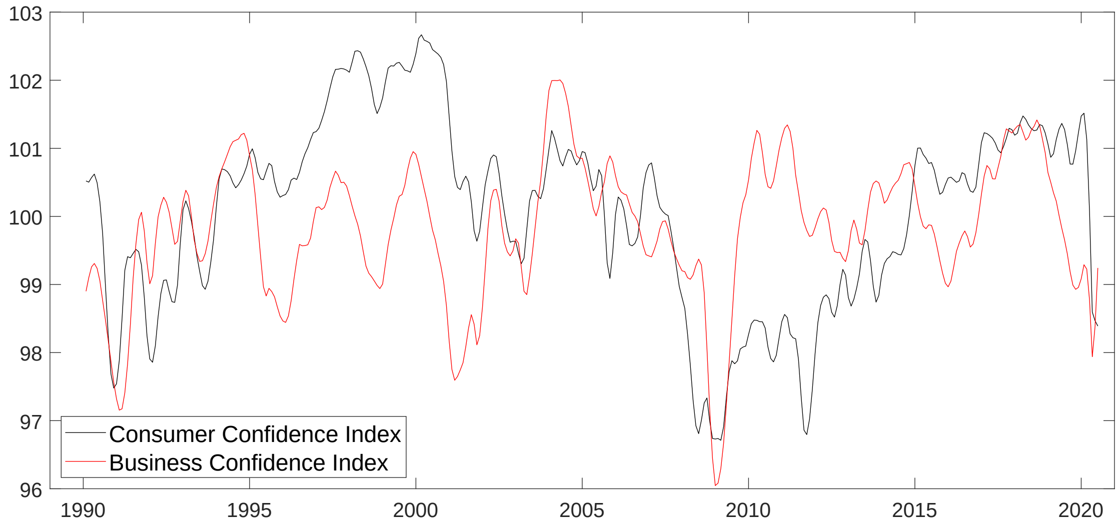
[10]The United States, France, Germany, Japan, Spain, Italy, the United Kingdom, Sweden, Canada.
[11]This second component has been used to construct other measures of uncertainty.

consumer confidence index developed by the OECD gives a measure of future evolution of households' consumption and savings with answers about their expected financial situation, their sentiment about the economic situation, unemployment and capability of savings. The questions concern the expectations about the financial situation of households, the expectations for the economic situation and the number of unemployed in the next twelve months. An index above 100 signals a boost in the confidence towards the future economic situation and an index below 100 translates a pessimistic attitude and a growing uncertainty. This growing uncertainty increases rapidly in recessions as the period following the 2007-2008 financial crisis where the pessimistic attitude has been persistent (see Figure 1.3). This index exhibits a peak during the current COVID-19 pandemic with lockdown measures which is a high period of uncertainty for consumers regarding their future situations (financial, job,...) and the future macroeconomic situation. However, as measures of uncertainty are mainly based on the variance, some authors warn that these indexes can't clearly distinguish between a change in the variance of demand and a change in the level of expected demand (Haddow et al., 2013; Leduc and Liu, 2016).

Interest Rate Spreads as predictors of future downturns

Interest rate spreads are defined as the difference between long-term interest rates and short-term interest rates. They are often considered as a predictor of a recession one year later if this difference is small or negative (Estrella and Mishkin, 1998; Rudebusch and Williams, 2009; Bauer and Mertens, 2018a,b). In practice, for long-term rates, a common choice is to use the 10-year Treasury bill rate reflecting the visions of investors in the bond market. For short-term rates, there are several possibilities: 2-year, 1-year, 3-month Treasury bill rates. In the academic literature, the 3-month rate is often applied. Financial commentators apply the 2-year rate which is considered as an indicator of the stance of monetary policy. Interest rate spreads are high during the period following

Figure 1.3: Confidence Indexes



Note: The measure spans the time period 1990:M1-2020:M6. The solid black line represents the consumer confidence index. The solid red line represents the business confidence index.
Source: OECD database

the collapse of Lehman Brothers (Figure 1.4). It is also worth nothing that interest rate spreads are high during period of geopolitical tensions (Gulf War, Iraq War and 09/11 attack) and increase rapidly during recessions.[12]

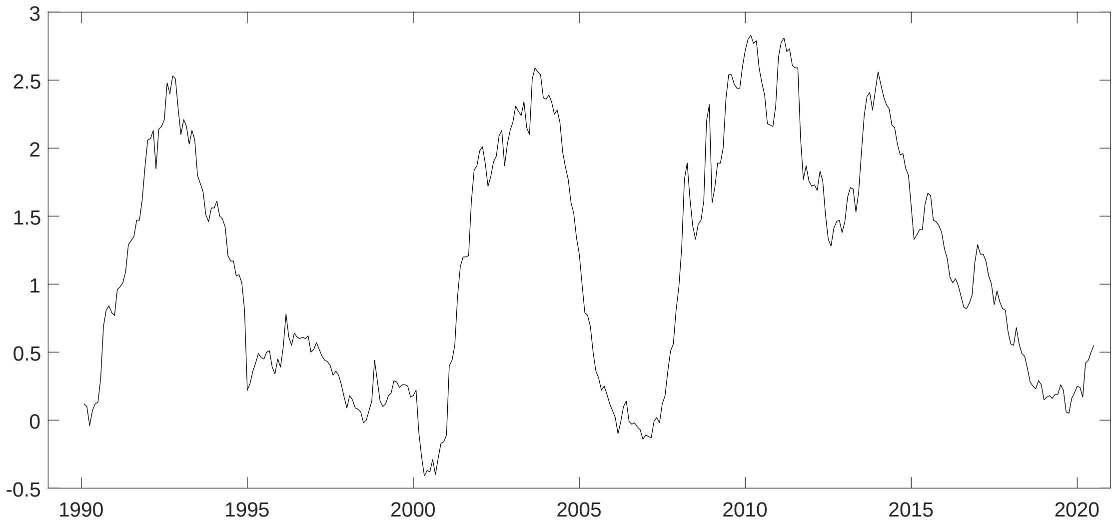
Forecast Errors

Forecast errors have been proposed by Scotti (2016) to construct a daily index of macroeconomic uncertainty for some countries.[13] The uncertainty index is computed as the square root of a weighted average of the squared of the difference between the Bloomberg forecasters median expectation and the realization of a set of macroeconomic variables. In the same line, Rossi and Sekhposyan (2015) have proposed a macroeconomic uncertainty index based on the comparison between the realized forecast error of real GDP

[12]During the European debt crisis, medias and financial commentators have focused on the spread between the Greece 10-year Government Bond yield and the Germany 10-year Government Bond yield to try to infer macroeconomic information on the future for Greece.

[13]The United States, Canada, Japan, the United Kingdom and the euro area.

Figure 1.4: Spread 10Y-2Y



Note: The measure spans the time period 1990:M1-2020:M6.
Source: FRED Saint-Louis database

and the historical forecast error distribution. Ismailov and Rossi (2018) applied the same methodology to develop an exchange rate uncertainty index for the European Union and a set of developed countries.[14]

Another approach consists in estimating an econometric model with time-varying volatility. In this case, the volatility of the forecast errors will be considered as a proxy of uncertainty. Bali et al. (2014) have developed a US macroeconomic uncertainty index applying variables that could affect investor consumption and investment opportunities from GARCH models.[15] This econometric framework has been applied for the estimation of an interest rate uncertainty index (Fernández-Villaverde et al., 2011), an uncertainty index on fiscal policy (Fernández-Villaverde et al., 2015), inflation (Chan,

[14]The United States, Switzerland, the United Kingdom, Japan and Canada.

[15]The difference between yields on BAA-rated and AAA-rated corporate bonds, the aggregate dividend yield on the S&P500 index, monthly growth rate of real GDP per capital, monthly inflation, monthly unemployment, the difference between yields on ten-year and three-month Treasury securities, the difference between the three-month T-bill and its 12-month backward moving average and the excess return on the value-weighted NYSE / Amex / Nasdaq equity market index.

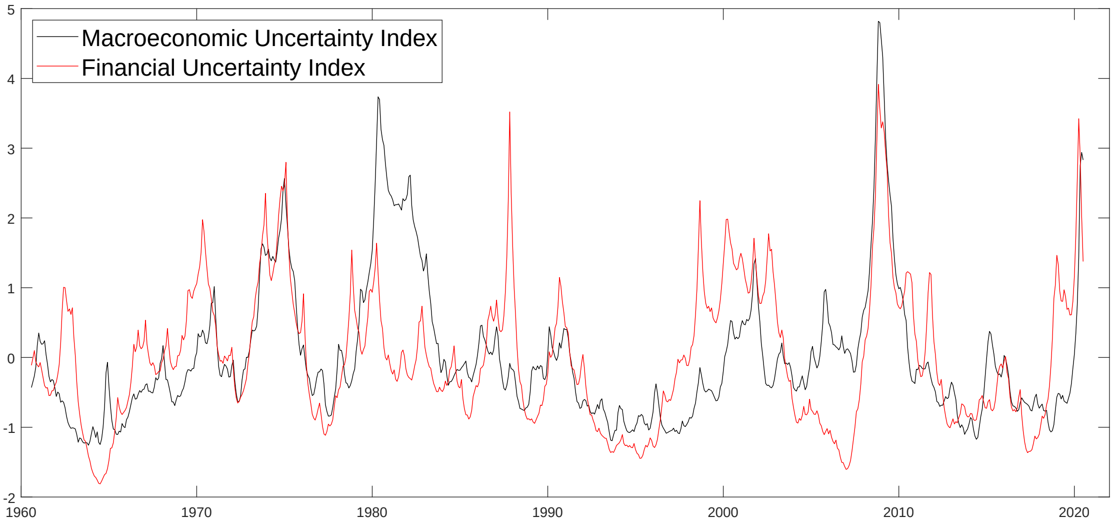
2017) and commodity market (Joëts et al., 2018).

1.1.3 Decomposition of Uncertainty Shocks: Macroeconomics VS Finance

The most recent empirical literature on uncertainty focuses not on estimating the level but rather the nature of uncertainty shocks. Ludvigson et al. (2021) have decomposed uncertainty between macroeconomic uncertainty and financial uncertainty. According to them, financial uncertainty could be very linked to recessions, both as a cause and as a propagating mechanism. Their measure of macroeconomic uncertainty is based on the framework advocated by Jurado et al. (2015) applying a set of macroeconomic and financial time series (industrial production, real income, hours, unemployment, prices, stock market indices, ...). According to Jurado et al. (2015), volatility measures are partly predictable. In order to get a "true"measure of uncertainty, the predictable component of each series must be removed. Moreover, they argued that a large set of macroeconomic time series should be used and not only one time series like in Rossi and Sekhposyan (2015). These authors have computed the conditional volatility from a volatility stochastic model of the unforecastable component of the future values of each series by taking the difference between the conditional forecasts obtained from a large dynamic factor model and the realizations of the variables. The measure of macroeconomic uncertainty is computed as an average of the conditional volatility of each time series (see Figure 1.5).

Applying the same methodology, Ludvigson et al. (2021) have developed a financial uncertainty index (see Figure 1.5) from a set of 148 monthly financial indicators: Treasury bill yields, price-earnings ratio, risk factors of Fama and French (1992) among others. Both indexes exhibit a spike during the 1973 oil crisis but they also exhibit significant differences before 1990. The financial uncertainty index is high during the 1987 financial crisis and macroeconomic uncertainty is high during the 1981–1982 recession (see Figure 1.5). It is worth nothing however that these indexes have many similarities after 1990 with a correlation equal to 0.69 over the period 1990-2020 even if the Russian financial crisis in 1998 is higher for the financial uncertainty index only.[16] Redl (2020) applied this econometric framework to get macroeconomic and financial uncertainty indexes for a set of countries.[17]

Figure 1.5: Macroeconomic Uncertainty Index of Jurado et al. (2015) and Financial Uncertainty Index of Ludvigson et al. (2021)



Note: The measures are standardized spanning the time period 1960:M7-2020:M6.
Source: Ludvigson et al. (2021)

The approach of the decomposition of shocks has been used for another aspect beyond the macroeconomics/finance distinction. Mumtaz and Theodoridis (2017) decomposed uncertainty shocks between common (or world) shock and country-specific shock for a set of 11 OECD countries.[18] In order to develop common and country-specific un-

[16]The correlation for the full sample is equal to 0.58. The correlation over the period 1960-1990 is equal to 0.48.

[17]France, Germany, Italy, Spain, Sweden, Switzerland, Netherlands, Japan, Canada, the United Kingdom.

[18]The United-States, the United-Kingdom, Canada, Germany, France, Italy, Spain, Netherlands, Sweden, Japan and Australia.

certainty indexes, they applied a dynamic factor model with stochastic volatility and decomposed time-varying volatilities. Their common uncertainty is interpreted as the average volatility of the unpredictable part of the common component. Similarly, their country-specific uncertainty is interpreted as the average volatility of the unpredictable part of the country-specific component (Carriero et al., 2016).

1.1.4 Textual Analysis

Recently, textual analysis has been used as an alternative approach in order to construct new measures of uncertainty. Baker et al. (2016) have developed the Economy Policy Uncertainty (EPU) indexes for many countries.[19] As the measure can be computed for a wide range of countries, it is possible to compare the effects of uncertainty shocks across countries. To measure US policy-related economic uncertainty, the authors have used an average of several components. The first component is the news index (see Figure 1.6), based on the frequency of newspaper references to economic policy uncertainty. The authors have searched digital archives of 10 leading newspaper since 1985.[20] More precisely, the authors have searched articles containing terms related to economy ("economic "or "economy "), policy ("congress", "legislation", "white house", "regulation ", "federal reserve "or "deficit ") and uncertainty ("uncertainty "or "uncertain ").[21] The second component relies on reports by the Congressional Budget Office which establishes lists of temporary federal tax code provisions.[22] The last components draw

[19]Australia, Belgium, Brazil, Canada, Chile, China, Colombia, Croatia, Denmark, France, Germany, Greece, Hong Kong, India, Ireland, Italy, Japan, South Korea, Mexico, Netherlands, Pakistan, Russia, Singapore, Spain, Sweden the United Kingdom and the United States.

[20]USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the New York Times, and the Wall Street Journal

[21]For the other countries, they conduct all searches in the native language of the newspaper in question. For example, for France, they search the following words: "incertitude ", "économie ", "réglementations ", "BCE ", "Banque Centrale ", "dépenses ",...

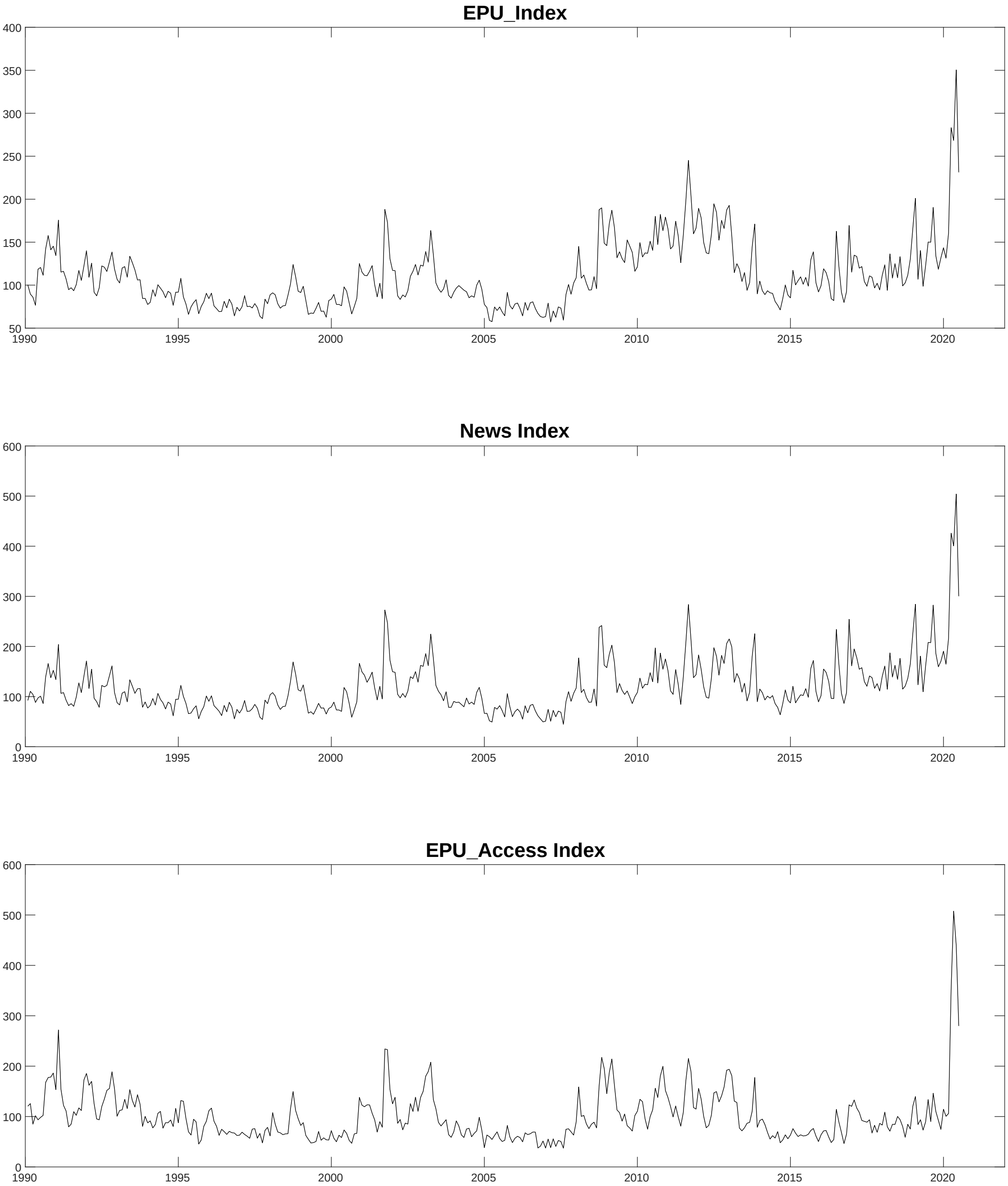
[22]This component is US-specific and can't be used to construct the measure of economic policy uncertainty for the other countries.

on the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters using the dispersion of the forecast variables directly influenced by fiscal and monetary policy: the consumer price index and federal government purchases.

An alternative to the economic policy uncertainty index is the news index based on the Access World News database of over 2000 US newspapers. It means that this index allows to take into account many more articles than the previous one (Figure 1.6). These indexes exhibit spikes during events affecting uncertainty as the Gulf War, presidential elections, the terrorist attacks on September 11, 2001, the stimulus debate in early 2008, the collapse of Lehman Brothers, the 2011 debt ceiling dispute or the current COVID-19 pandemic. Even if there exists many similarities between these measures concerning their construction, we can see that some uncertainty peaks are higher or lower according to the measure used like the Gulf War which is higher for the measure based on Access World News database (see Figure 1.6).

From textual analysis methods, new specific uncertainty measures can be derived. For example, Baker et al. (2016) have developed a specific measure of US monetary policy uncertainty (see Figure A5). This measure draws on the news index but also includes terms related to monetary policy ("quantitative easing", "fed funds rate", "Volcker", "open market operations", ...). Other indexes are linked to fiscal policy, trade policy and health policy searching adapted categorical policy keywords. The advantage of these specific indexes is the following: changing the set of keywords could modify some peaks in the uncertainty measures. For example, the 09/11 terrorist attack is particularly high in the case of the monetary policy index. The trade policy uncertainty index identifies two new peaks: the negotiations of the North American Free Trade Agreement (NAFTA) and the trade conflicts between China and the United States in 2018-2019. The fiscal policy uncertainty index is particularly high during periods of political tension within the US: the debt ceiling crisis in 2011, elections in 2012, the *fiscal cliff* in 2013 and the government shutdown in 2013. The health policy uncertainty

Figure 1.6: Economic Policy Uncertainty Indexes of Baker et al. (2016)



Note: The measures span the time period 1990:M1-2020:M6.
Source: Baker et al. (2016)

index presents peaks during the Clinton's health care plan debate in 1993, the Affordable Care Act (ACA) in 2010 and the current COVID-19 pandemic. These authors have also developed a quarterly migration-related policy uncertainty index applying the same methodology but adding terms related to migration ("Schengen", "migrant", "immigration", "refugee", etc. . .).

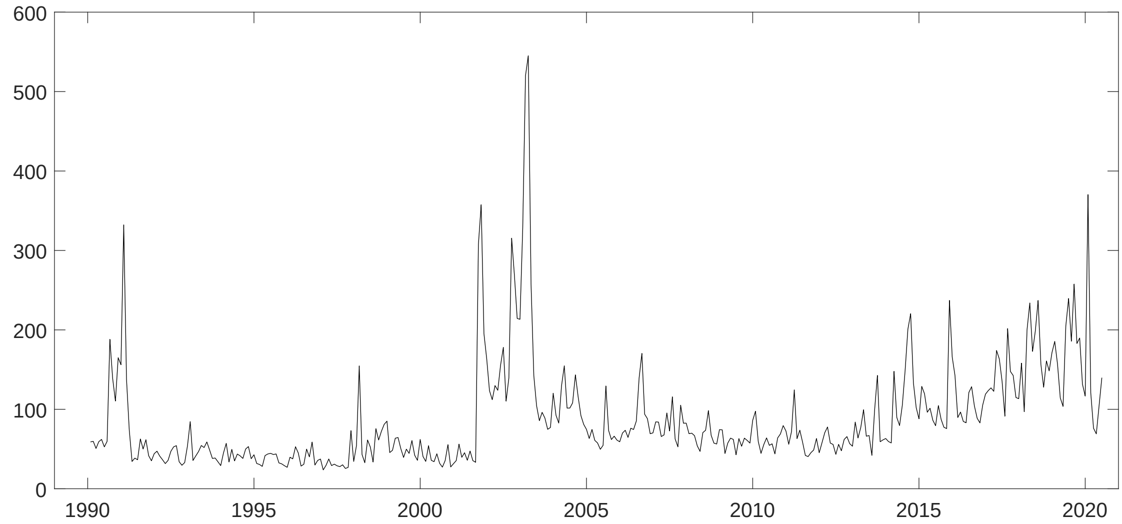
Davis (2016) has computed a worldwide economic policy uncertainty index applying a GDP-weighted average on the national economic policy uncertainty indexes. Ahir et al. (2018) have developed another global uncertainty measure. They have constructed quarterly indices of economic uncertainty for 143 countries whose population exceeds 2 million and a world uncertainty index using the Economist Intelligence Unit (EIU) reports since 1996.[23] In order to construct a world uncertainty index, they count the occurrence of the word "uncertainty"in the quarterly EIU reports. Caldara and Iacoviello (2022) have developed a global geopolitical risk index counting the occurrence of terms related to geopolitical tensions in 11 international newspaper.[24] The authors have identified articles containing mentions related to geopolitical risk such as military-related tensions involving large regions of the world and the United States, terms related to nuclear tensions, war threats, terrorist threats, war acts and terrorist acts. This index reaches its highest values during the Gulf War, the Iraq War and the 09/11 terrorist attack (see Figure 1.7). It is worth nothing that this index exhibits spikes during periods of geopolitical tensions but also during the more recent trade policy conflicts between China and the United States.

Following the same methodology, Baker et al. (2019) developed a newspaper-based Equity Market Volatility (EMV) tracker where the key words are linked to economy ("economic","economy"), equity market ("financial","stock market", "Standard and Poors",. . .) and uncertainty or volatility ("uncertainty", "volatile",. . .). This index is high during fi-

[23]These reports examine and discuss the main economic, financial and political trends in a country.

[24]The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal and The Washington Post

Figure 1.7: Geopolitical Risk Index

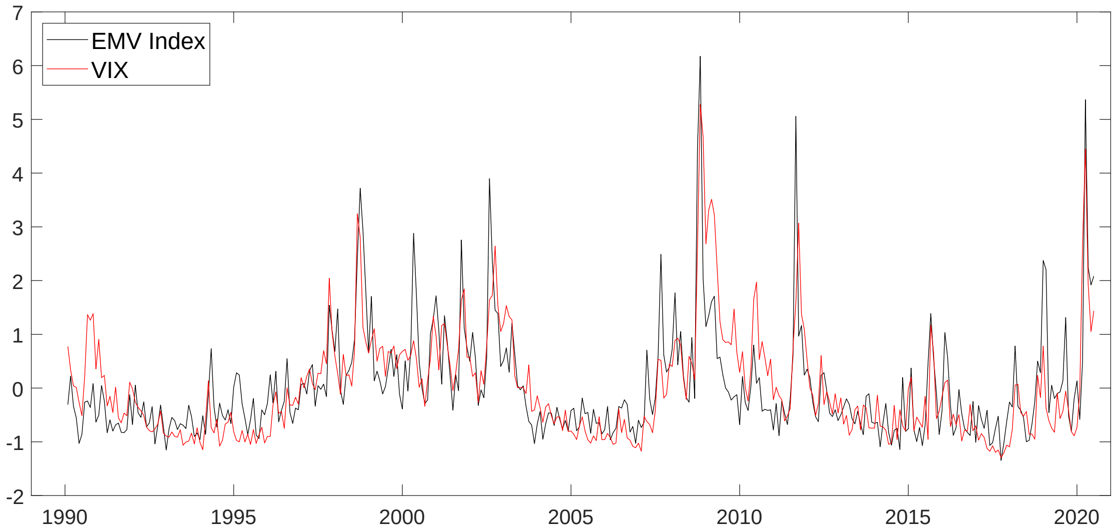


Note: The measure spans the time period 1990:M1-2020:M6.
Source: Caldara and Iacoviello (2022)

nancial crisis (the Russian financial crisis in 1998, the dot-com bubble in 2000, the collapse of Lehman Brothers in 2008) but also during the debt ceiling crisis in 2011, during the COVID-19 crisis (see Figure 1.8). This index presents many similarities with the VIX with a correlation close to 0.8 (see Figure 1.8).

In the context of the current COVID-19 pandemic, Baker et al. (2020a) have developed a newspaper-based infectious disease equity market volatility tracker quantifying the role of infectious diseases (COVID-19, ebola, sars,...) in stock market volatility. The key words in newspapers are related to economy (economic, economy, financial), equity market (stock market, equity, equities, Standard and Poors), volatility (volatility, volatile, uncertain, uncertainty, risk, risky) and pandemic (epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1) to construct a daily index (see Figure 1.9). Unsurprisingly, the highest peak is related to the current COVID-19 pandemic. Moderate peaks are related to previous infectious diseases (ebola, sars,...). Applying textual analysis and machine learning techniques, Larsen (2021) has devel-

Figure 1.8: Comparison between the VIX and the Equity Market Volatility index of Baker et al. (2019)



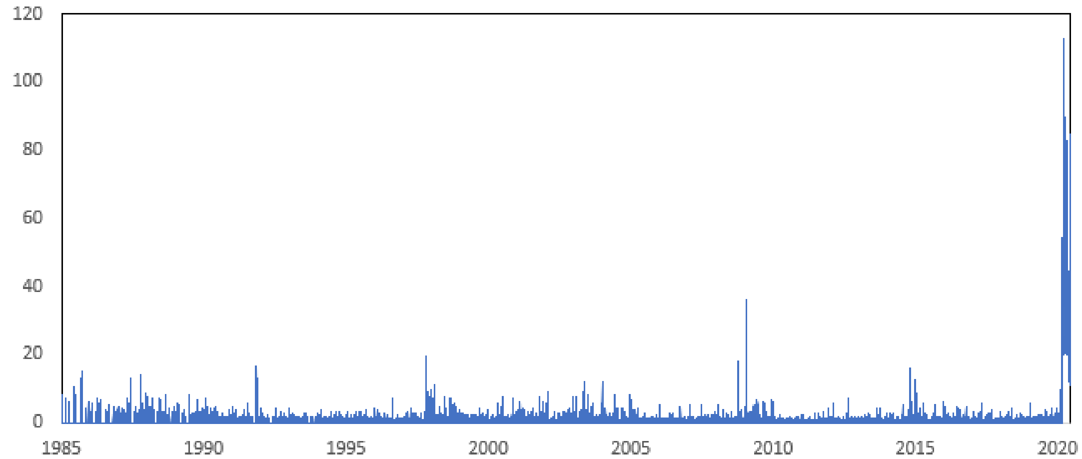
Note: The measures are standardized.
Source: Baker et al. (2019)

oped a wide range of uncertainty proxies for Norway. More recent news indexes focus on climate uncertainty (Gavriilidis, 2021).

The search for words like "uncertainty"only is not very accurate because it is too vague and general. The results can refer to different concepts and ideas which are not specific to economics. To take into account the context in which keywords have been used, Puttman (2018) has developed a new approach of textual analysis using big data methodology and the emotional content of newspapers in order to construct a financial stress indicator. Puttman (2018) has relied on five leading newspapers since 1889 and has selected articles in which one term is related to financial markets in the title.[25] In order to measure the emotional content of these articles, he has used sentiment dictionaries where words are separated into two categories: “positive” and "negative"

[25]The word must belong to a list 120 words divided in 11 topics: bonds; business; central banks; economy; general; gold; silver; inflation; railroads; stocks; trade and trouble.

Figure 1.9: Daily newspaper-based infectious disease equity market volatility tracker of Baker et al. (2020a)



Note: The measure spans the time period 1985:M1-2020:M6.
Source: Baker et al. (2020a)

words.[26] According to the dictionary, the author considers a title as having a negative connotation if it includes more "negative" words than "positive" words. A shortcoming of this approach is that language has evolved for a century. Language in the end of the 19^{th} century isn't the same as today. Especially in tweets, new words and expressions have appeared which were not used at the end of the 19^{th} century or at the beginning of the 20^{th} century. Similarly, there are certainly some words at the end of the 19^{th} century which are no longer used today.

Another possibility to measure uncertainty is to apply textual analysis on internet research. Castelnuovo and Duc (2017) have developed a measure for the United States using Google Trends and terms that are often cited in the Beige Book of the Federal

[26]To be more precise, Puttman (2018) has used four sentiment dictionaries where the first is very general where a word like "evil" is considered as a negative word (Mohammad and Turney, 2013). The second evaluates customer reviews (Liu et al., 2005). The third dictionary measures language on microblogs and tweets (Nielsen, 2011). The last is applied to the financial press (Loughran and Mcdonald, 2011) where a word like "bankrupt " is considered as a negative word.

Reserve.[27] Baker et al. (2020b) have developed a twitter-based economic uncertainty index extracting tweets containing the terms related to economy and uncertainty.

1.1.5 Composite Indexes and Lessons

Despite their obvious interests, many measures represent just one dimension of uncertainty. In the previous categories, we have seen that a large set of measures and methodologies has been developed for the last 10 years. Some authors have proposed a global measure applying these different measures of uncertainty. Two methods have been proposed in the literature: the principal component analysis (PCA) and the dynamic factor model (DFM). The aim is to identify the common component to develop an overall uncertainty index since most of uncertainty measures are positively correlated with each other (Table A1). Hence, they tend to vary together suggesting that there exists a common component. Haddow et al. (2013) have developed a global index of uncertainty for the United Kingdom based from a PCA using several indicators measuring uncertainty in the United Kingdom.[28] The global index is the first factor of the PCA. Larsen (2017) has developed a set of uncertainty indexes (macroeconomics, financial, mergers & acquisitions,...) applying textual analysis methods for Norway and a PCA to develop a general index. Charles et al. (2018) have developed a global measure for the United States from a DFM framework applying six measures: the VIX, the economic policy uncertainty index developed by Baker et al. (2016), the macroeconomic uncertainty index proposed by Jurado et al. (2015), the measure of dispersion developed by Bachmann et al. (2013), the corporate bond spreads and the financial uncertainty index proposed

[27] The Beige Book is a report published by the Federal Reserve Board. Each Federal Reserve Bank gives information on current economic condition in its district. The Beige Book summarizes information by district.

[28] Three-month option-implied volatility of the FTSE All-Share index, the number of press articles citing "economic uncertainty", the results of a survey about the forecast on the evolution of the number of unemployed in one year and the score of the following question in the Confederation of British Industry surveys : "What factors are likely to limit your capital expenditure authorizations over the next twelve months ? "

by Ludvigson et al. (2021).

The next section will expand this literature in two ways. Firstly, we will apply more uncertainty measures to compute a general measure of uncertainty using both methods (PCA and DFM). Secondly, we will interpret other factors in the PCA allowing to explain fluctuations in uncertainty as in Larsen (2017, 2021).

1.2 Measuring general uncertainty: a PCA approach

1.2.1 Data

We propose to compute a US monthly measure of general uncertainty spanning over the period January 1990 to June 2020. As the empirical literature described in the previous section, we can't establish the distinction between risk and uncertainty highlighted by Knight (1921). We refer to a mixture of risk and uncertainty (Bloom, 2014). We apply the following available monthly measures:[29] the VIX, the macroeconomic uncertainty index (MU) of Jurado et al. (2015), the financial uncertainty index (FU) developed by Ludvigson et al. (2021), the economic policy uncertainty index (EPU), the news index (NewsUS), the economic policy uncertainty index using Access World News database (EPU_Access), the monetary policy uncertainty index (MPU), the trade policy index (TPU), the fiscal policy uncertainty (FPU), the health policy uncertainty index (HPU), the geopolitical risk index (GPR), the corporate bonds spread (Bspread), the newspaper-based Equity Market Volatility tracker (EMV), the consumer confidence index (IDC), the business confidence index (IDE).[30] We apply the 10Y-2Y yield spread (Spread).[31] Finally, we insert the newspaper-based infectious disease equity market volatility tracker

[29]Some measures are not available on authors website and most of the measures are available at a monthly frequency and for the United States.

[30]In the rest of this chapter, we are going to use the inverses of the consumer and business confidence indexes in order to have an interpretation of a variation of these measures identical to the others.

[31]Using 10Y-3m yield spread, the results are qualitatively the same. These results are available upon request.

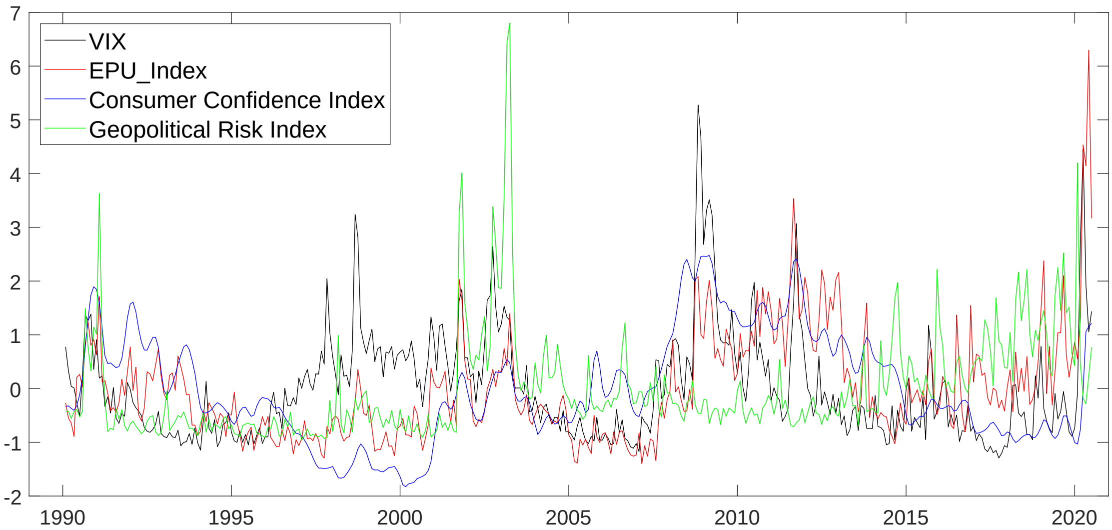
of Baker et al. (2020a) converting it at a monthly frequency ($Disease$).[32] These uncertainty measures vary in different ways over time. We can note a significant negative correlation between Spread and IDE and positive between Spread and IDC (Table A1). If we consider that an increase of Spread could indicate future growth (Bauer and Mertens, 2018a,b), firms can be able to anticipate this future growth because they have more information than consumers. Therefore, there will be a boost in the business confidence towards the future economic situation. This can explain why there is a negative relationship between Spread and IDE and positive between Spread and IDC. The trade policy uncertainty (TPU) is negatively correlated with many measures. This index highlights episodes of trade tension which are not taken into account by other indexes as the VIX. The matrix of correlation shows that some measures are highly correlated as the VIX and the financial uncertainty index (FU). However, this correlation isn't equal to 1. In other words, these measures vary together but also have distinct variations. Figure 1.10 represents the evolution of four measures from different categories.[33] There is a large disparity between uncertainty indexes. Some events are not identified as uncertainty peaks in some indicators but they are in others. Let consider the collapse of Lehman Brothers in 2008, the VIX is higher than any other measures while the geopolitical measure is lower for this event that does not appear as an uncertainty shock. In other words, each indicator provides different information about uncertainty. To synthesize these measures in a single index losing as little information as possible, we apply a principal component analysis.[34]

[32]We compute the average of each month.

[33]Other combinations are possible. We plot this graph to illustrate our point.

[34]Charles et al. (2018) have run a PCA and a dynamic factor model (DFM) to develop a composite index. The authors found many similarities between the resulting composite indexes with a correlation close to 0.99.

Figure 1.10: Comparison of various uncertainty indexes



Note: Indexes are standardized.

1.2.2 PCA Results

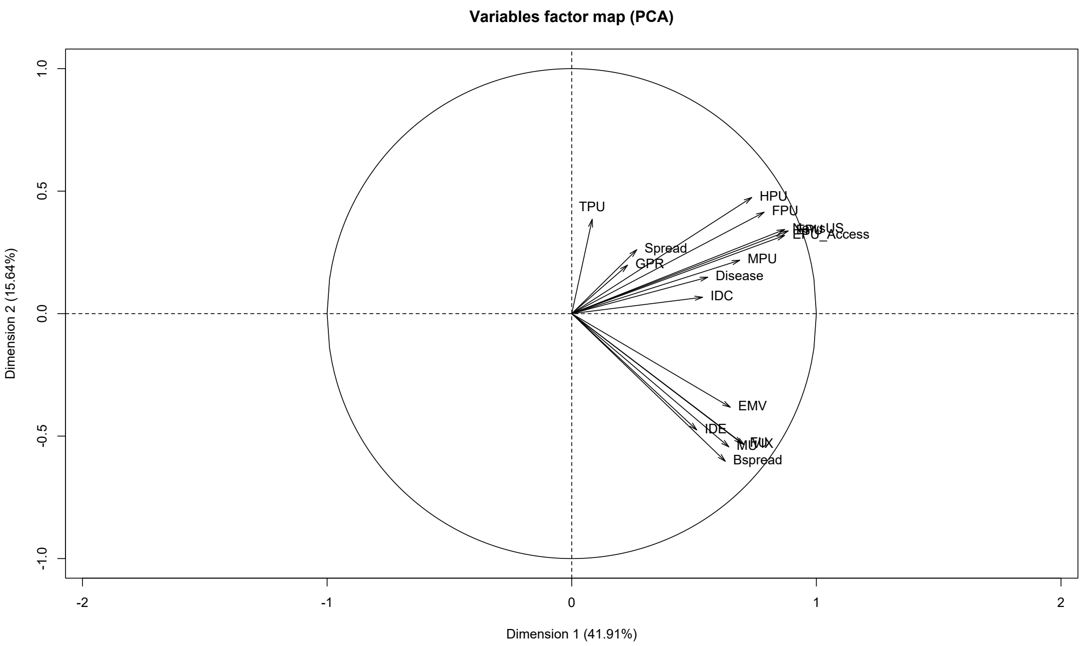
In appendix B, Table B1 reports the eigenvalues of the matrix of correlation between the 17 measures.[35] This table shows that most of the variance can be explained by the first factor (41.91%). We retain the factors with eigenvalues greater than 1 following the Kaiser criterion. Thus, we select four factors.[36] On the correlation circle or the variables factor map (Figure 1.11), all measures are positively correlated with the first factor (Table B2). We compute the squared cosines (cos^2) to measure the quality of the representation of the measures on this first factor (Table B3). A value close to 1 means that the measure is well represented.[37] The measures are mainly represented on the first factor, except TPU, GPR and Spread: 0.01, 0.09 and 0.14 respectively. Given that the

[35]The indexes don't have the same scale. We apply a normalized principal component analysis.

[36]The elbow method selects three factors only. This is not important since our analysis will mainly focus on the first two factors.

[37]On the first factor, the squared cosine of the VIX is equal to 0.5 meaning that 50% of the VIX is represented on the first factor.

Figure 1.11: Variables Factor Map (Factor 1 and Factor 2)



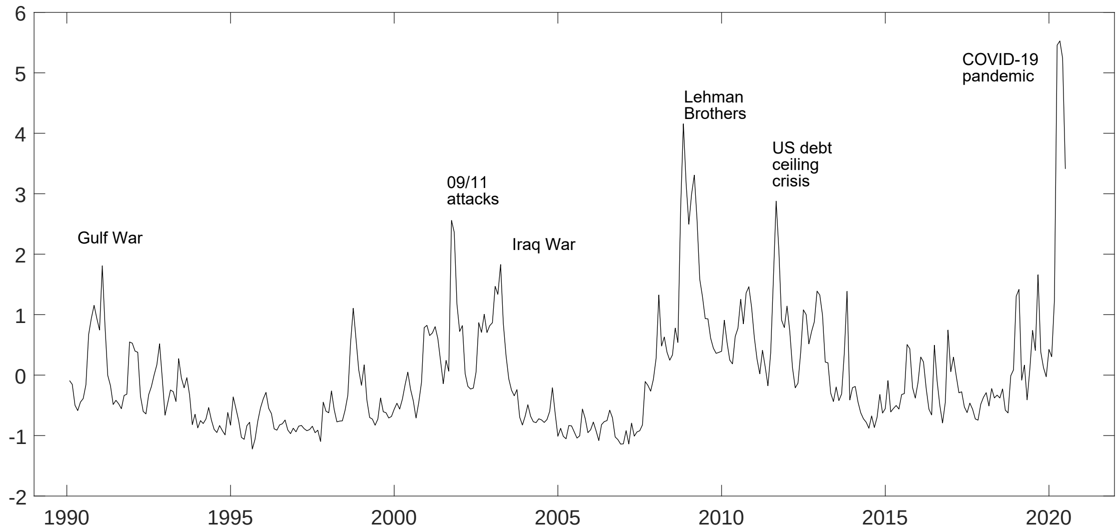
squared cosines of TPU is close to 0, we can't interpret this variable on the first factor.[38] The first factor constitutes our general uncertainty index (GU). Figure 1.12 represents the evolution over time of the general measure of uncertainty. It is important to pay attention to the evolution of this measure and not just its value on a specific date.

We can identify different uncertainty peaks corresponding to well identified events as the Gulf War, the Russian financial crisis and Long-Term Capital Management in 1998, the 9/11 terrorist attacks, the Iraq War, the collapse of Lehman Brothers, the US debt-ceiling dispute in 2011 and the COVID-19 pandemic.[39] These are shocks (financial, macroeconomic, geopolitical, policy,...) that drastically increase the general uncertainty. Figure B1 represents the comparison between our synthetic measure and

[38]For the other factors, we will not refer to the squared cosines or occasionally as the most correlated variables (positively or negatively) are the best represented.

[39]As sensibility analysis tests, we run 17 PCA using 16 measures, *i.e.* , removing a different measure among the selected indexes each time. The resulting synthetic measures are very similar with a high level of correlation. Results are available upon request.

Figure 1.12: US General Uncertainty (1990-2020)

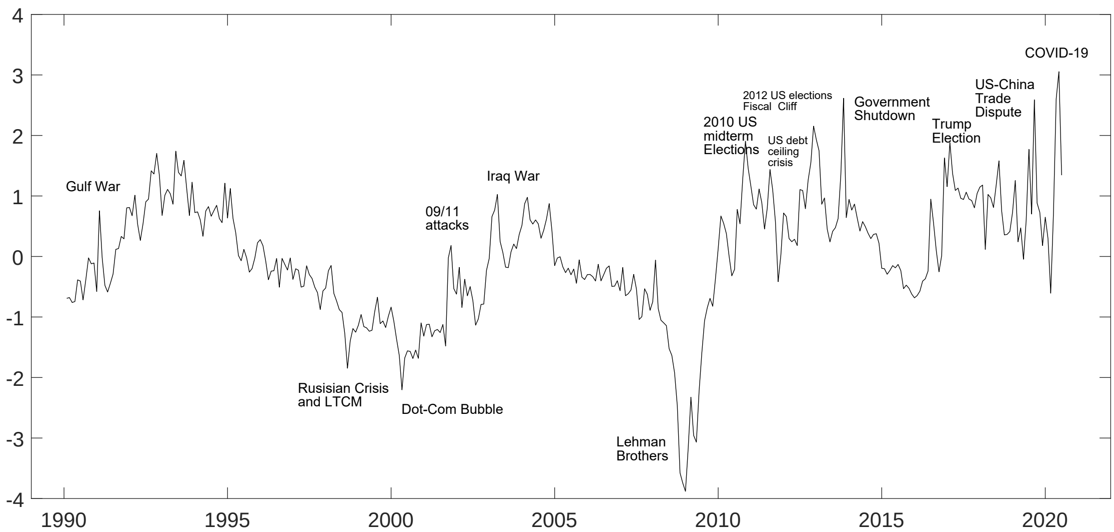


Note: The index is standardized.

the composite uncertainty index (CUI) proposed by Charles et al. (2018). We get similarities between both composite indexes with a correlation close to 0.89 but also some differences. Bloom (2009) identified uncertainty peaks applying a threshold of 1.65 standard deviations above the mean corresponding to a significance threshold at the 5% level. Applying this threshold, the composite index of Charles et al. (2018) identifies the 9/11 terrorist attacks, the collapse of Lehman Brothers and the US debt-ceiling dispute in 2011 as uncertainty peaks. Our synthetic index also identifies these peaks but highlights two more peaks: the Gulf War and the Iraq War. We can explain these differences by the introduction of more uncertainty indexes in the PCA and especially more policy and news indexes.

Beyond the first factor approximating general uncertainty, the other factors allow to identify other dimensions. On the second factor, we get two groups. EPU_Index, EPU_Access, NewsUS, MPU, Spread, IDC, TPU, FPU, HPU and GPR constitute the first group. These indexes are positively correlated with the second factor. In the second group, financial variables are negatively correlated with the second factor. The second factor seems to discriminate between two types of uncertainty shock: macroeconomic and financial. However, two measures that are more related to macroeconomics by definition belong to the group of financial uncertainty variables: IDE and MU. In front of these results, it is more difficult to interpret the second factor. In order to better understand the second factor, we plot it in Figure 1.13.

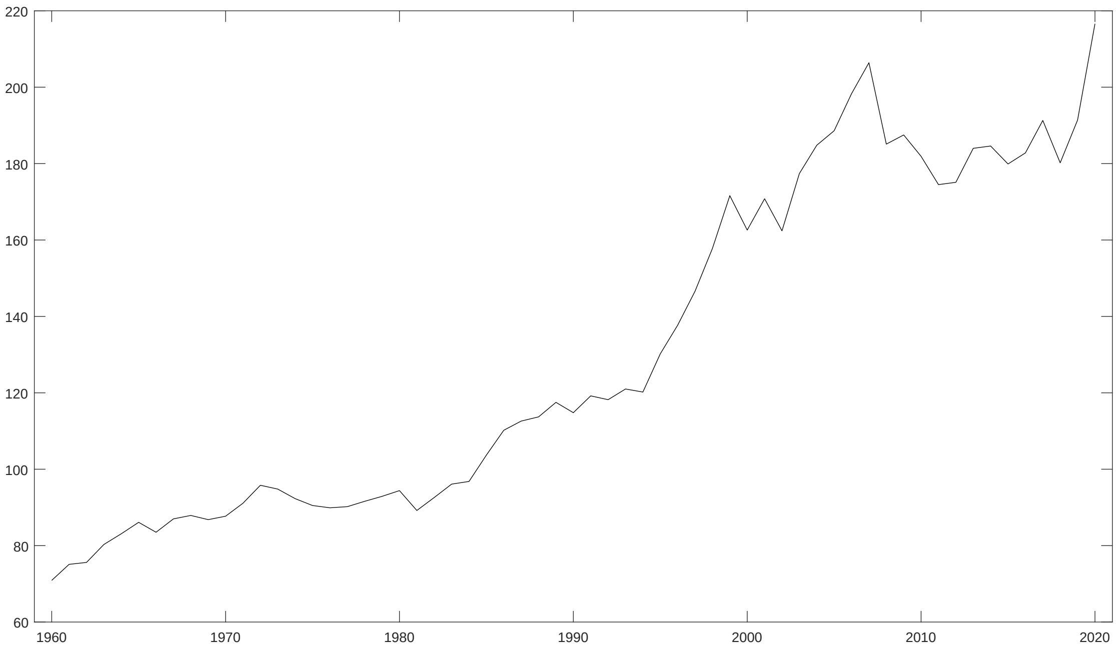
Figure 1.13: Second Factor



Examining the graph, when the second factor is extremely negative, we find events which are related to the major financial events of the last two decades: the Dot-com bubble in 2000; the collapse of Lehman Brothers in 2008; the Russian financial crisis and Long-term capital management in 1998. So, a negative peak could be considered as a financial uncertainty shock. Inversely, when this second factor is highly positive, we can find events which are not linked to financial crises but more related to macroeconomics and politics and geopolitical risks such as the Gulf War, the Iraq War, the 09/11 terrorist attacks and the fiscal cliff. We identify elections in the United States like the 2010 midterm elections, the 2012 United States presidential election, the 2012 United

States House of Representatives elections. An election can generate uncertainty about future macroeconomic performances. The result of an election will influence the future economic policies and therefore, the future macroeconomic performances. As an illustration, the 2012 United States House of Representatives elections where the Republican Party has kept the control of the House of Representatives may have caused the issue of the *fiscal cliff* in January 2013. The US Federal Government has been divided. Without an agreement between the Democratic Party and the GOP, the United States could have gone into recession with the rise in taxes and the decrease in public spending scheduled in January 2013. The US federal government shutdown in 2013 following the disagreement between the Republican-led House of Representatives and the Democratic-Led Senate is also a significant peak on the second factor. The position of the measure $Disease$ in the group of non-financial uncertainty variables can be explained by the fact that the previous infection diseases did not have a very significant impact on economic activity contrary to the COVID-19 pandemic which has severely hit economic activity with lockdown measures. As a consequence, the nature of the COVID-19 uncertainty shock is linked to non-finance. These observations confirm that the second factor highlights an opposition between financial uncertainty and non-financial uncertainty. However, how can we explain the troubling results about the measures MU and IDE ? Concerning the business confidence index (IDE), the financial sector has taken an increasing importance for three decades (Krippner, 2005; Davis and Kim, 2015). As an illustration, the domestic credit to the private sector ratio as a share of GDP of the United States, which is considered as an indicator of financial development (See, among many others Asif et al., 2020; Dogan et al., 2020; Erdoğan et al., 2020), has highly increased since the 1990s (Figure 1.14. Especially in the US, firms are more dependent on the financial markets. It explains why firms can answer according to their expectations on financial markets. Hence, this measure could be interpreted as being oriented towards finance. Concerning the measure of macroeconomic uncertainty of Jurado et al. (2015), the result is more troublesome, we had already started to evoke similarities between the macroeconomic uncertainty and the financial uncertainty index. By examining more deeply the construction of MU, there are 25 financial series among the 132 variables used to develop the index. With the deepening of financialization of the US economy, these financial series could have become more important. Moreover, many variables can be sensitive to the stock market fluctuations as consumer price indexes, money stock or interest rates and therefore, the measure is increasingly biased towards the financial side. As a consequence, the second factor indeed discriminates between financial and non-financial uncertainty.

Figure 1.14: Domestic credit to the private sector (% of GDP)



Source: World Bank Data

We plot the second and the third factor on the variables factor map (Figure B2).[40] MPU, TPU, EMV, GPR and EPU_Access are the measures the most positively corre-

[40]We could have plotted the variables factor map with the first and the third factor. However, this visualization is clearer to interpret the third factor.

lated with the third factor. Therefore, these indexes are the best represented. The third factor distinguishes two groups: measures of uncertainty based on textual analysis are opposed to other indicators. So, the underlying variable behind the third factor would be the public broadcasting surrounding uncertainty peaks. Interestingly, the fourth factor distinguishes GPR and $Disease$ (Figure B3). Thus, the fourth factor highlights two particular dimensions in uncertainty : the geopolitical risk and the pandemic risk.

1.3 Impact of General Uncertainty on Economic Activity

To investigate the impact of uncertainty shocks on economic activity, structural VAR models have mainly been applied (See, among many others, Bloom, 2009; Jurado et al., 2015; Baker et al., 2016; Leduc and Liu, 2016). We consider the following $VAR(p)$:

$$X_t = A_0 + \sum_{j=1}^{p} A_j X_{t-j} + \eta_t \tag{1.1}$$

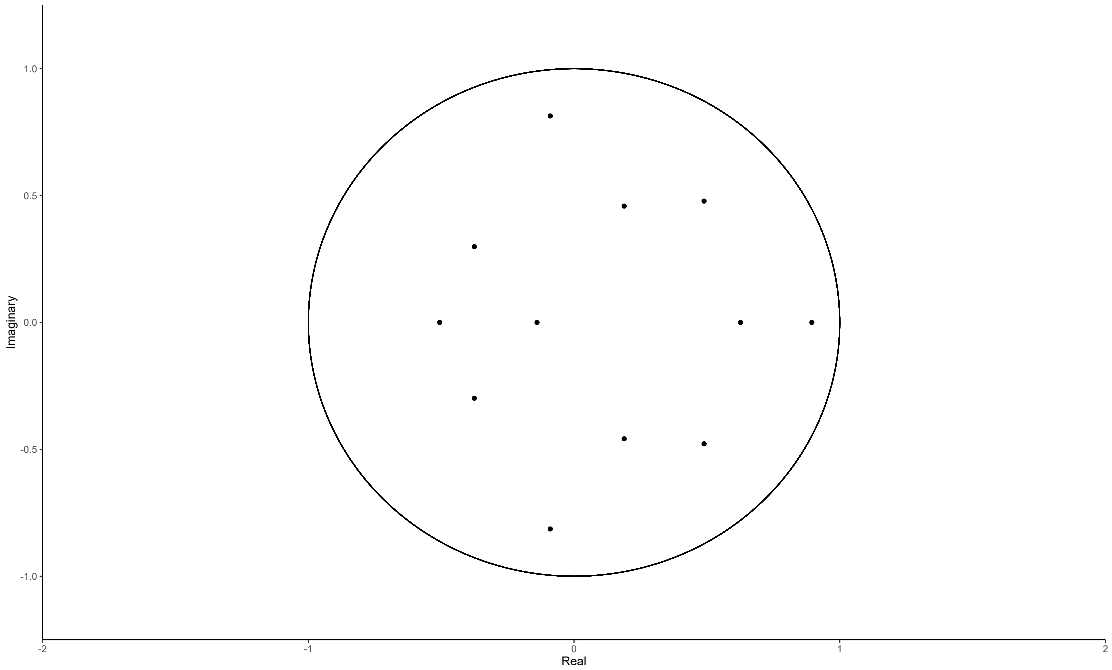
$$\eta_t \sim \mathcal{N}(0, \Omega) \tag{1.2}$$

with $X_t = (OIL_t, Y_t, GU_t)'$ where GU_t denotes the general uncertainty index computed from the PCA. Y_t denotes the industrial production as the proxy of growth and current economic conditions at a monthly frequency and in log difference to get a stationary variable. OIL_t denotes oil prices deflated by the consumer price index to capture international shocks contrary to previous works that did not take it into account. The results reported in Figure 1.15 demonstrate that no unit root lies outside the unit root circle, indicating the stationarity of the VAR.[41]

The covariance matrix Ω can be decomposed according to the Cholesky decompo-

[41] The results of the regression for each equation in the VAR model are shown in Table B4.

Figure 1.15: Inverse roots of AR characteristic polynomial



Source: Author's own calculations.
Note: The VAR is specified with 4 lags.

sition such that $\Omega = PP'$ where P denotes the lower-triangular matrix of the Cholesky decomposition. In the empirical literature, the identification of uncertainty shocks in the SVAR follows a Cholesky decomposition imposing restrictions on the contemporaneous effects (See, among many others, Bloom, 2009; Jurado et al., 2015; Baker et al., 2016). In this chapter, we apply a novel identification strategy proposed by Ludvigson et al. (2021): the *event constraints* from narrative sign restrictions. [42]

Let the reduced form innovations $\eta_t = (\eta_{OILt}, \eta_{Yt}, \eta_{GUt})'$ and the related structural shocks $e_t = (e_{OILt}, e_{Yt}, e_{GUt})'$ be linked as follows:

$$\eta_t = B\, e_t \tag{1.3}$$

[42]We apply the MATLAB code provided by Ludvigson et al. (2021) that takes as input three variables in the VAR model. That explains the choice of the number of variables that we include in the model.

$$E[e_t e_t'] = I \tag{1.4}$$

$$diag(B) \geq 0 \tag{1.5}$$

B is a 3×3 matrix with 9 parameters. The reduced-form covariance structure of η_t only provides $n(n+1)/2 = 6$ restrictions. Additional restrictions have to be imposed to identify the effects of the structural shocks e_t on the endogenous variables in X_t. Otherwise, the model is under-identified and many solutions can satisfy the covariance restriction : $\Omega = BB'$. Let $\hat{\mathcal{B}}$ denotes the set of solutions named *unconstrained set* such that:

$$\hat{\mathcal{B}} = \{B = \hat{P}Q : Q \in \mathbb{O}_n, diag(B) \geq 0, \Omega = BB'\} \tag{1.6}$$

where $\mathbb{O}_n$ denotes the set of $n \times n$ orthogonal matrices ($QQ' = I_n$). By construction:

$$E[\eta_t \eta_t'] = BB' = \hat{P}Q\left(\hat{P}Q\right)' = \hat{P}QQ'\hat{P}' = \hat{P}\hat{P}' = \hat{\Omega} \tag{1.7}$$

To construct the set $\hat{\mathcal{B}}$, the algorithm is initialized by setting $B = P$ where P denotes the lower-triangular matrix of the Cholesky decomposition. Then, we rotate B by randomly drawing 1.5 million matrices Q following (Ludvigson et al., 2021). Each rotation is performed by drawing a $n \times n$ matrix M of $\mathcal{N}(0, I_n)$. Then, Q is taken to be the orthogonal matrix in the QR decomposition of M where R denotes an upper-triangular matrix. By construction, the covariance restriction $\Omega = BB'$ is satisfied. Let $e_t(B) = B^{-1}\eta_t$ be the structural shocks implied by a matrix $B \in \hat{\mathcal{B}}$ for a given η_t. Thus, 1.5 million different B imply 1.5 million unconstrained values of $e_t(B)$ for $t = 1, \ldots, T$. We get 1.5 million unconstrained shocks e_{GUt}, 1.5 million unconstrained shocks e_{Yt} and 1.5 million unconstrained shocks e_{OILt} for $t = 1, \ldots, T$.

The identification strategy of uncertainty shocks in the SVAR is based on the *event constraints* and external variable constraints. *Event constraints* restrict the structural shocks at specific dates imposing them to be large or exceed a threshold. These specific structural shocks must be consistent and credible with our understanding of the historical events considered. We define our *event constraints* denoted $\bar{g}_{Ei}$ as follows:

1. $\bar{g}_{E1} : e_{GU\tau_1} \geq \bar{k_1}$ at $\tau_1 = 1991 : 01$ (Gulf War)

2. $\bar{g}_{E2} : e_{GU\tau_2} \geq \bar{k_2}$ at $\tau_2 = 2001 : 09$ (09/11 terrorist attacks)

3. $\bar{g}_{E3} : e_{GU\tau_3} \geq \bar{k_3}$ at $\tau_3 = 2003 : 03$ (Iraq War)

4. $\bar{g}_{E4} : e_{GU\tau_4} \geq \bar{k_4}$ at $\tau_4 = 2008 : 09$ (Lehman Brothers)

5. $\bar{g}_{E5} : e_{GU\tau_5} \geq \bar{k_5}$ at $\tau_5 = 2011 : 08$ (Debt Ceiling Crisis)

6. $\bar{g}_{E6} : e_{GU\tau_6} \geq \bar{k_6}$ at $\tau_6 = 2020 : 03$ (COVID-19)

The different restrictions require that the uncertainty shocks corresponding to the Gulf War, the 09/11 terrorist attacks, the Iraq War, the bankruptcy of Lehman Brothers, the debt ceiling crisis and the COVID-19 pandemic crisis exceed the threshold denoted $\bar{k_1}, \bar{k_2}, \bar{k_3}, \bar{k_4}$, $\bar{k_5}$ and $\bar{k_6}$ respectively. These restrictions are related to the largest peaks exceeding the threshold of 1.65 standard deviations above the mean proposed by Bloom (2009) examining the general uncertainty index.[43] The *event constraints* $\bar{g}_{E1}, \bar{g}_{E2}, \bar{g}_{E3}, \bar{g}_{E4}, \bar{g}_{E5}, \bar{g}_{E6}$ can be represented by a system of inequality constraints on B:

$$\bar{g}_E \left(e_t \left(B\right); \bar{\tau}, \bar{k}\right) \geq 0 \tag{1.8}$$

where $\bar{k} = \left(\bar{k_1}, \bar{k_2}, \bar{k_3}, \bar{k_4}, \bar{k_5}, \bar{k_6}\right) > 0$ and $\bar{\tau} = (\bar{\tau_1}, \bar{\tau_2}, \bar{\tau_3}, \bar{\tau_4}, \bar{\tau_5}, \bar{\tau_6})$.

Other constraints can also be applied in order to identify the structural shocks namely the correlations between shocks and external variables. According to Ludvigson et al. (2021), external variables can facilitate identification in the VAR when economic reasoning implies they should be informative about the shocks. The correlations between

[43] Caggiano et al. (2021) used a similar approach selecting the dates where the VIX index exceeds the threshold of 1.65.

the external variables and structural uncertainty shocks are applied to generate additional inequality constraints. Following the authors, we define the *correlation constraints*:

1. $\bar{g}_{C1} : 0 \geq corr\left(e_{GUt}, S_{1t}\right)$

2. $\bar{g}_{C2} : corr\left(e_{GUt}, S_{2t}\right) \geq 0$

where S_1 denotes the CRSP value-weighted stock market index which is considered as a measure of stock market return and S_2 denotes the real price of gold in log difference.

The first correlation constraint requires that uncertainty shocks are negatively correlated with stock market returns. The second correlation constraint means that uncertainty shocks must be positively correlated with the variation of the real price of gold which is considered as a safe asset by investors. The correlation constraints $\bar{g}_{C1}, \bar{g}_{C2}$ can be represented by a system of inequality constraints on B:

$$\bar{g}_C\left(e_t\left(B\right); S\right) \geq 0 \tag{1.9}$$

Finally, we select the matrices B satisfying the following system of inequalities corresponding to the full set of constraints:

$$\hat{\mathcal{B}} = \{B = \hat{P}Q : Q \in \mathbb{O}_n, diag(B) \geq 0, \Omega = BB', \bar{g}_E\left(e_t\left(B\right); \bar{\tau}, \bar{k}\right) \geq 0, \bar{g}_C\left(e_t\left(B\right); S\right) \geq 0\} \tag{1.10}$$

A crucial point is to estimate the parameters $\bar{k_1}$, $\bar{k_2}$, $\bar{k_3}$, $\bar{k_4}$, $\bar{k_5}$ and $\bar{k_6}$. Let's take the example of the first condition: $\bar{g}_{E1} : e_{GU\tau_1} \geq \bar{k_1}$ at $\tau_1 = 1991 : 01$ (Gulf War). Given that we have 1.5 million time series of e_{GUt}, we have 1.5 million values for e_{GUt} at the time $t = 1991 : 01$. According to Ludvigson et al. (2021), the threshold $\bar{k_1}$ should correspond to the $75th$ percentile value of the empirical distribution of e_{GUt} for $t = 1991 : 01$. The same procedure is applied for the estimation of $\bar{k_2}$, $\bar{k_3}$, $\bar{k_4}$, $\bar{k_5}$ and

$\bar{k_6}$ at their respective date. These parameters can be interpreted as the minimum size required of the extensive shocks for the events associated with these constraints.

To compute the impulse response functions, we can write the SVAR model in its moving average (MA) representation:

$$X_t = \mu + \sum_{i=0}^{\infty} \phi_i \ Be_{t-i} \tag{1.11}$$

For each matrix B satisfying the full set of constraints, impulse response functions at a horizon h after a shock of the jth variable are computed such that:

$$\frac{\delta \ X_{t+h}}{\delta \ e_{jt}} = \phi_h \ b^j \tag{1.12}$$

where b^j denotes the jth column of the matrix B.[44]

Table 1.1: Variance Decomposition: Fraction variation in industrial production

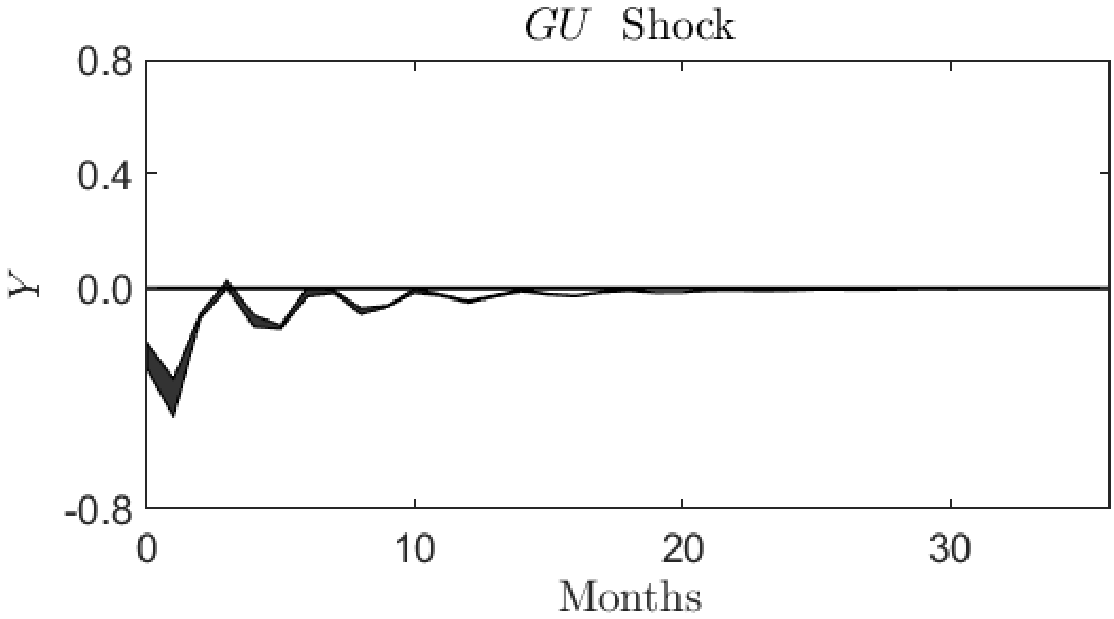
	$h = 1$	$h = 12$	h_∞	h_{max}
$GUshock$	[0.1568 ; 0.3044]	[0.1636 ; 0.2971]	[0.1656 ; 0.2983]	[0.1656 ; 0.3044]

Notes: The figure shows results from the identified set for system $X_t = (OIL_t, Y_t, GU_t)'$ using the full set of constraints described in (1.10) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The table shows the fraction of h-step-ahead forecast error variance of Y_t that is explained by uncertainty shocks. h_{max} reports the maximum fraction of forecast error variance explained across all VAR forecast horizons h. The numbers in brackets represent the ranges for these numbers across all solutions in the identified set. The sample spans the period 1990:01 to 2020:06.

Contrary to IRFs graphs from classical SVAR with recursive schemes (e.g Cholesky identification), this methodology provides as many impulse response functions as the number of matrices B retained instead of one. Here, 6484 matrices B satisfy all restrictions Therefore, 6484 impulse response functions are estimated. Figure 1.16 reports the identified set of impulse response of a general uncertainty shock on industrial production. For each horizon h, the shaded area reports the identified set of IRFs associated with matrices B satisfying the full set of constraints described by the system (1.10).

[44]When $h = 0$, $\phi_h = I_n$.

Figure 1.16: Impulse Response Functions



Notes: The figure shows results from the identified set for system $X_t = (OIL_t, Y_t, GU_t)'$ using the full set of constraints described in (1.10) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The shaded area reports the identified set of impulse response functions to positive, one standard deviation shocks in units of percentage points. The sample spans the period 1990:01 to 2020:06.

Ludvigson et al. (2021) underlined that their new SVAR approach does not require confidence band for inference. Instead, the authors refer at the entire set of solutions. The lower bound of the shaded area represents the minimum value among the 6484 possible IRF values and the upper bound represents the maximum value. It means that the IRF value fluctuates between these both values. We find that a general uncertainty shock has a negative impact on industrial production which is persistent for more than 12 months.[45] Table 1.1 shows the associated forecast error variance decomposition (FEVD) that is the share of the variance explained by the uncertainty measure in industrial production at various forecast horizons: $h = 1$; $h = 12$ and h_{max} is the horizon at which

[45]The results are qualitatively equivalent applying a classical Cholesky decomposition in a SVAR model (Figure B4).

the fraction of forecast error variance is maximized. Because we have a set of solutions, we have a range of forecast error variances for each horizon. Uncertainty shocks have a relative importance on the forecast error variance of industrial production representing around 0.16 to 0.30. Our findings are in line with a theoretical literature where uncertainty about the future has consequences on agents' behavior (Dixit, 1989; Blanchard, 2009). The negative effect highlights a *wait and see* behavior where uncertainty leads firms to delay investment and hiring decisions (Bernanke, 1983; Pindyck, 1991) and consumers to rise their savings for precautionary reasons (Leland, 1968). These results may partly explain the weak recovery despite historically low interest rates following the 2007-2008 financial crisis.

1.4 Robustness Checks

1.4.1 PCA: Longer Sample

In order to check whether the assumption of financialization mentioned above is observable in the data, we run a PCA on a longer sample. The variables MU and IDE could have a different position on the variables factor map. Moreover, we have seen that MU and FU have many similarities after 1990 but also have differences before 1990. We run a PCA on a sample that is close to the sample of the measure of macroeconomic uncertainty of Jurado et al. (2015). We run a PCA on the 1962-2020 period with the following measures for which data are available: VIX, MU, FU, IDC, and IDE.[46] Appendix C reports the results. As previously, all measures are positively correlated with the first factor. Examining the second factor, MU and IDE are indeed not anymore linked to financial variables (Figure C1). However, their squared cosines are weak on the second factor (Table C3). The uncertainty index of Jurado et al. (2015) can be con-

[46]Following Bloom (2009), we complete our data applying the monthly standard deviation of the S&P500 index measuring the realized volatility to extend the VIX date. These data are available since 1962.

sidered as measuring macroeconomic uncertainty but only on a longer period. However, when we restrict the analysis on a recent period, this measure is more linked to finance. The difference of results between these two different PCA is in line with the increasing weight of finance in the economy and the fact that some variables have progressively leaned towards finance. This interpretation reinforces the observation that there is a distinction between macroeconomic or nonfinancial uncertainty and financial uncertainty on the second factor.[47] Therefore, we can reconsider the decomposition of uncertainty shocks of Ludvigson et al. (2021) for the last three decades.

1.4.2 SVAR model: Hodrick Prescott filter

In our baseline SVAR, we transform industrial production and oil prices applying the logarithm difference to get stationary variables. An alternative is to detrend data applying the Hodrick-Prescott (HP) filter following the seminal paper of Bloom (2009). We denote Y_t^C as the industrial production index detrended by the HP filter. Following Ravn and Uhlig (2002), we take the smoothing parameter $\lambda = 129600$ for monthly data. Applying the full set of constraints, we get a negative effect of a general uncertainty shock with the decline in industrial production (Figure 1.17). The decline is much more persistent than in the previous analysis. The results are qualitatively equivalent taking the parameters $\bar{k}$ to their median values.

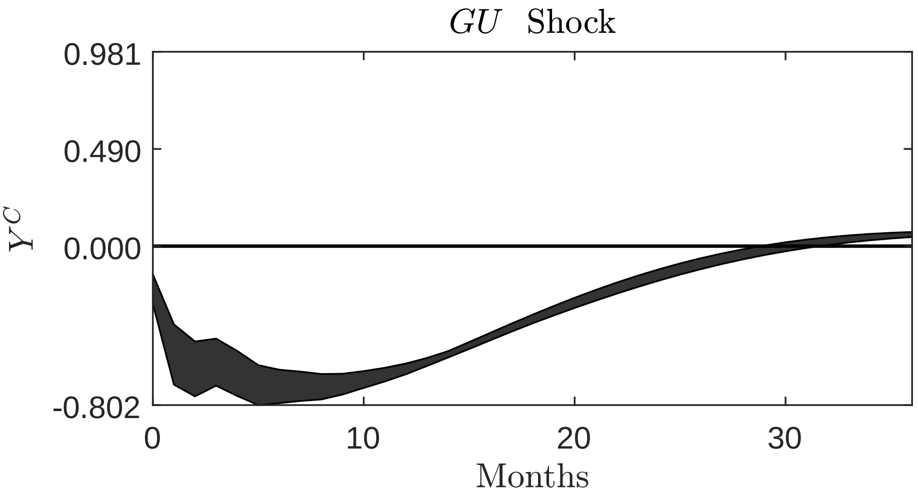
1.4.3 Dynamic Factor Model

Following Charles et al. (2018), we apply the dynamic factor model (DFM) of Doz et al. (2012) based on the quasi maximum likelihood to develop composite indexes.[48] The PCA approach is to generate common factors from a large database loosing as little

[47]We run a PCA with the five measures over the time period 1990-2020. Unfortunately, on the second factor, the results don't allow to interpret MU and IDE anymore. These results are available upon request.

[48]We follow the criterion proposed by Bai and Ng (2002, 2007) to select the number of dynamic factors in the model.

Figure 1.17: Impulse Response Functions using the HP filter

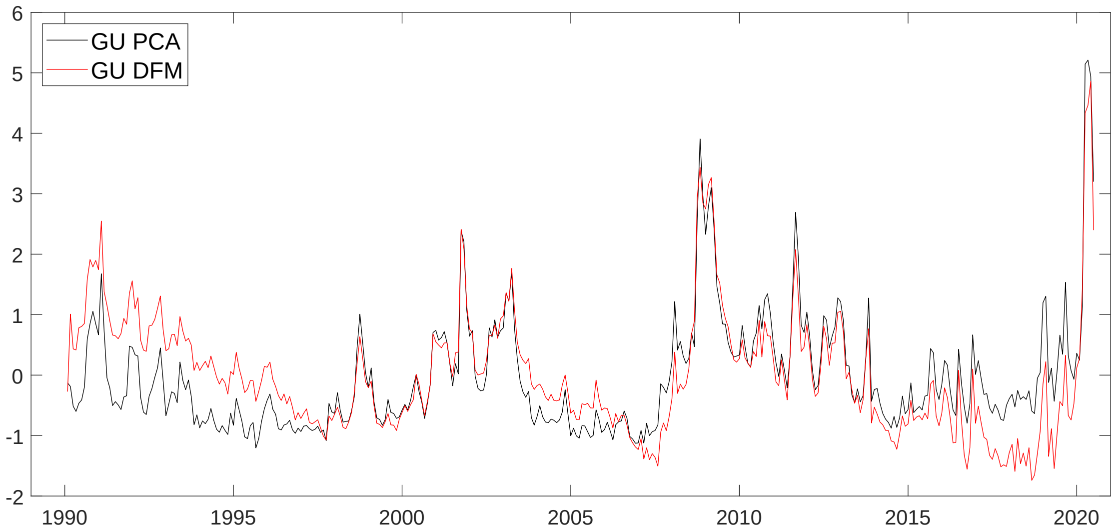


Notes: The figure shows results from the identified set for system $X_t = \left(OIL_t^C, Y_t^C, GU_t\right)'$ using the full set of constraints described in (1.10) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions to positive, one standard deviation shocks in units of percentage points. The sample spans the period 1990:01 to 2020:06.

information as possible. The factors are generated from the database. As the PCA, the DFM approach allows to reduce information of a large database into a smaller number of variables called "latent factors". However, in the DFM approach, the point of view is different. The database is driven by two orthogonal components: the idiosyncratic components and the common or latent factors. In this approach, the causality is reversed. The common factors represent the underlying structure generating the database contrary to the PCA approach. Extracting the first common factor of the DFM, all measures are positively correlated with the first factor capturing the common component of uncertainty indexes. The composite index from the DFM is very similar to the composite index from the PCA (Figure 1.18) with a correlation close to 0.83. We identify the same uncertainty peaks where the COVID-19 pandemic is the highest uncertainty peak. Thus, we get equivalent synthetic indexes applying both methodologies despite their methodological differences as Charles et al. (2018).

The second factor of the DFM presents many similarities with the PCA with a cor-

Figure 1.18: Comparison between the first factor from the PCA and the DFM

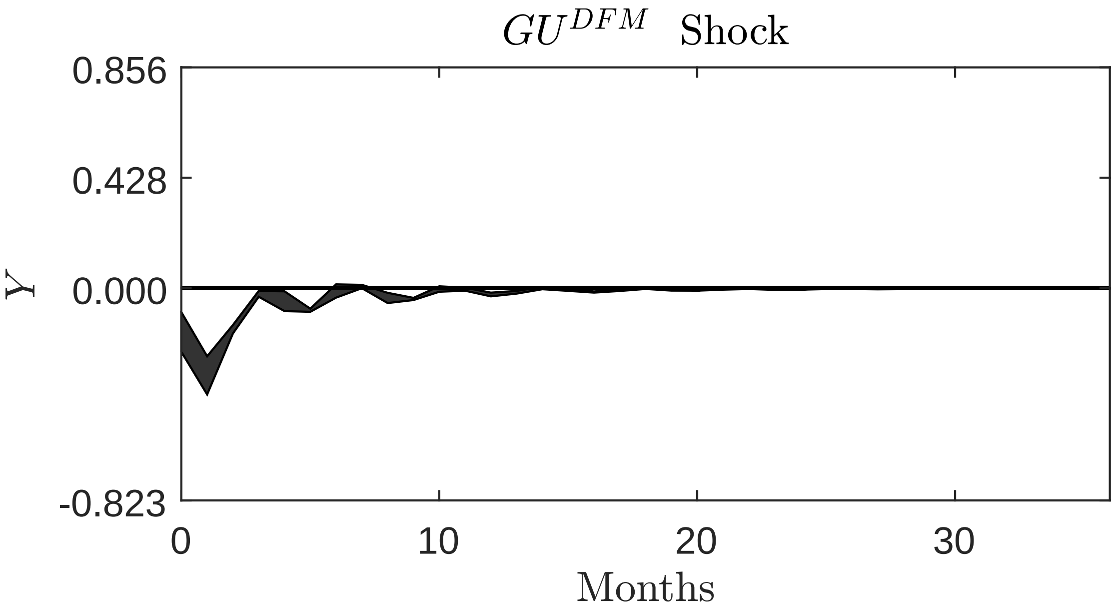


Note: Indexes are standardized.

relation close to 0.82 (Figure D1). The measures related to finance are negatively correlated with the second factor (Table D1). Thus, we can keep the interpretation of the decomposition of uncertainty shocks between nonfinancial and financial uncertainty shocks. Interestingly, MU and IDE are also negatively correlated with the second factor showing again that these variables are linked to finance. Moreover, we can keep the interpretation of the public broadcasting as news-based measures are the most positively correlated with the third factor of the DFM. We get similarities with the factor from the PCA (Figure D2) with a strong correlation (0.85).[49] Running our SVAR model, we keep the negative effect of uncertainty shocks on economic activity (Figure 1.19). The results are robust applying the Hodrick-Prescott filter to detrend macroeconomic variables.

[49]The results don't allow to interpret the fourth factor of the DFM contrary to the PCA.

Figure 1.19: Impulse Response Functions



Notes: The figure shows results from the identified set for system $X_t = \left(OIL_t, Y_t, GU_t^{DFM}\right)'$ using the full set of constraints described in (1.10) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The shaded area reports the identified set of impulse response functions to positive, one standard deviation shocks in units of percentage points. The sample spans the period 1990:01 to 2020:06.

1.5 Conclusion

Determining which uncertainty measure is the right one is rather uncertain. The goal of this chapter is to estimate a global indicator of uncertainty and then to study its impact on economic activity. Many methods have been proposed. Most of the measures that we have reviewed in this chapter refer to one dimension of uncertainty (macroeconomic, finance, policy, geopolitical risk, pandemic, …) providing different information. Applying a PCA, we develop a synthetic measure of uncertainty for the Unites States taking into account all these aspects. Our general measure has profound similarities with the composite index of Charles et al. (2018). However, we have inserted more variables in the analysis than these authors did and especially more economic policy variables. Our general measure is able to identify more extreme uncertainty peaks such as the Gulf War and the Iraq War. Our PCA analysis allows to determine the factors explaining the fluctuations in uncertainty. The first factor is related to shocks increasing drastically the general level of uncertainty in the United States. The second factor establishes the distinction between financial uncertainty shocks and non-financial uncertainty shocks. The other factors highlight the public broadcasting, the geopolitical risk and the pandemic risk as dimensions of the fluctuations in uncertainty.

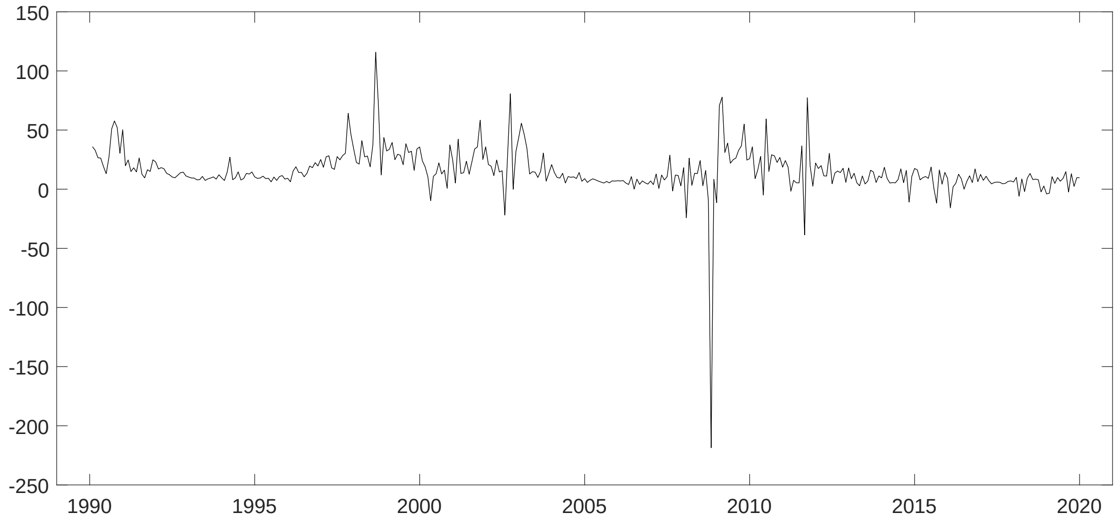
We run a SVAR model applying the restrictions related to the *event constraints* of Ludvigson et al. (2021). We impose a minimum size on uncertainty shocks at specific dates. We get a negative effect of uncertainty on industrial production translating a *wait and see* behaviour. The results are robust detrending the variables with the Hodrick-Prescott filter and if we use different parameterizations for the size of uncertainty shocks. It is worth nothing that the effect of an uncertainty shock is more persistent examining its impact on the output gap.

Examining the second factor, we observe a disturbing result. The second factor establishes a distinction between financial uncertainty and non financial uncertainty as in the decomposition of uncertainty shocks proposed by Ludvigson et al. (2021). However, on the variables factor map, the measure of macroeconomic uncertainty of Jurado et al. (2015) seems to be more linked to finance for the 1990-2020 period. These results underline the limits that the decomposition of uncertainty shocks of Ludvigson et al. (2021). Over a longer period (1962-2020), their measure is no longer linked to the financial variables on the second factor. In other words, if we want to study the impact of macroeconomic uncertainty shocks over a relatively recent sample, we should be careful when applying the macroeconomic uncertainty index developed by Jurado et al. (2015). As financial variables impact macroeconomic indicators, we can understand the methodological choice of Jurado et al. (2015) of inserting financial time series to develop a macroeconomic uncertainty index. However, these financial series may have become more and more important in the construction of this uncertainty index with the financialization of the economy in the last decades. Future research should focus on computing a better macroeconomic uncertainty measure that would be more independent of finance. This task is all the more important since many empirical studies apply and refer, perhaps wrongly, to this so-called macroeconomic uncertainty index.

Appendix

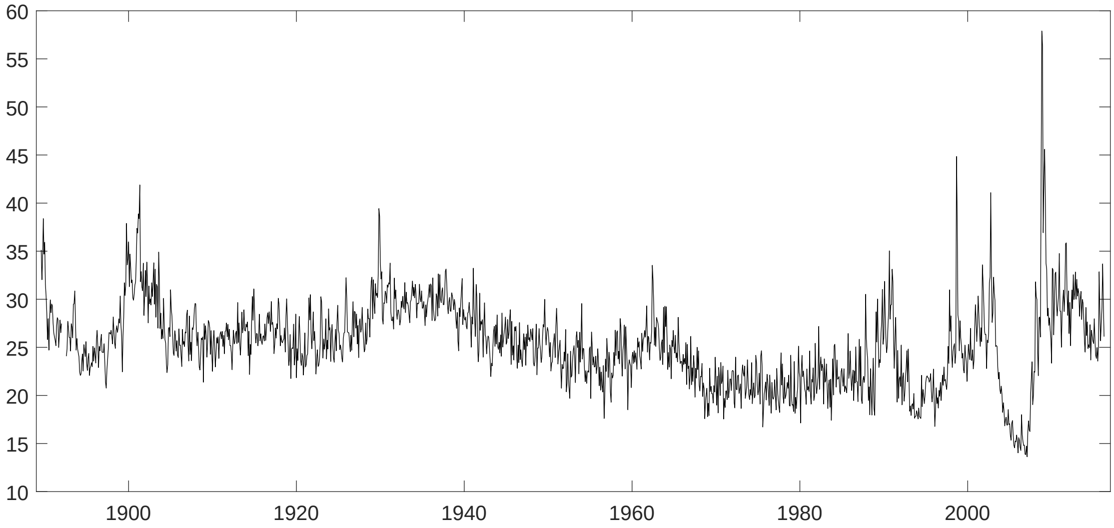
A Measures of Uncertainty

Figure A1: Variance Risk Premium



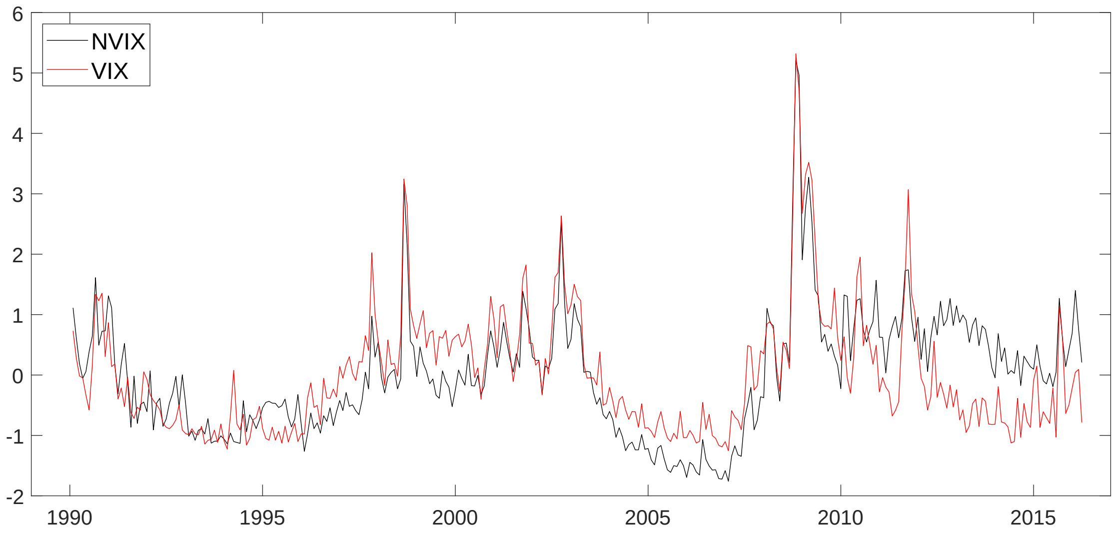
Note: The measure spans the time period 1990:M1-2019:M12.
Source: Zhou (2018)

Figure A2: News Implied Volatility Index of Manela and Moreira (2017)



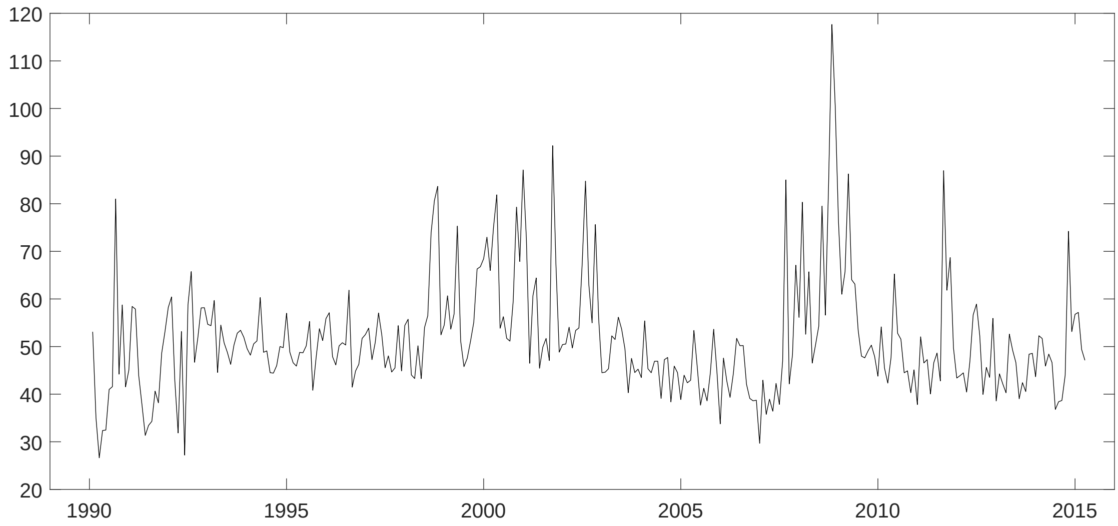
Note: The measure spans the time period 1889:M7-2016:M3.
Source: Manela and Moreira (2017)

Figure A3: Comparison: News Implied Volatility Index of Manela and Moreira (2017) and the VIX



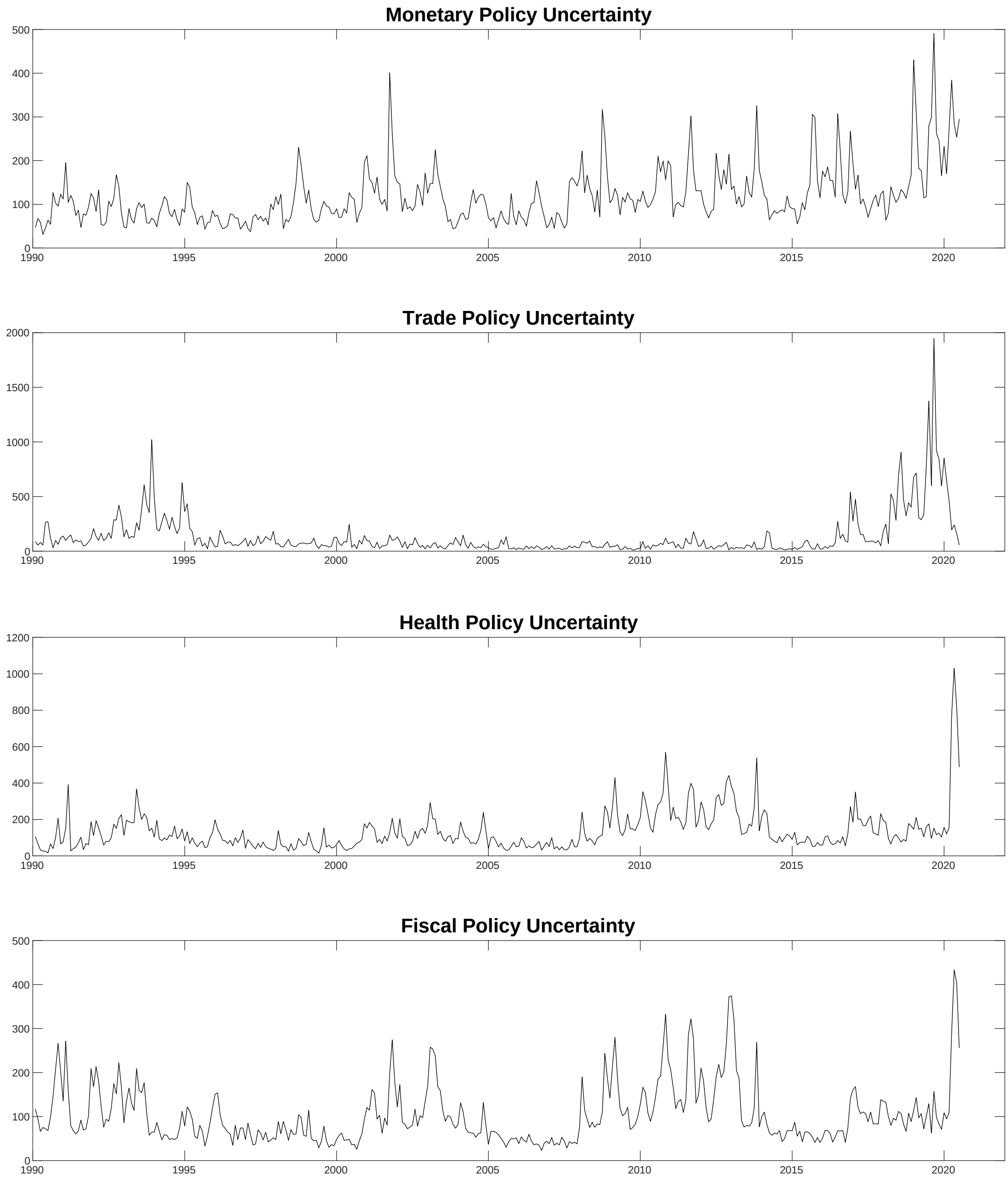
Note: The indexes are standardized.

Figure A4: IVOL Index



Note: The measure spans the time period 1990:M1-2015:M3.
Source: Caldara et al. (2016)

Figure A5: Derived Economic Policy Uncertainty Indexes of Baker et al. (2016)



Note: The measures span the time period 1990:M1-2020:M6.
*Source:*Baker et al. (2016)

Table A1: Table of Correlation

	VIX	EPU	NewsUS	MPU	GPR	IDC	IDE	Bspread	Spread	EPU_Access	MU	FU	FPU	TPU	HPU	EMV	Disease
VIX	**1.00**																
EPU	**0.44**	**1.00**															
NewsUS	**0.42**	**0.92**	**1.00**														
MPU	**0.35**	**0.69**	**0.81**	**1.00**													
GPR	0.07	**0.22**	**0.35**	**0.35**	**1.00**												
IDC	**0.26**	**0.54**	**0.31**	**0.18**	-0.02	**1.00**											
IDE	**0.48**	**0.26**	**0.27**	**0.22**	0.01	**0.33**	**1.00**										
Bspread	**0.67**	**0.37**	**0.34**	**0.29**	0.11	**0.35**	**0.61**	**1.00**									
Spread	0.09	**0.35**	**0.15**	0.05	0.08	**0.62**	-0.11	**0.12**	**1.00**								
EPU_Access	**0.45**	**0.83**	**0.83**	**0.54**	**0.19**	**0.49**	**0.40**	**0.31**	**0.26**	**1.00**							
MU	**0.63**	**0.39**	**0.33**	**0.27**	0.04	**0.48**	**0.53**	**0.76**	0.11	**0.35**	**1.00**						
FU	**0.82**	**0.45**	**0.45**	**0.40**	0.12	**0.19**	**0.48**	**0.72**	0.02	**0.40**	**0.69**	**1.00**					
FPU	**0.35**	**0.81**	**0.75**	**0.46**	**0.18**	**0.54**	**0.29**	**0.25**	**0.37**	**0.89**	**0.26**	**0.29**	**1.00**				
TPU	**-0.14**	**0.19**	**0.31**	**0.38**	**0.25**	**-0.17**	-0.07	**-0.15**	**-0.20**	**0.13**	**-0.17**	0.02	0.07	**1.00**			
HPU	**0.26**	**0.78**	**0.73**	**0.45**	0.04	**0.43**	**0.12**	**0.20**	**0.33**	**0.81**	**0.25**	**0.23**	**0.84**	0.07	**1.00**		
EMV	**0.76**	**0.42**	**0.51**	**0.52**	0.06	0.08	**0.37**	**0.50**	-0.09	**0.43**	**0.46**	**0.65**	**0.28**	-0.01	**0.25**	**1.00**	
Disease	**0.31**	**0.47**	**0.56**	**0.33**	0.02	0.06	**0.15**	**0.12**	-0.09	**0.59**	**0.32**	**0.31**	**0.36**	0.02	**0.59**	**0.37**	**1.00**

Notes: The measures are monthly and span the time period over January 1990 to June 2020. The correlations which are not in bold are not statistically significant at the 5% level.

B Baseline PCA 1990-2020

Table B1: Eigenvalues and Variance

Factor	eigenvalue	percentage of variance	cumulative percentage of variance
Factor 1	7.12	41.91	41.91
Factor 2	2.66	15.64	57.54
Factor 3	1.97	11.61	69.15
Factor 4	1.25	7.38	76.53
Factor 5	0.85	5.01	81.54
Factor 6	0.71	4.16	85.70
Factor 7	0.58	3.43	89.13
Factor 8	0.45	2.67	91.80
Factor 9	0.36	2.10	93.91
Factor 10	0.27	1.57	95.48
Factor 11	0.22	1.30	96.77
Factor 12	0.15	0.91	97.68
Factor 13	0.13	0.74	98.43
Factor 14	0.11	0.65	99.08
Factor 15	0.09	0.52	99.59
Factor 16	0.04	0.26	99.85
Factor 17	0.03	0.15	100.00

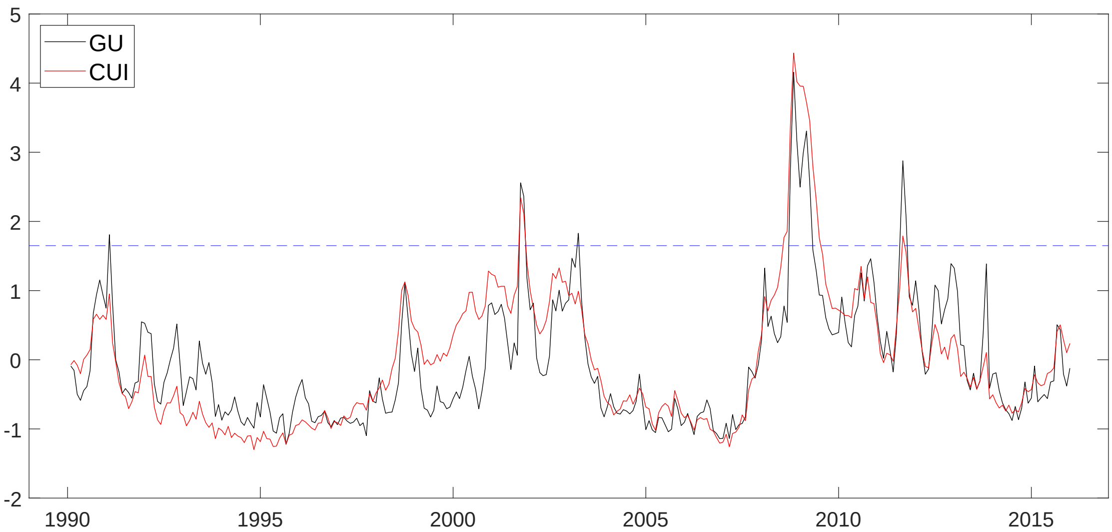
Table B2: Factor Loadings

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17
VIX	0.71	-0.54	0.05	-0.03	-0.24	-0.10	-0.13	0.20	0.13	-0.05	-0.08	0.00	0.16	-0.19	0.02	-0.01	-0.01
EPU	0.88	0.34	-0.04	0.05	-0.01	-0.10	0.03	-0.06	-0.09	-0.03	-0.14	-0.18	-0.05	-0.04	0.11	-0.00	0.09
NewsUS	0.87	0.34	0.25	0.03	-0.01	-0.00	-0.02	-0.10	-0.08	0.04	-0.05	-0.11	-0.09	-0.05	0.04	-0.02	-0.12
MPU	0.69	0.22	0.42	0.23	-0.05	-0.19	-0.02	-0.40	-0.06	0.08	-0.07	0.17	0.09	-0.01	-0.07	0.01	0.02
GPR	0.23	0.20	0.32	0.65	-0.21	0.56	-0.07	0.05	0.08	-0.07	0.03	-0.00	0.03	0.04	0.03	-0.00	0.01
IDC	0.53	0.07	-0.69	0.20	0.18	-0.09	0.10	-0.15	0.21	-0.19	-0.04	-0.09	0.12	0.09	-0.05	0.01	-0.03
IDE	0.51	-0.47	-0.03	0.04	0.60	0.15	-0.24	-0.05	0.14	0.20	-0.02	0.04	-0.00	0.01	0.10	-0.00	0.00
Bspread	0.63	-0.60	-0.10	0.21	0.07	0.06	0.10	0.02	-0.29	0.14	0.18	-0.14	0.05	-0.01	-0.10	0.02	0.01
Spread	0.27	0.26	-0.71	0.33	-0.33	-0.13	0.08	0.06	0.14	0.28	0.06	0.06	-0.08	-0.02	0.03	0.00	-0.00
EPU_Access	0.87	0.32	-0.05	-0.15	0.12	0.09	-0.14	0.12	0.10	-0.02	0.00	0.01	-0.09	-0.02	-0.17	-0.11	0.03
MU	0.64	-0.54	-0.17	0.04	0.06	0.12	0.38	-0.11	-0.03	-0.19	0.06	0.14	-0.13	-0.09	0.05	-0.02	0.00
FU	0.70	-0.53	0.17	0.06	-0.13	-0.10	0.12	0.24	-0.05	0.04	-0.23	0.06	-0.04	0.19	-0.02	0.00	-0.01
FPU	0.79	0.41	-0.22	-0.05	0.10	0.03	-0.23	0.18	-0.11	-0.12	0.02	0.10	-0.05	-0.02	-0.03	0.14	-0.00
TPU	0.08	0.38	0.59	0.32	0.33	-0.32	0.29	0.25	0.15	-0.00	0.12	-0.01	0.01	-0.02	0.01	0.01	0.00
HPU	0.74	0.47	-0.16	-0.29	-0.01	0.03	0.05	0.11	-0.18	-0.00	0.14	0.09	0.15	0.08	0.11	-0.07	-0.01
EMV	0.65	-0.38	0.32	-0.14	-0.28	-0.23	-0.24	-0.11	0.17	-0.09	0.24	-0.04	-0.07	0.10	0.04	0.01	0.01
Disease	0.56	0.15	0.22	-0.59	-0.11	0.31	0.31	-0.05	0.21	0.14	-0.00	-0.04	0.04	0.00	-0.03	0.07	0.01

Table B3: Squared Cosines

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17
VIX	0.50	0.29	0.00	0.00	0.06	0.01	0.02	0.04	0.02	0.00	0.01	0.00	0.03	0.04	0.00	0.00	0.00
EPU	0.78	0.11	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.03	0.00	0.00	0.01	0.00	0.01
NewsUS	0.76	0.12	0.06	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.01
MPU	0.47	0.05	0.17	0.05	0.00	0.04	0.00	0.16	0.00	0.01	0.00	0.03	0.01	0.00	0.00	0.00	0.00
GPR	0.05	0.04	0.10	0.43	0.04	0.32	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IDC	0.29	0.00	0.48	0.04	0.03	0.01	0.01	0.02	0.04	0.04	0.00	0.01	0.01	0.01	0.00	0.00	0.00
IDE	0.26	0.23	0.00	0.00	0.36	0.02	0.06	0.00	0.02	0.04	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Bspread	0.39	0.36	0.01	0.04	0.00	0.00	0.01	0.00	0.08	0.02	0.03	0.02	0.00	0.00	0.01	0.00	0.00
Spread	0.07	0.07	0.50	0.11	0.11	0.02	0.01	0.00	0.02	0.08	0.00	0.00	0.01	0.00	0.00	0.00	0.00
EPU_Access	0.76	0.10	0.00	0.02	0.01	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.03	0.01	0.00
MU	0.41	0.30	0.03	0.00	0.00	0.01	0.14	0.01	0.00	0.04	0.00	0.02	0.02	0.01	0.00	0.00	0.00
FU	0.48	0.28	0.03	0.00	0.02	0.01	0.02	0.06	0.00	0.00	0.06	0.00	0.00	0.03	0.00	0.00	0.00
FPU	0.62	0.17	0.05	0.00	0.01	0.00	0.06	0.03	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.00
TPU	0.01	0.15	0.35	0.10	0.11	0.10	0.09	0.06	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
HPU	0.54	0.22	0.03	0.08	0.00	0.00	0.00	0.01	0.03	0.00	0.02	0.01	0.02	0.01	0.01	0.01	0.00
EMV	0.42	0.15	0.10	0.02	0.08	0.05	0.06	0.01	0.03	0.01	0.06	0.00	0.01	0.01	0.00	0.00	0.00
Disease	0.31	0.02	0.05	0.34	0.01	0.10	0.09	0.00	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figure B1: General Uncertainty (GU) VS CUI



Notes: The solid black line represents the general uncertainty index (GU). The solid red line represents the composite uncertainty index (CUI) of Charles et al. (2018) spanning the period 1990-2015. The measures are standardized. The horizontal dashed blue line represents the threshold 1.65.

Figure B2: Variables Factor Map (Factor 2 and Factor 3)

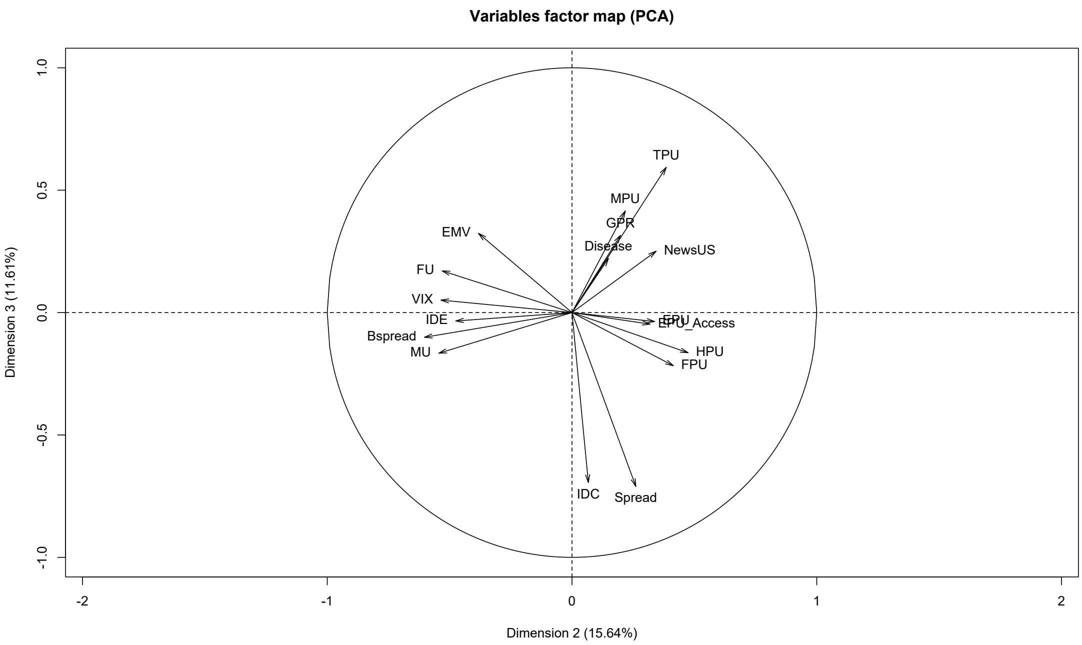


Figure B3: Variables Factor Map (Factor 2 and Factor 4)

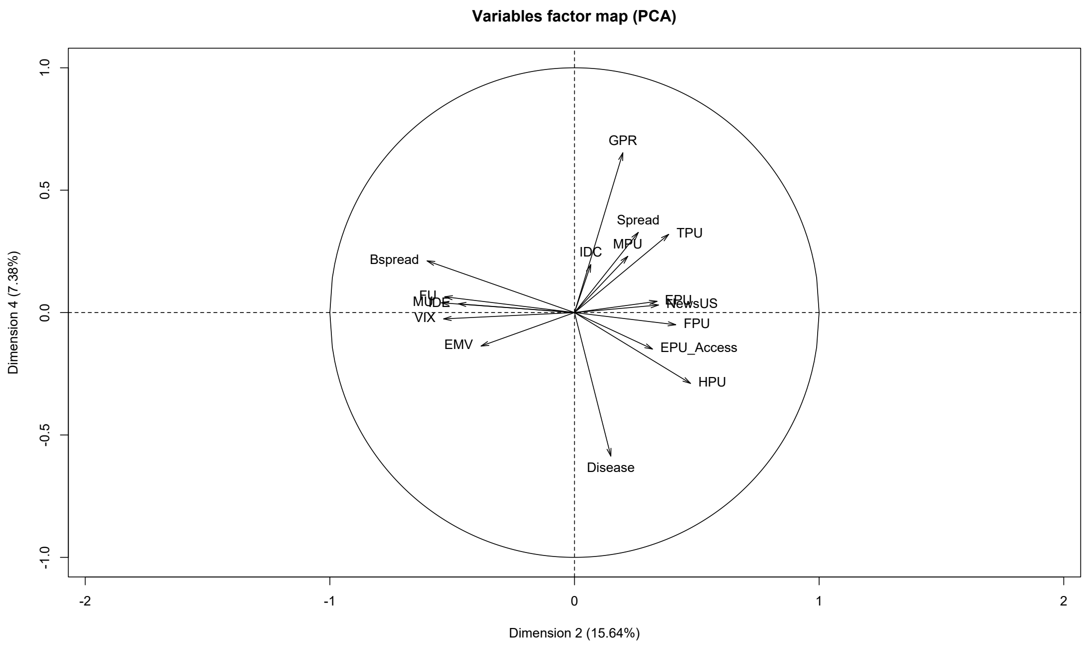
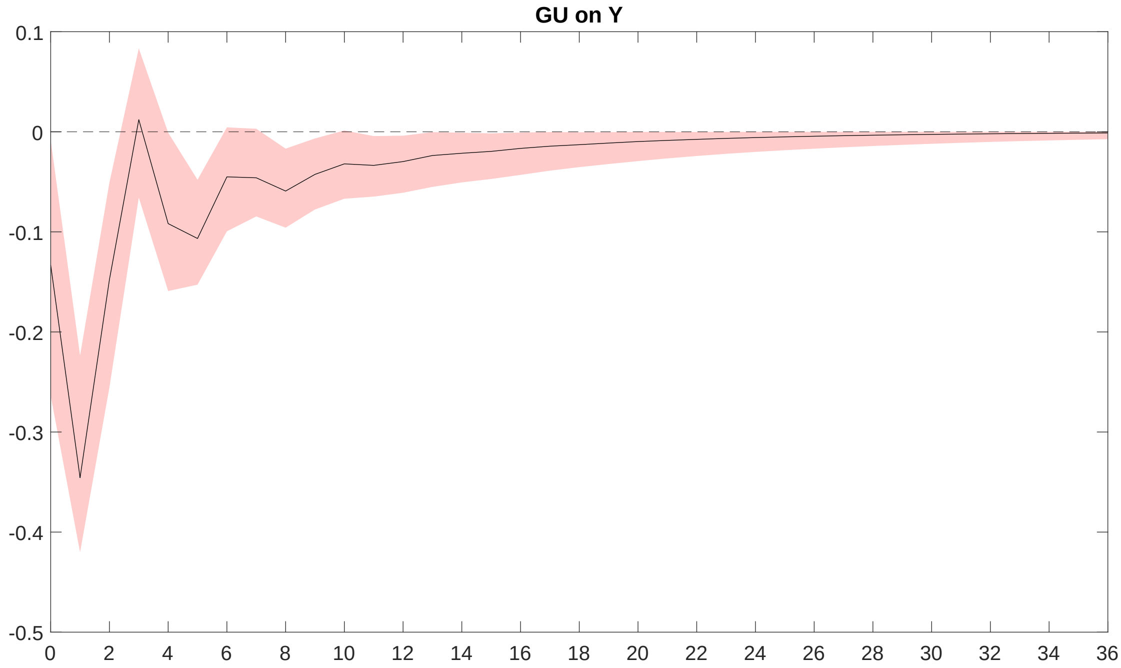


Table B4: Regression Results

	OIL	GU	Y
(Intercept)	0.00	0.01	0.00
	(0.00)	(0.03)	(0.00)
OIL_{t-1}	0.28^{***}	-0.49	0.03^{***}
	(0.06)	(0.29)	(0.01)
GU_{t-1}	-0.05^{***}	0.95^{***}	-0.01^{***}
	(0.01)	(0.06)	(0.00)
Y_{t-1}	-1.73^{**}	-8.14^{**}	0.07
	(0.59)	(3.04)	(0.06)
OIL_{t-2}	-0.04	-0.04	-0.01
	(0.06)	(0.32)	(0.01)
GU_{t-2}	0.05^{***}	-0.23^{**}	0.01^{***}
	(0.01)	(0.08)	(0.00)
Y_{t-2}	-1.18	-4.08	-0.29^{***}
	(0.62)	(3.19)	(0.06)
OIL_{t-3}	-0.07	0.86^{**}	-0.00
	(0.06)	(0.32)	(0.01)
GU_{t-3}	-0.01	0.05	-0.00
	(0.02)	(0.08)	(0.00)
Y_{t-3}	1.83^{*}	-2.33	0.16^{*}
	(0.82)	(4.24)	(0.08)
OIL_{t-4}	-0.08	0.31	0.01
	(0.06)	(0.31)	(0.01)
GU_{t-4}	0.01	0.08	0.00
	(0.01)	(0.06)	(0.00)
Y_{t-4}	-0.07	3.82	0.14
	(0.83)	(4.26)	(0.08)
R^2	0.20	0.78	0.33
Adj. R^2	0.17	0.77	0.31
Num. obs.	362	362	362

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Figure B4: Impulse Response Functions: SVAR Model applying a Cholesky Decomposition



Notes: The figure represents the response of industrial production following a general uncertainty shock applying the Cholesky decomposition. The red shaded area represents the 95% confidence interval. The sample spans the period 1990:01 to 2020:06.

C PCA over the period 1962-2020

Table C1: Eigenvalues and Variance

Factor	eigenvalue	percentage of variance	cumulative percentage of variance
Factor 1	2.94	58.88	58.88
Factor 2	0.92	18.33	77.22
Factor 3	0.61	12.26	89.48
Factor 4	0.29	5.86	95.34
Factor 5	0.23	4.66	100.00

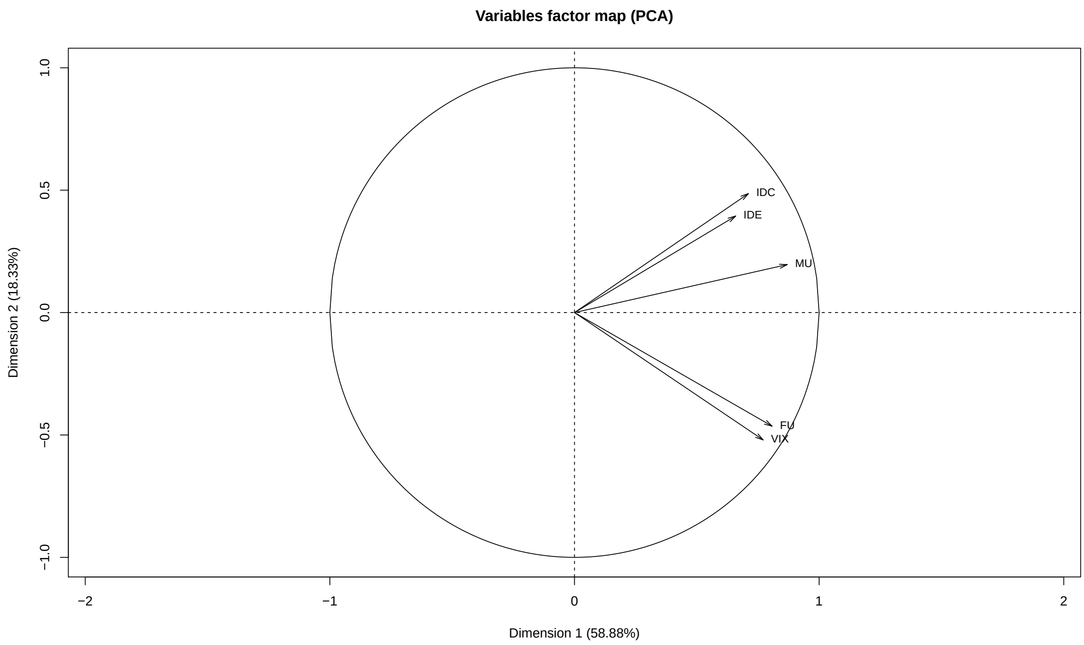
Table C2: Factor Loadings

	F1	F2	F3	F4	F5
VIX	0.77	-0.52	0.06	0.27	-0.24
MU	0.87	0.20	-0.15	-0.36	-0.23
FU	0.81	-0.46	-0.04	-0.14	0.33
IDC	0.71	0.49	-0.42	0.26	0.10
IDE	0.66	0.39	0.64	0.05	0.06

Table C3: Squared Cosines

	F1	F2	F3	F4	F5
VIX	0.59	0.27	0.00	0.07	0.06
MU	0.76	0.04	0.02	0.13	0.05
FU	0.65	0.22	0.00	0.02	0.11
IDC	0.51	0.24	0.18	0.07	0.01
IDE	0.43	0.16	0.40	0.00	0.00

Figure C1: Variables factor map (Factor 1 and Factor 2)

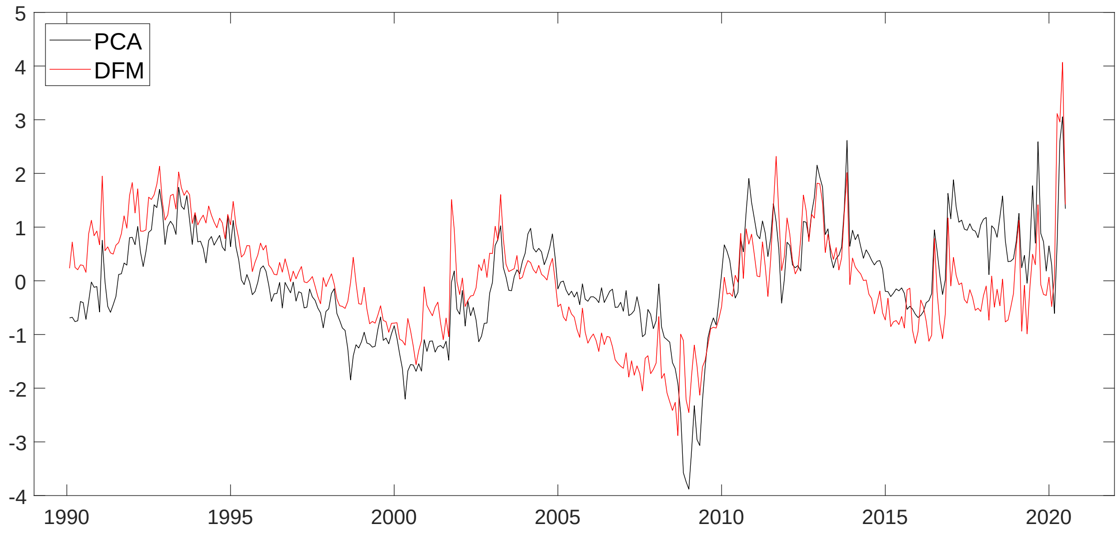


D Dynamic Factor Model

Table D1: Correlation

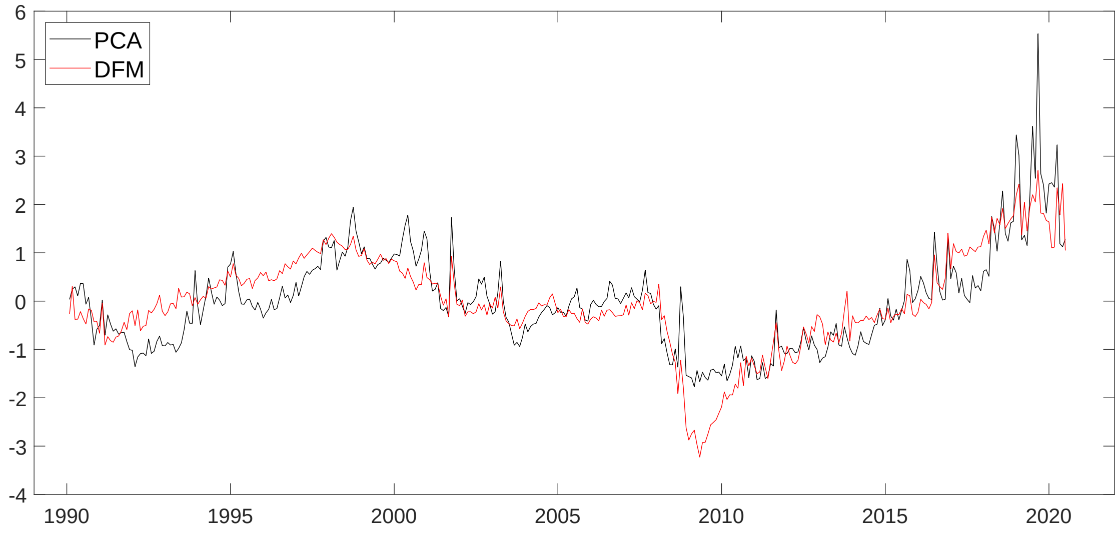
	F1 DFM	F2 DFM	F3 DFM	F4 DFM
VIX	0.60	-0.09	-0.21	-0.24
EPU	0.70	0.49	-0.13	-0.04
NewsUS	0.63	0.48	0.17	0.20
MPU	0.38	0.25	0.22	0.32
GPR	0.04	0.04	0.20	0.30
IDC	0.60	0.14	-0.75	-0.59
IDE	0.59	-0.08	-0.20	-0.35
Bspread	0.48	-0.37	-0.39	-0.23
Spread	0.35	0.29	-0.64	-0.51
EPU_Access	0.84	0.60	-0.04	-0.19
MU	0.56	-0.40	-0.48	-0.33
FU	0.54	-0.20	-0.14	-0.12
FPU	0.71	0.57	-0.15	-0.17
TPU	-0.03	0.26	0.48	0.40
HPU	0.57	0.51	-0.09	-0.04
EMV	0.47	0.00	0.09	0.03
Disease	0.44	0.28	0.21	0.11

Figure D1: Comparison between the second factor from the PCA and the DFM



Note: Indexes are standardized.

Figure D2: Comparison between the third factor from the PCA and the DFM



Note: Indexes are standardized.

Chapter 2

A Positive Effect of Uncertainty Shocks on the Economy: Is the Chase Over ?[†]

[†]A first version of this chapter (co-written with Francisco Serranito and Julien Vauday) has been accepted by *World Economy* (**Forthcoming**).

Introduction

What is an uncertainty shock? How large and persistent are the effects of uncertainty shocks on the economy? And, finally, are the effects of macroeconomic uncertainty shocks different from those of financial uncertainty shocks? This chapter will address these questions which became fundamental in the economic debate on the growth path after a financial crisis. Indeed, uncertainty could be one of the main causes of the weak recovery following the 2007-2008 financial crisis (Blanchard, 2009; Stock and Watson, 2012; Bloom et al., 2013).

Since the seminal paper of Bloom (2009), a booming economic research has emerged on measuring the effects of uncertainty shocks on economic activity. A wide range of proxies measuring uncertainty has been proposed. Recent contributions include measures based on volatility of stock markets (See, among many others, Bloom, 2009; Gilchrist et al., 2014; Caldara et al., 2016), measures based on the dispersion on expectations about the future economic conditions (See, among many others, Bloom, 2009; Bachmann et al., 2013; Leduc and Liu, 2016), measures based on recent textual analysis techniques of newspapers (See, among many others, Baker et al., 2016; Davis, 2016; Caldara and Iacoviello, 2022). Other studies try to decompose uncertainty between macroeconomic and financial uncertainty applying econometric methodologies (Jurado et al., 2015; Ludvigson et al., 2021).[1] A last branch of empirical studies developed composite indexes combining the measures of the previous categories to summarize the different information (Haddow et al., 2013; Charles et al., 2018) - see Himounet (2022) for an overview.

[1]As already stated, the modern approach to assessing uncertainty is based on either a measure of financial market volatility or a measure of "news " that counts the frequency by which some keywords appear in the press. Recently, Manasse et al. (2020) proposed an original framework to assess political uncertainty. Using the Brexit event as a natural experiment, they demonstrate that the probability of the outcome of the Referendum derived from the bookmakers' odds can be a good proxy of the political risk in the pound foreign exchange market. This is because, in the case of the UK, the Brexit Referendum has been preceded by an exceptionally liquid online betting market.

Structural VAR (SVAR) models have been mostly applied in the empirical literature to identify and investigate the impact of uncertainty shocks on macroeconomic variables (See, among many others, Bloom, 2009; Jurado et al., 2015; Baker et al., 2016; Leduc and Liu, 2016). If any, most research finds a negative effect of uncertainty: a decline in industrial production and a rise in unemployment. These previous findings are consistent with a theoretical literature arguing that uncertainty can have an influence on agents' behaviour (Dixit, 1989; Blanchard, 2009). Uncertainty can lead firms to delay investment and hiring decisions (Bernanke, 1983; Pindyck, 1991) and it can lead consumers to rise their savings for precautionary reasons (Leland, 1968).

Recently, the empirical consensus on the negative impact of uncertainty has been broken by the studies of Ludvigson et al. (2021) and Larsen (2021) who demonstrate that uncertainty shocks may trigger an increase in industrial production. More specifically, among all uncertainty shocks, only the macroeconomic ones will have a positive effect on the economy. This striking result is explained by the implementation of a new econometric framework to identify uncertainty shocks in a SVAR model, namely the *event constraints* methodology developed by Ludvigson et al. (2021). Applying a similar despite somehow different methodology based on the *narrative sign restrictions* of Antolín-Díaz and Rubio-Ramírez (2018), Larsen (2021) finds also a positive effect of macroeconomic uncertainty on Norway's economic activity. The explanation about the positive effect of uncertainty would be related to *growth options* theories (Segal et al., 2015). The recent technology of Artificial Intelligence (AI) might be a good illustration of such a theory. Indeed, predicting today the future industrial achievements that will result from research and development spending in AI is challenging and uncertain, but predicting that the potential future benefits of these innovations will be huge seems quite obvious. A mechanism behind this intuition may be found in a work by Oi (1961). The idea is quite simple: the shape of the profit function of firms is such that when facing a price uncertainty represented by an equiprobable lottery of having a high or a low price, this yields a higher expected profit than the profit a firm gets if it faces the mean price certainly. Hence, assuming that price uncertainty is due to more general uncertainty, then, uncertainty is preferred by firms that are not risk averse.

The goal of this chapter is to question this surprising conclusion. The identification of shocks through events constraints can be seen as a sub-family of the (narrative) sign restrictions approach for VARs (Antolín-Díaz and Rubio-Ramírez, 2018). This methodology of identifying shocks is appealing because it imposes restrictions on the structural parameter set that are in general considered "weaker" than more traditional identification hypothesis. Therefore, these restrictions have a higher probability of not being rejected by the data. Since narrative sign restrictions are based on economic appraisals of historical events, it is easy to discuss and hopefully agree on the validity of the proposed restrictions. As stated by Antolín-Díaz and Rubio-Ramírez (2018): *"a single narrative sign restriction may dramatically sharpen and even change the inference of SVARs originally identified via traditional sign restrictions"*. The narrative proposed for each restriction must be convincing enough since one single narrative sign restriction may change the whole results. It seems therefore legitimate to check whether Ludvigson et al. (2021)'s conclusions are not driven by just one specific constraint among the set of *event constraints* imposed during the identification strategy and, if so, to question the narrative of this constraint.

We have identified two main shortcomings that could explain the positive correlation between macroeconomic uncertainty and economic activity. Firstly, the choice of the events used in the analysis is questionable. Indeed, the event constraints methodology advocated by Ludvigson et al. (2021) imposes a minimum size required on structural uncertainty shocks at specific dates. Examining their list of events, a restriction on the structural macroeconomic uncertainty shock in 1970:12 is selected. This choice is surprising given that the uncertainty indexes do not exhibit a peak at this date. This date corresponds to the beginning of the unsustainability period due to the collapse of the

Bretton Woods system according to the authors. By removing one by one the restrictions used in their model, we obtain the positive effect of macroeconomic uncertainty highlighted by these authors, only if the constraint related to a high structural shock of macroeconomic uncertainty on 1970:12 is not completely removed from the analysis. Therefore, we show that the positive effect estimated is only related to this specific constraint and not to the three other constraints that concern the macroeconomic uncertainty. We get the same results starting the sample at 1972:01 to remove this constraint in another way.

Secondly, some significant uncertainty shocks have not been taken into account in their model. Major uncertainty shocks such as the 09/11 attacks, the Russian financial crisis and LTCM in 1998 for financial uncertainty have been omitted in the set of restrictions considered by Ludvigson et al. (2021). We add new restrictions to take into account the 09/11 attacks and the Russian financial crisis which are often cited as uncertainty shocks in the literature (See, among many others, Bloom, 2009; Baker et al., 2016; Larsen, 2021; Himounet, 2022). Adding these new restrictions, we no longer find the positive effect of macroeconomic uncertainty shocks. We get a negative effect showing that their results seem not to be robust to the choice of events related to structural uncertainty shocks. In the end, the controversial result of a positive effect of macroeconomic uncertainty on economic activity does not yet seem to be proven. Whether financial or macroeconomic, there is no evidence allowing for the rejection of the hypothesis that uncertainty has a negative impact on economic activity.

The rest of this chapter is organized as follows. Section 1 presents a brief review on how to identify shocks with a SVAR framework. Section 2 questions the narrative events constrains selected by Ludvigson et al. (2021) and their impact on the economic activity. Section 3 presents results adding new constraints. In section 4, some robustness checks are analyzed. The last section presents conclusions.

2.1 Identifying Structural Uncertainty Shocks

2.1.1 A Brief Review of the Literature

Usually, structural VAR models (SVAR) have been applied to investigate the impact of uncertainty on macroeconomic activity. Consider the SVAR(p) model:

$$X_t = A_0 + \sum_{j=1}^{p} A_j X_{t-j} + B\ e_t \tag{2.1}$$

where X_t denotes the vector of endogenous variables. e_t denotes a vector of zero-mean, serially uncorrelated structural shocks with identity covariance matrix:

$$E[e_t e_t'] = I \tag{2.2}$$

The corresponding reduced-form $VAR(p)$ is defined as follows:

$$X_t = A_0 + \sum_{j=1}^{p} A_j X_{t-j} + \eta_t \tag{2.3}$$

$$\eta_t = B\ e_t \tag{2.4}$$

where η_t denotes a vector of zero-mean, serially correlated shocks with a covariance matrix Ω:

$$E[\eta_t \eta_t'] = \Omega \tag{2.5}$$

In the SVAR model, the key point is to identify structural shocks. The traditional approach is to use a recursive scheme imposing the contemporaneous matrix B to be the lower-triangular matrix of the Cholesky decomposition of Ω:

$$\Omega = BB' \tag{2.6}$$

Other identification procedures can be applied. Ramey (2016) and Rossi (2021) review the different methodologies identifying structural shocks in a SVAR model. These strategies of identification include different schemes on contemporaneous restrictions, heteroskedasticty-based identification, sign-restrictions, narrative methods, high frequency identification, proxy SVARs with external instruments, long term restrictions, factor-augmented VARs and DSGE models.[2] Recently, new methodologies have been developed in the empirical literature such as Inoue and Rossi (2021) with the functional shocks in the VAR and Ludvigson et al. (2021) with events constraints. In the following, we will discuss in further details the framework advocated by Ludvigson et al. (2021) to identify structural shocks.

2.1.2 Identifying shocks with *events constraints*

Following Ludvigson et al. (2021), we denote $X_t = (U_{Mt}, Y_t, U_{Ft})'$ the vector of endogenous variables described in (2.1). U_{Mt} denotes the macroeconomic uncertainty index, Y_t denotes the industrial production in log-level and U_{Ft} denotes the financial uncertainty index.[3] The macroeconomic uncertainty index and the financial uncertainty index have been estimated applying the methodology of Jurado et al. (2015).[4] The covariance matrix Ω can be decomposed according to the Cholesky decomposition such that $\Omega = PP'$. P denotes the lower-triangular matrix of the Cholesky decomposition. The structural shocks $e_t = (e_{Mt}, e_{Yt}, e_{Ft})'$ are related to the reduced form innovations $\eta_t = (\eta_{Mt}, \eta_{Yt}, \eta_{Ft})'$ by the relationship: $B\,e_t = \eta_t$. The matrix B is a $3{\times}3$ matrix with 9 parameters. The reduced-form covariance structure of η_t only provides $n(n+1)/2 = 6$

[2]See Ramey (2016) and Rossi (2021) for a detailed presentation of these SVAR identification strategies.

[3]The results of the regression for each equation in the VAR model are shown in Table A1.

[4]The correlation between both uncertainty indexes is close to 0.6 with a p-value equal to 0. The aim of this chapter is to question the results of Ludvigson et al. (2021) examining their new SVAR identification procedure and not the potential similarities between their both uncertainty indexes. The problem of similarities between their macroeconomic and financial uncertainty indexes has been discussed by Himounet (2022).

restrictions. Additional restrictions have to be imposed to identify the effects of the structural shocks e_t on the endogenous variables in X_t. Otherwise, the model is under-identified and many solutions can satisfy the covariance restriction : $\Omega = BB'$. Let $\hat{\mathcal{B}}$ denotes the set of solutions named *unconstrained set* such that:

$$\hat{\mathcal{B}} = \{B = \hat{P}Q : Q \in \mathbb{O}_n, diag(B) \geq 0, \Omega = BB'\} \tag{2.7}$$

where $\mathbb{O}_n$ denotes the set of $n \times n$ orthogonal matrices ($QQ' = I_n$). By construction:

$$E[\eta_t \eta_t'] = BB' = \hat{P}Q\left(\hat{P}Q\right)' = \hat{P}QQ'\hat{P}' = \hat{P}\hat{P}' = \hat{\Omega} \tag{2.8}$$

To construct the set $\hat{\mathcal{B}}$, the algorithm is initialized by setting $B = P$. Then, they rotate B by randomly drawing 1.5 million matrices Q. Each rotation is performed by drawing a $n \times n$ matrix M of $\mathcal{N}(0, I_n)$. Q is taken to be the orthogonal matrix in the QR decomposition of M and R denotes an upper-triangular matrix. By construction, the covariance restriction $\Omega = BB'$ is satisfied. Let $e_t(B) = B^{-1}\eta_t$ be the shocks implied by a matrix $B \in \hat{\mathcal{B}}$ for a given η_t. 1.5 million different B imply 1.5 million values of $e_t(B)$ for $t = 1, \ldots, T$. Thus, we get 1.5 million time series of e_{Mt}, 1.5 million time series of e_{Yt} and 1.5 million time series of e_{Ft} for $t = 1, \ldots, T$.[5]

The identification of uncertainty shocks in the SVAR will be based on imposing some *event constraints* and external variable constraints on these 1.5 millions of series. *Event constrains* restrict the structural shocks based on a reading of the times throughout history. The structural shocks must be consistent with our *ex-post* understanding of historical events. For *event constraints* selection, the authors have applied a mix between a "pure" narrative approach framework and restrictions determined by the study of of the maximum of structural shocks $e_t = (e_{Mt}, e_{Yt}, e_{Ft})'$. In their simulations, the maximum values over the 1.5 millions rotations are located on the following dates. The date on

[5] We apply the MATLAB program provided by Ludvigson et al. (2021) in their replication files.

which the structural financial uncertainty shock e_{Ft} most often reaches its maximum is 2008:09 corresponding to the collapse of Lehman Brothers. The second date is 1987:10 corresponding to the Black Monday. The date where the structural macroeconomic uncertainty shock e_{Mt} most often reaches its maximum is again 2008:09. The second is 1970:12 corresponding to the beginning of the unsustainability following the collapse of the Bretton Woods system according to the authors. Their study of the maximum in structural uncertainty shocks allows to define some *event constraints* in their application imposing structural uncertainty shocks to be strong at these specific dates.

2.1.3 Application and Baseline Results of Ludvigson et al. (2021)

In their SVAR model, Ludvigson et al. (2021) have defined their *event constraints* as follows:

1. $\bar{g}_{E1} : e_{F\tau_1} \geq \bar{k_1}$ at $\tau_1 = 1987 : 10$ (Black Monday)
2. $\bar{g}_{E2} : \left(e_{F\tau_2} \geq \bar{k_2}\right)$ or $\left(e_{M\tau_2} \geq \bar{k_3}\right)$ at $\tau_2 = 2008 : 09$ (Lehman Brothers)
3. $\bar{g}_{E3} : e_{M\tau_3} \geq \bar{k_4}$ at $\tau_3 = 1970 : 12$ (Bretton Woods)
4. $\bar{g}_{E4} : 0 \geq \sum\limits_{t=\tau_4} e_{Yt}$ for $\tau_4 \in [2007 : 12, 2009 : 06]$ (Great Recession)
5. $\bar{g}_{E5} : e_{M\tau_5} \geq 0$ and $e_{F\tau_5} \geq 0$ at $\tau_5 = 1979 : 10$ (Volcker)
6. $\bar{g}_{E6} : e_{M\tau_6} \geq 0$ and $e_{F\tau_6} \geq 0$ at $\tau_6 \in [2011 : 07, 2011 : 08]$ (Debt Ceiling Crisis)

The first condition requires that the financial uncertainty shock of October 1987 corresponding to the black Monday must be large exceeding the threshold $\bar{k_1}$. The second condition imposes that either the financial uncertainty shock or the macroeconomic uncertainty shock (or both) in September 2008 corresponding to the collapse of Lehman Brothers be large exceeding the thresholds $\bar{k_2}$ and $\bar{k_3}$ respectively. The third condition requires that the macroeconomic uncertainty shock found in December 1970 must be large exceeding the threshold $\bar{k_4}$. These three constraints have been determined by the study of the maximum in structural shocks e_t that we have mentioned previously. The next constraints are more related to narrative restrictions regarding historical events. The fourth condition means that the cumulation of real activity shocks during the Great Recession must be negative meaning that their sum may not be above average. The fifth condition imposes restrictions on both types of uncertainty shocks. At the month of October 1979 with the Volcker experiment, both types of uncertainty shocks must be positive. The last condition imposes restrictions on two months: 2011:07 and 2011:08 corresponding to the 2011 debt-ceiling crisis. Both types of uncertainty shocks must be positive at these months. The six event constraints $\bar{g}_{E1}, \bar{g}_{E2}, \bar{g}_{E3}, \bar{g}_{E4}, \bar{g}_{E5}, \bar{g}_{E6}$ can be represented by a system of inequality constraints on B:

$$\bar{g}_E \left(e_t \left(B\right); \bar{\tau}, \bar{k}\right) \geq 0 \tag{2.9}$$

where $\bar{k} = \left(\bar{k_1}, \bar{k_2}, \bar{k_3}, \bar{k_4}\right) > 0$ and $\bar{\tau} = (\bar{\tau_1}, \bar{\tau_2}, \bar{\tau_3}, \bar{\tau_4}, \bar{\tau_5}, \bar{\tau_6})$.

According to Ludvigson et al. (2021), this approach differs from the narrative approach given that the same SVAR is applied to identify all shocks simultaneously unlike the previous empirical studies which have used a two-step procedure that identifies some shocks ahead of others. Other constraints have been proposed from correlation with external variables. According to Ludvigson et al. (2021), external variables can facilitate the identification in the VAR when economic reasoning implies they should be informative about the shocks. The correlations between the external variables and structural uncertainty shocks have been used to generate additional inequality constraints:

1. $\bar{g}_{C1} : 0 \geq corr\left(e_{jt}, S_{1t}\right), j = M, F$
2. $\bar{g}_{C2} : corr\left(e_{jt}, S_{2t}\right) \geq 0, j = M, F$

where S_1 denotes the CRSP value-weighted stock market index which is considered as a measure of stock market returns and S_2 denotes the real price of gold in log difference.

The first correlation constraint requires that uncertainty shocks must be negatively correlated with stock market returns. The second correlation constraint means that both types of uncertainty shocks must be positively correlated with the variation of the real price of gold that is considered as a safe asset by investors. The correlation constraints $\bar{g}_{C1}, \bar{g}_{C2}$ can be represented by a system of inequality constraints on B:

$$\bar{g}_C\left(e_t\left(B\right);S\right) \geq 0 \tag{2.10}$$

The matrices B satisfying the following system of inequalities are retained :

$$\hat{\mathcal{B}} = \{B = \hat{P}Q : Q \in \mathbb{O}_n, diag(B) \geq 0, \Omega = BB', \bar{g}_E\left(e_t\left(B\right);\bar{\tau},\bar{k}\right) \geq 0, \bar{g}_C\left(e_t\left(B\right);S\right) \geq 0\} \tag{2.11}$$

A crucial point is to estimate the parameters $\bar{k_1}$, $\bar{k_2}$, $\bar{k_3}$, $\bar{k_4}$. For illustration, we will describe the first condition $\bar{g}_{E1} : e_{F\tau_1} \geq \bar{k_1}$ at $\tau_1 = 1987 : 10$ (Black Monday). Given that 1.5 million time series of e_{Ft} have been estimated, we get 1.5 million values for e_{Ft} at $t = 1987 : 10$. According to Ludvigson et al. (2021), the threshold $\bar{k_1}$ should correspond to the $75th$ percentile value of e_{Ft} at $t = 1987 : 10$ which is equal to 4.1634. The same procedure has been applied for $\bar{k_2}$, $\bar{k_3}$, $\bar{k_4}$ at their respective dates. For $\bar{k_2}$, they take the $75th$ percentile value of e_{Ft} at $t = 2008 : 09$ which is equal to 4.5672. For $\bar{k_3}$, they take the $75th$ percentile value of e_{Mt} at $t = 2008 : 09$ which is equal to 4.7314. For $\bar{k_4}$, they take the $75th$ percentile value of e_{Mt} at $t = 1970 : 12$ which is equal to 4.048. These parameters can be interpreted as the minimum size required of the structural shocks for the events associated with the constraints.

At the beginning, there was 1.5 million matrices B. Imposing the restrictions of Ludvigson et al. (2021) in the data will then suppress a number of matrices B. For example, imposing the first restriction $\bar{g}_{E1}$ will reduce the number from 1.5 millions to 375000. Adding the other constraints mentioned previously to get the full set of restrictions described by the system (2.11), the number of matrices B is extremely reduced.

Indeed, the number of matrices B satisfying the full set of restrictions is equal to 169. Ludvigson et al. (2021) estimate as many impulse response functions as the number of matrices B retained. Therefore, 169 impulse response functions are estimated. To compute the impulse response functions, we can write the VAR model described by (2.1) in its moving average (MA) representation:

$$X_t = \mu + \sum_{i=0}^{\infty} \phi_i \; B e_{t-i} \tag{2.12}$$

For each matrix B satisfying the full set of constraints, impulse response functions at a horizon h after a shock of the jth variable are computed such that:

$$\frac{\delta \; X_{t+h}}{\delta \; e_{jt}} = \phi_h \; b^j \tag{2.13}$$

where b^j denotes the jth column of the matrix B.[6]

Figure 2.1 reproduces the impulse response functions of Ludvigson et al. (2021). For each panel, for each horizon h, the shaded area represents IRFs for all values among the 169 matrices B satisfying the full set of constraints described by the system (2.11). The lower bound of the shaded area represents the minimum value among the 169 IRF values and the upper bound represents the maximum value among the 169 IRF values.[7] It means that the IRF value can fluctuate between these both values. For example, examining the effect of a financial uncertainty shock on industrial production (lower middle panel) at the horizon $h = 20$, the lower bound of the shaded area is equal to -1.06 corresponding to the minimum value among the 169 possible values. The upper bound of the shaded area is equal to -0.89 corresponding to the maximum value among the 169 possible values. Therefore, the IRF value given restrictions at the horizon $h = 20$ fluctuates between -1.06 and -0.89 highlighting a negative effect for this horizon. We

[6]When $h = 0$, $\phi_h = I_n$.

[7]Ludvigson et al. (2021) underlined that their new SVAR approach does not require confidence band for inference. Instead, the authors refer at the entire set of solutions.

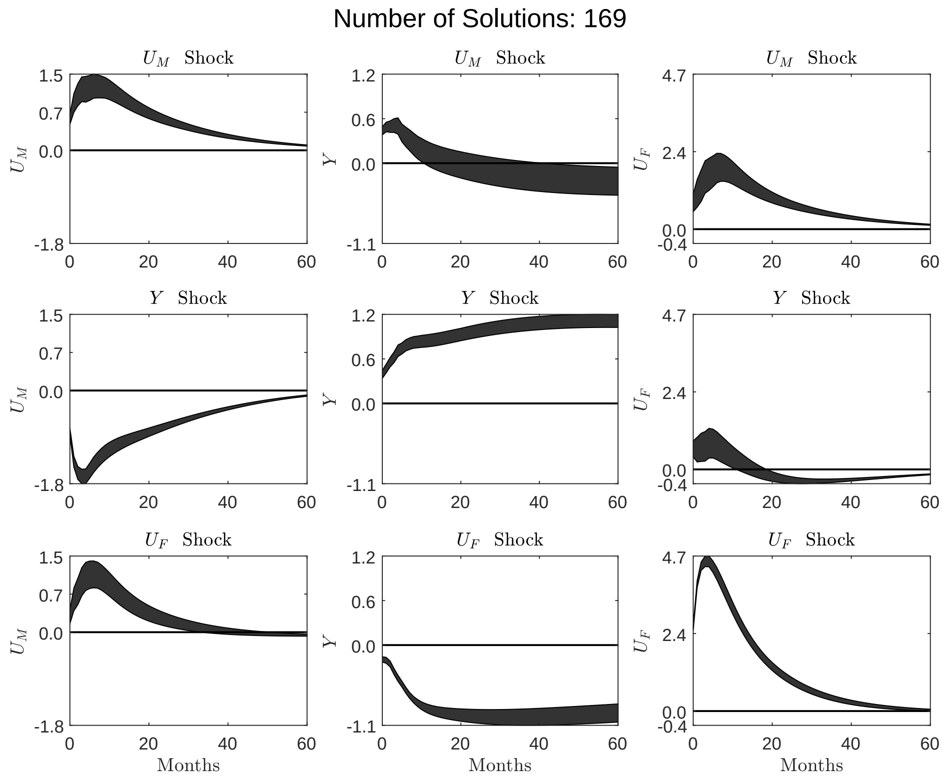
can do a link with bayesian methodologies. Applying the methodology of Ludvigson et al. (2021), we don't estimate a single value of the IRF and its interval confidence symbolizing uncertainty on this estimation but this uncertainty concerns the number of matrices retained given restrictions. These restrictions are chosen as a summary of what we observe in the data of the macroeconomic and financial uncertainty indexes as strong uncertainty shocks at specific dates. What is the share of retained matrices given our knowledge of past uncertainty shocks ? If we add new information, *i.e.* a new restriction, we must revise the number of matrices given our new knowledge.

An increase in macroeconomic uncertainty rises financial uncertainty (upper right panel) and inversely (lower left panel). The results indicate that financial uncertainty shocks have a negative impact on industrial production which is very persistent for more than 5 years (lower middle panel). However, macroeconomic uncertainty shocks have a positive effect on industrial production (upper middle panel) breaking the empirical consensus on the negative effect of uncertainty. The effect is no longer interpretable after 12 months as the zero value belongs to the shaded area.[8] Table 2.1 shows the associated forecast error variance decomposition (FEVD) that is the share of the variance explained by the uncertainty measures in industrial production at various forecast horizons: $h = 1$; $h = 12$ and h_{max} is the horizon at which the fraction of forecast error variance is maximized. Because we have a set of solutions, we have a range of forecast error variances for each horizon. Financial uncertainty shocks have a small contribution to the one-step-ahead forecast error variance of industrial production: between 0.06 and 0.12. However, their importance increases over time so that they account for 0.38 to 0.54 of the forecast error variance in Y at the h_{max} horizon. Inversely, macroeconomic uncertainty shocks have a relative importance to the one-step-ahead forecast error variance of industrial production (0.36 to 0.60). This importance decreases over time with a small contribution to the 12-step-ahead forecast error variance of industrial production

[8] We don't find any matrices B satisfying the full set of restrictions if we run their model on a longer sample: 1960:07-2019:12. Therefore, we cannot compute the IRFs.

(0.07 to 0.21).

Figure 2.1: Impulse Response Functions of Ludvigson et al. (2021)



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the full set of constraints described in (2.11) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the full set of constraints described in (2.11). The sample spans the period 1960:07 to 2015:04.

2.2 How to select events constraints restrictions ?

In this section, we will question the events constraints put forward by Ludvigson et al. (2021) and their effect on the results of a positive impact of uncertainty.

Table 2.1: Variance Decomposition: Fraction variation in Y

	$h = 1$	$h = 12$	h_{∞}	h_{max}
$U_M shock$	[0.36 ; 0.60]	[0.07 ; 0.21]	[0.02 ; 0.07]	[0.37 ; 0.72]
$U_F shock$	[0.06 ; 0.12]	[0.31 ; 0.40]	[0.32 ; 0.51]	[0.38 ; 0.54]

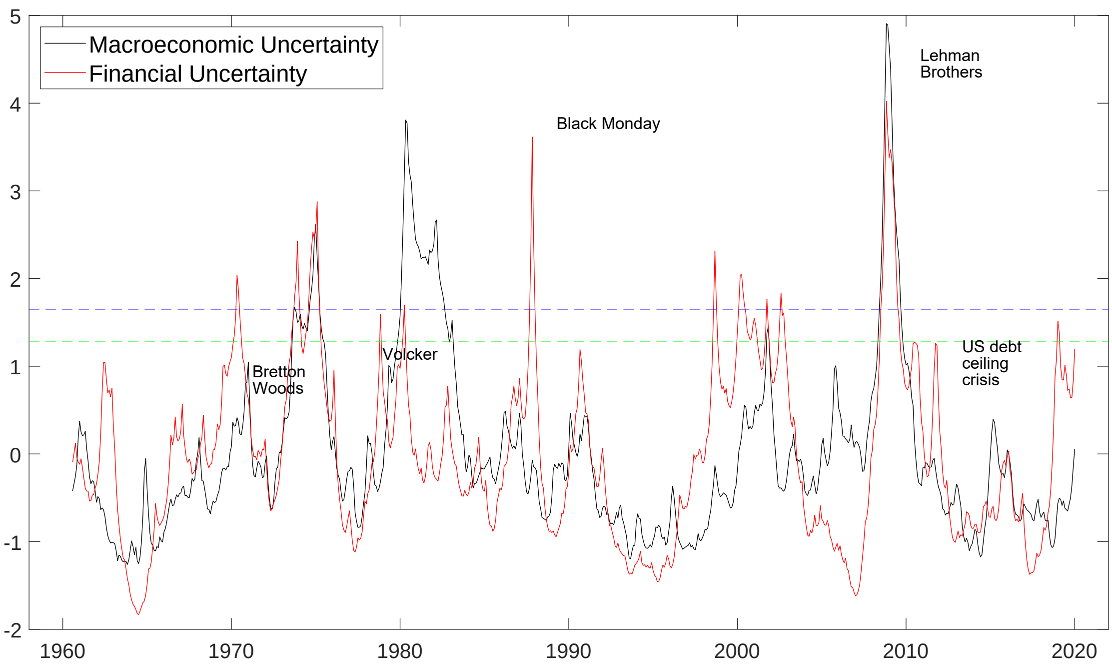
Notes: The figure shows results from the identified set for system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the full set of constraints described in (2.11) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The table shows the fraction of h-step-ahead forecast error variance of Y that is explained by uncertainty shocks. h_{max} reports the maximum fraction of forecast error variance explained across all VAR forecast horizons h. The numbers in brackets represent the ranges for these numbers across all solutions in the identified set. The sample spans the period 1960:07 to 2015:03.

2.2.1 The collapse of the Bretton Wood system

Undoubtedly, in the stimulating chase of a positive effect of uncertainty, the work of Ludvigson et al. (2021) is very interesting and innovative. However, their analysis suffers from some caveats. Our goal in this section is to extend their methodology. The first discussion concerns the choice of the constraints proposed by Ludvigson et al. (2021). Even if the approach of the study of the maximum in structural shocks e_t can be interesting, it does not really correspond to the narrative approach. The first three *event constraints* are not based on a reading of uncertainty indexes contrary to Caggiano et al. (2021) and Larsen (2021) which have examined the peaks of their uncertainty indexes. In his seminal paper, Bloom (2009) considers an uncertainty peak as significant at the 5% level if the uncertainty index exceeds 1.65 standard deviation above the mean. The restrictions of Caggiano et al. (2021) are based on the dates that Bloom (2009) has identified following the threshold of 1.65. Examining the list of *event constraints* of Ludvigson et al. (2021), some restrictions on the high structural uncertainty shocks as the collapse of Lehman Brothers in 2008 and the Black Monday in 1987 can be justified following the criterion of Bloom (2009). The macroeconomic uncertainty shock and the financial uncertainty shock associated with Lehman Brothers exceed the threshold of 1.65 (Figure 2.2). It is the same for the financial uncertainty shock associated with the

Black Monday. However, the choice of the shock restriction on the structural macroeconomic uncertainty shock in 1970:12 can be surprising. This date should correspond to the beginning of the unsustainability of the Bretton Woods system according to the authors. Examining uncertainty indexes in Figure 2.2, we note that the level of macroeconomic uncertainty is not very high at this date and it does not exceed the threshold of 1.65.[9] The same comment is true for the financial uncertainty index at this date. This observation raises questions about the justification of this constraint despite the interesting approach of the study of the maximum in e_t. How will the results change if we remove the constraint $\bar{g}_{E3}$ related to Bretton Woods ?

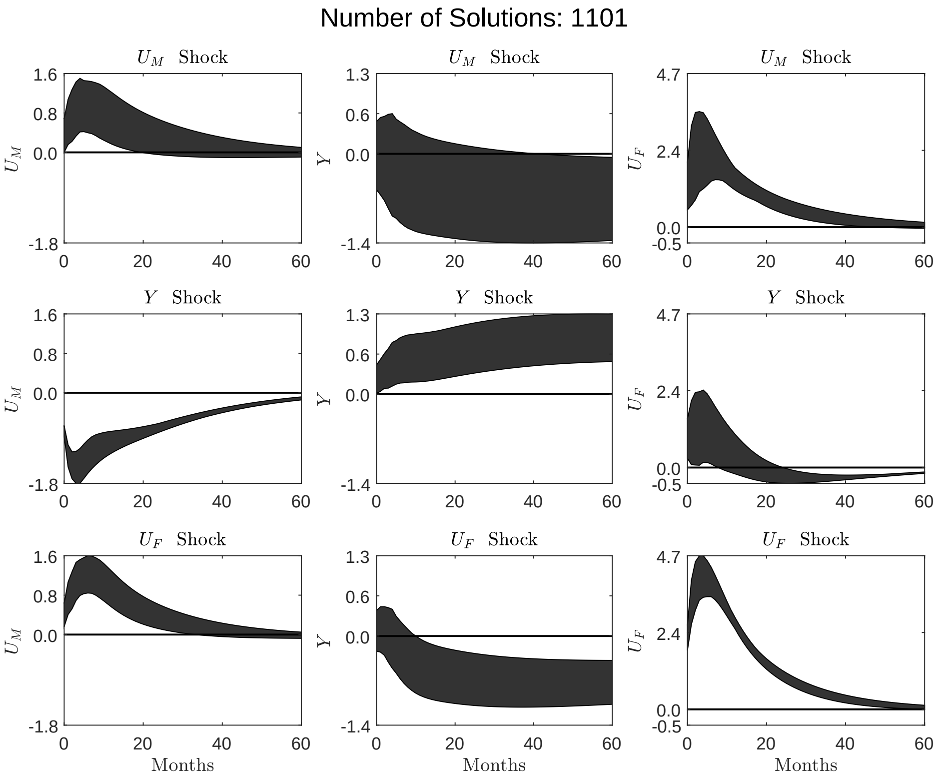
Figure 2.2: Macroeconomic Uncertainty VS Financial Uncertainty



Source: Ludvigson et al. (2021)
Notes: The measures are standardized. The solid red line corresponds to the financial uncertainty index of Ludvigson et al. (2021). The solid black line corresponds to the macroeconomic uncertainty index of Ludvigson et al. (2021). The horizontal dashed blue line represents the threshold 1.65. The horizontal dashed green line represents the threshold 1.28.

[9]The shock on 1970:12 also does not exceed the threshold of 1.28 if we are at the 10% level.

Figure 2.3: Impulse Response Functions removing $\bar{g}_{E3}$



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the set of constraints described in (2.11) but removing $\bar{g}_{E3}$ with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

Removing the constraint $\bar{g}_{E3}$, the number of matrices B increases to 1101. The IRF bands are larger than previously (Figure 2.3). We have the same results about the impact of financial uncertainty shocks on industrial production with a negative effect after 11 months. However, about the effect of macroeconomic uncertainty shock on industrial production, it is difficult to assign an interpretation to the shock since 0 is between the minimum and the maximum of the IRFs bands (upper middle panel). Could this constraint explain their result on the positive effect of macroeconomic uncertainty ? To try to answer this question, we run the model of Ludvigson et al. (2021) removing one by one the different event constraints. We run the model removing $\bar{g}_{E1}$ and maintaining $\bar{g}_{E2}$, $\bar{g}_{E3}$, $\bar{g}_{E4}$, $\bar{g}_{E5}$, $\bar{g}_{E6}$. Then, we run the model removing $\bar{g}_{E2}$ and maintaining $\bar{g}_{E1}$, $\bar{g}_{E3}$, $\bar{g}_{E4}$, $\bar{g}_{E5}$, $\bar{g}_{E6}$. We repeat the same procedure for the constraints $\bar{g}_{E4}$, $\bar{g}_{E5}$, $\bar{g}_{E6}$. We always get their positive effect of macroeconomic uncertainty showing that the constraint related to Bretton Woods can explain their positive effect. To add another proof, we run their model on a subsample: 1972:01-2015:04. Using this subsample, we start after the events related to Bretton Woods and therefore, we remove the restriction $\bar{g}_{E3}$ in another way. We get a slightly negative effect of financial uncertainty shocks and macroeconomic uncertainty shocks on industrial production but in the long term (Figure 2.4).[10]

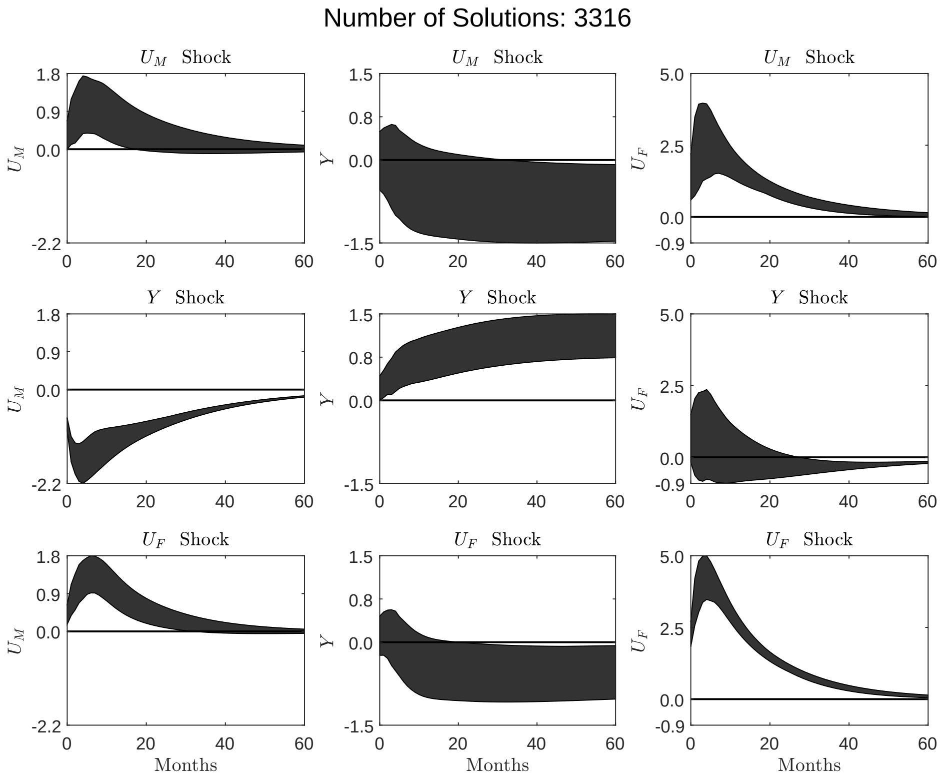
It is obvious that the collapse of the Bretton Woods system was a turning point for the world economy and, thus, its end can be inserted in narrative restrictions. However, the real end of the Bretton Woods system was announced in August 1971 by Richard Nixon with the *Nixon shock*. Therefore, to really take into account Bretton Woods, we must modify the constraint $\bar{g}_{E3}$ taking τ_3 =1971:08 instead of 1970:12. We get a negative effect of macroeconomic uncertainty shocks on industrial production (Figure 2.5) instead of the positive effect highlighted by Ludvigson et al. (2021). These findings show that their positive effect of macroeconomic uncertainty is not robust modifying their constraint related to the date of the Bretton Woods. We don't find any solutions expanding the sample to 2019:12.

2.2.2 Real Uncertainty Index

Following Ludvigson et al. (2021), we replace the macroeconomic uncertainty index with their real uncertainty index (U_R) which is a sub-index of macroeconomic uncertainty. The macroeconomic uncertainty index of Ludvigson et al. (2021) is estimated

[10]We get a negative effect of macroeconomic uncertainty shocks using the sample 1972:01-2019:12.

Figure 2.4: Impulse Response Functions using the period 1972:01 to 2015:04

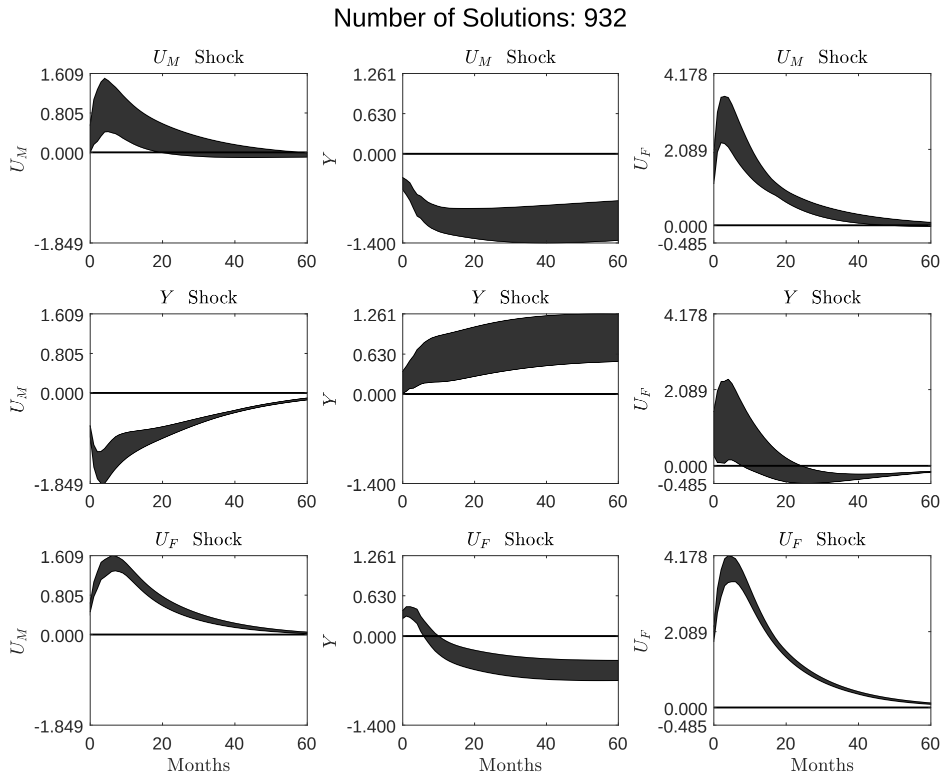


Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the set of constraints with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1972:01 to 2015:04.

with the methodology of Jurado et al. (2015) applying a set of 132 macroeconomic time series which are taken from the McCracken database.[11] These 132 macroeconomic time series can be divided in eight different groups: "Output and Income", "Labor Market", "Housing", "Consumption, Orders and Inventories", "Money and Credit", "Interest and Exchange Rates", "Prices" and stock market indexes. Ludvigson et al. (2021) have pointed out that their macroeconomic uncertainty index can fluctuate due to uncertainty

[11] A detailed list of the time series is available on the McCracken website.

Figure 2.5: Impulse Response Functions modifying the constraint $\bar{g}_{E3}$



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the set of constraints with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. We modify the constraint $\bar{g}_{E3}$ taking $\tau_3 = 1971:08$. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

in real activity variables such as output and unemployment but also due to price variables or financial market variables. To separate the fluctuations due to real activity variables from the fluctuations due to price and financial variables, these authors compute a real uncertainty index aggregating 73 time series among the 132 used (Figure B1). These 73 time series are related to the first four groups corresponding to real activity : output and income, labor market, housing (constructions) and the group related to consumption, orders and inventories. Using their full set of constraints, Ludvigson et al.

(2021) have found a positive effect of real uncertainty on industrial production which is more persistent than the positive effect of macroeconomic uncertainty : in Figure B2 are reproduced their results and we get the positive effect of real uncertainty. Removing the constraint $\bar{g}_{E3}$ related to Bretton Woods, the positive effect of real uncertainty is no more detected as the zero value belongs to the interval (see Figure B3).[12] However, the existence of this constraint can be justified since the real uncertainty index exhibits a spike on 1970:12 where the level exceeds 1.65 standard deviations above the mean. We repeat the procedure taking $\tau_3 = 1971 : 08$ instead of $1970 : 12$ in the restrictions as previously and we also find that real uncertainty shocks have a negative impact on industrial production (Figure B4). We get the same results expanding the sample to 2019:12.

The fact that the positive effect of macroeconomic uncertainty depends uniquely on the $\bar{g}_{E3}$ constraint, that is about BW, is surprising. When looking at the possible theoretical explanations of a positive effect of uncertainty proposed by the authors, they refer to the "growth option" theory and to several works by Oi (1961) and others. The main intuitions and mechanisms behind these theoretical arguments are based either on (i) the hope of generating huge profits in the future by investing in a radically new technology despite its precise potential outcomes remains uncertain or on (ii) the shape of the profit function that yields much higher profit with a high price than a low price thus making the price uncertainty of having the high or the low price with equiprobability more rewarding than having the mean price for sure. The link between those two explanations and the economic effects of the end of the Bretton Woods system are not straightforward.

Nevertheless, the fact that changing the date of the $\bar{g}_{E3}$ constraint by only a few months changes the result so drastically is puzzling. Even more puzzling is that trying to solve this puzzle, we ran some robustness checks (see section 5.1) which for we

[12]Using the subsample 1972-2015, we have the same results. We can't interpret the effect of real uncertainty shocks on industrial production.

have just changed the constraint by one month, either November 1970 or January 1971 instead of December 1970. Again, the positive effect totally vanishes to be replaced by a strong significant negative effect.

Another element is worth mentioning. When looking at the different variables that enter the real uncertainty index of Ludvigson et al. (2021), we observe a surge of growth in this specific month of December 1970 (see Appendix B) which is a catch up after the mild recession of 1969-1970. Hence, just keeping uncertainty peaks for this specific month may artificially associate a high uncertainty to a very specific episode of strong growth. This may explain the positive sign found with the constraint on December 1970. Moreover, we shall remind that the uncertainty measure of Ludvigson et al. (2021) is based on the residuals of econometric specifications, that is the part that is unexplained by the model estimated. As a matter of fact, since the 1969-1970 recession has lasted 11 months, from December 1969 to November 1970, the most probable forecast for the following month was another month of recession which is not what happened. So the strong catch up in growth of December 1970 also constitutes an important forecast error (see Appendix B). Therefore, the strong growth and strong uncertainty indeed appeared in December 1970, but their common cause is the recession that occurred previously. The causality does not exist and, to be fair, this is in line with one of the main results of Ludvigson et al. (2021): the macroeconomic uncertainty is not causal, but rather an effect of recession, instead of the financial uncertainty that can be a cause of recession.

2.3 Introducing New Event Constraints

Except for the constraint related to 1970:12, other constraints on high uncertainty shocks like the collapse of Lehman Brothers, the Black Monday in 1987 can be justified as uncertainty indexes exhibit spikes at these particular dates. However, other uncertainty shocks have not been taken into account like the 09/11 attacks and the Russian financial crisis and Long Term Capital Management in 1998 examining the uncertainty indexes. These shocks are often cited as uncertainty shocks in this literature. We don't find any justifications for not including these significant uncertainty shocks in the analysis. Applying the methodology of *event constraints*, Caggiano et al. (2021) and Larsen (2021) have inserted restrictions related to uncertainty shocks at the 09/11 attacks and the Russian financial crisis because their uncertainty variables exhibit spikes at these specific dates. Are the results of a positive effect of uncertainty robust if we add new constraints? We will try to answer this question defining additional constraints as follows:

- $\bar{g}_{E7} : e_{M\tau_7} \geq \bar{k_5}$ at $\tau_7 = 2001 : 09$ (09/11 attacks)
- $\bar{g}_{E8} : e_{F\tau_8} \geq \bar{k_6}$ at $\tau_8 = 1998 : 08$ (Russian Crisis and LTCM)

The condition $\bar{g}_{E7}$ requires that the structural macroeconomic uncertainty shock associated with the 09/11 attacks must be large exceeding the parameter $\bar{k_5}$. The condition $\bar{g}_{E8}$ means that the structural financial uncertainty shock associated with Russian financial crisis and LTCM must exceed the parameter $\bar{k_6}$. We add the new restrictions to the full set of constraints of Ludvigson et al. (2021). The parameters $\bar{k_5}$ and $\bar{k_6}$ are taken to their 75th-percentile values of the unconstrained set like previously. The $75th$ percentile value of e_{Mt} at $t = 2001 : 09$ is equal to 2.0701 and the $75th$ percentile value of e_{Ft} at $t = 1998 : 08$ corresponds to 2.9724. However, we don't find any matrices B satisfying the new full set of constraints. We separately insert these constraints in their model. We introduce the condition $\bar{g}_{E7}$ in the full set of constraints of Ludvigson et al. (2021) taking the 75th-percentile value of e_{Mt} at $t = 2001 : 09$. However, we don't find any matrices B and thus, we cannot compute the IRFs. We alleviate this constraint taking the parameter $\bar{k_5}$ to the median value of the unconstrained set (1.3823) and we get the same set of 169 matrices B. Adding the constraint $\bar{g}_{E8}$ in the full set of restrictions of Ludvigson et al. (2021), we don't find any solutions.

We repeat the procedure with our new constraints but removing the constraint $\bar{g}_{E3}$

related to Bretton Woods. The parameters $\bar{k_5}$ and $\bar{k_6}$ are taken to the median values and the 75th-percentile values of the unconstrained set respectively.[13] We retain 93 matrices B satisfying the constraints. The striking result we obtain is that macroeconomic uncertainty shocks have a negative impact with the decline in industrial production (Figure 2.6, upper middle panel). This negative effect is very persistent over the years. These findings show that the SVAR identification strategy of these authors is not robust according to the chosen constraints.[14] Expanding the sample to 1960:07-2019:12, we get just one solution B where we find a negative effect of macroeconomic uncertainty.[15]

As previously, to really take into account the end of the Bretton Woods system, we keep the constraint $\bar{g}_{E3}$ but taking $\tau_3 = 1971 : 08$ and we add our constraints $\bar{g}_{E7}$ and $\bar{g}_{E8}$. We also get a persistent negative effect of macroeconomic uncertainty shocks on economic activity (Figure 2.7). Expanding the sample to 1960:07-2019:12 as previously, we don't find any matrices B satisfying the set of restrictions.

Moreover, examining their macroeconomic uncertainty index, a strong macroeconomic uncertainty shock has been omitted at the beginning of the 1980s which is the second highest peak. It corresponds to the Iran hostages crisis with Operation Eagle Claw in April 1980. However, introducing a restriction on structural macroeconomic uncertainty shocks at this date in all previous applications, we don't find any solutions to compute IRFs showing again that this methodology of *event constraints* can be very sensitive.

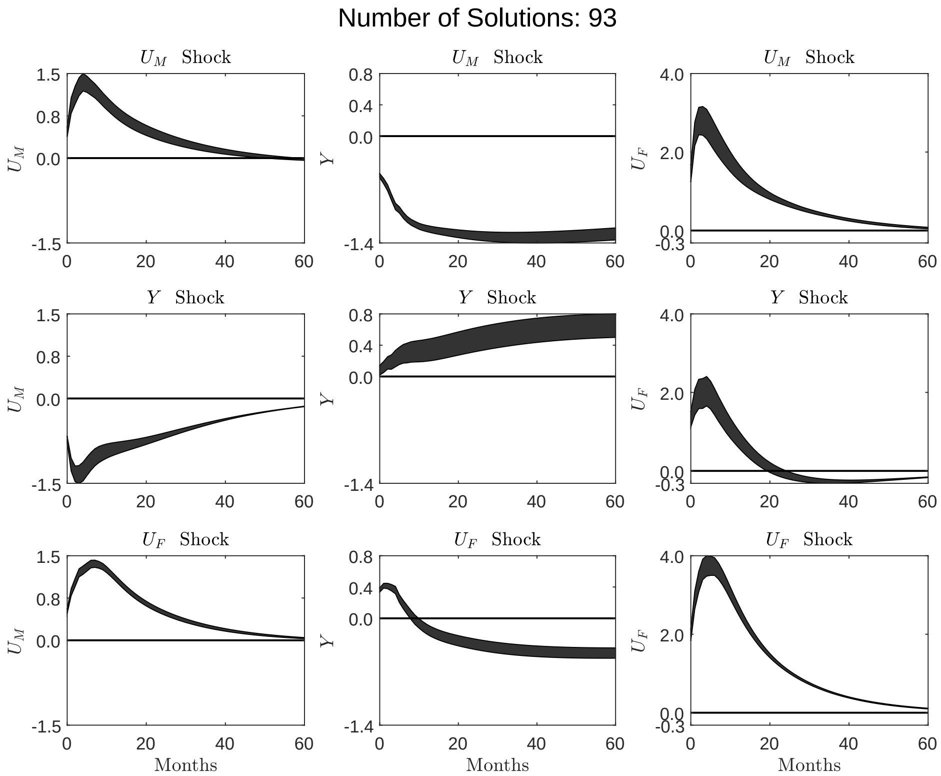
Summarizing the results of this section, we find that the positive effect of macroeconomic uncertainty shocks on industrial production highlighted by Ludvigson et al. (2021) is no longer valid if some new constraints are adding. Our constraints are related to higher uncertainty shocks as the 09/11 attacks and the Russian financial crisis and we also find a negative effect of macroeconomic uncertainty shocks on industrial

[13] We don't find any solutions taking the 75th-percentile value of e_{Mt} at $t = 2001 : 09$

[14] The results are robust applying the real uncertainty index.

[15] For this case, the parameters $\bar{k_5}$ and $\bar{k_6}$ are taken to their median values. Otherwise, we cannot compute the IRF.

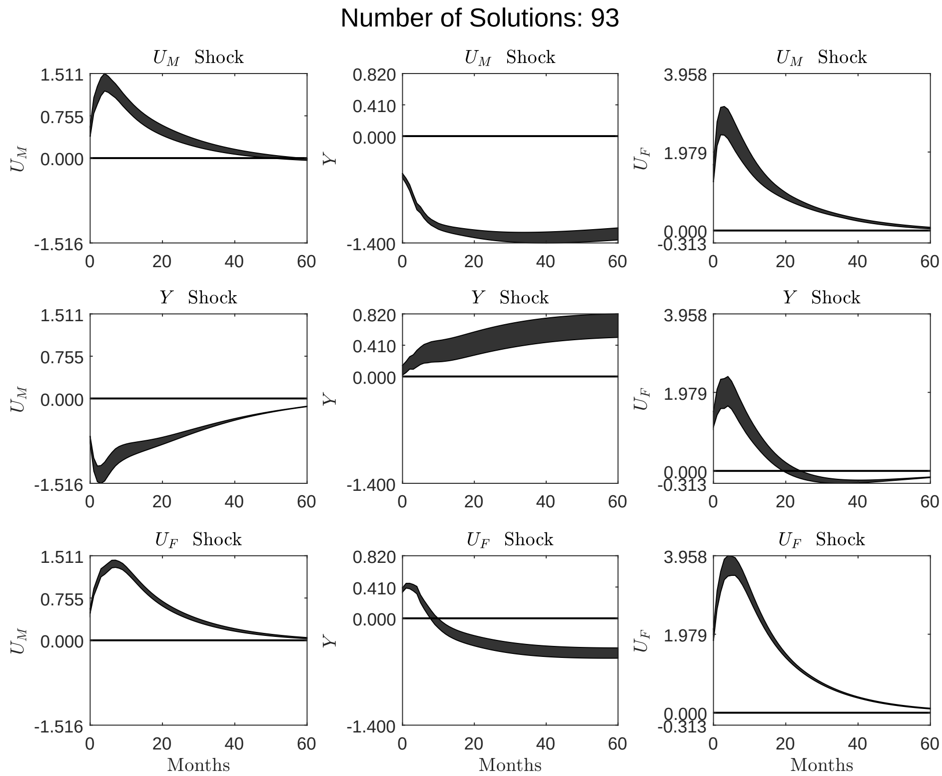
Figure 2.6: Impulse Response Functions using different constraints



Notes: The figure shows results from the identified set for system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the full set of constraints described in (2.11) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set adding $\bar{g}_{E7}$ and $\bar{g}_{E8}$ but removing $\bar{g}_{E3}$. The parameters $\bar{k_5}$ and $\bar{k_6}$ are taken to the median value and the $75th$ percentile values of the unconstrained set respectively. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the full set of constraints. The sample spans the period 1960:07 to 2015:04.

production. Moreover, by modifying and adding constraints in our applications, either we do not find solutions to compute IRFs or we get a negative effect of macroeconomic uncertainty shocks on economic activity. These findings show that their procedure of identification of structural shocks based on event constraints is very sensitive to the restriction set selected. A careful procedure of robustness checks must be set up if researchers want to apply this novel methodology of *event constraints*. Moreover, this

Figure 2.7: Impulse Response Functions modifying $\bar{g}_{E3}$ and adding $\bar{g}_{E7}$, $\bar{g}_{E8}$



Notes: The figure shows results from the identified set for system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the full set of constraints described in (2.11) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set adding $\bar{g}_{E7}$ and $\bar{g}_{E8}$. The constraint $\bar{g}_{E3}$ is modified by taking $\tau_3 = 1971:08$. The parameters $\bar{k_5}$ and $\bar{k_6}$ are taken to the median values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the full set of constraints. The sample spans the period 1960:07 to 2015:04.

methodology can't find any solutions if we try to add too many events. One way to solve this problem could be to increase the number of simulated matrices B but can ask the question about the optimal number of simulations. This question isn't discussed in Ludvigson et al. (2021). The number of simulations seems to be chosen exogenously. The methodology of Antolín-Díaz and Rubio-Ramírez (2018) based on traditional sign restrictions can represent an alternative. Instead of fixing the number of simulations of matrices B and checking what is the number respecting the restrictions, the authors fix the number of solutions to reach. The authors run the procedure of simulations of matrices B until a certain number of solutions satisfying the sign restrictions is reached. As an example, if the desired number of solutions is 1000 as in one of the applications of Antolín-Díaz and Rubio-Ramírez (2018), we will have to do more than 1.5 simulations to reach this number of solutions. If we double the number of simulations of Ludvigson et al. (2021) with 3 millions, we have just 352 solutions satisfying their set of restrictions (Figure 2.8). The number of solutions has been doubled but does not reach the desired number. By extrapolating, it would take more than 10 millions simulations to reach the number of desired solutions. The disadvantage of this methodology is that it can be very computationally expensive if many restrictions must be satisfied.

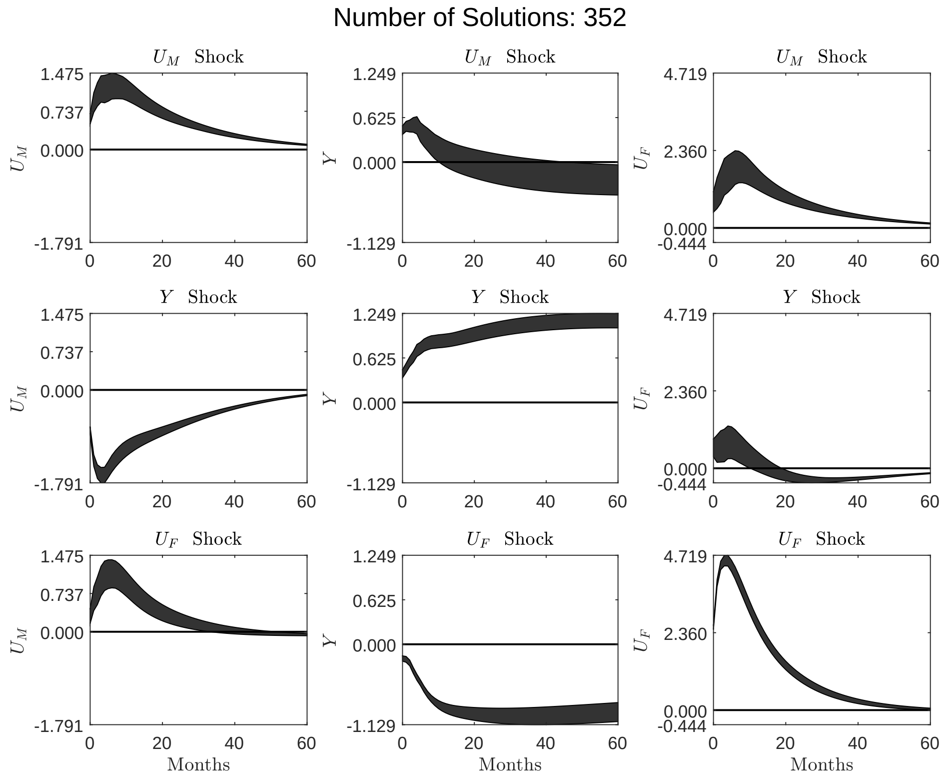
2.4 Robustness Checks

In this section, we will assess the robustness of the results in two ways. First, we check to what extent the qualitative results of Ludvigson et al. (2021) are modified considering the two months around the one of the $\bar{g}_{E3}$ constraint. Second, we replace the industrial production index with other macroeconomic variables.

2.4.1 The months around December 1970

The collapse of the Bretton Woods system is hard to relate to a specific month. We have already shown that if we consider 1971:08 instead of 1970:12, the former being a more credible candidate according to us, the positive effect does not old anymore. However, many things may happen in nine months. What if we consider November 1970 or January 1971 instead of December 1970? So we modify the date of the restriction related to Bretton Woods according to Ludvigson et al. (2021) taking alternatively these two months instead of December 1970.

Figure 2.8: Impulse Response Functions of Ludvigson et al. (2021): 3 millions of simulations



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the full set of constraints described in (2.11) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the full set of constraints described in (2.11). The number of simulations of matrices B is 3 millions. The sample spans the period 1960:07 to 2015:04.

We take τ_3 = 1970:11 in the constraint $\bar{g}_{E3}$. As the $75th$ percentile value of e_{Mt} at $t = 1970 : 11$ is negative (-0.42), we need to change slightly the restriction $\bar{g}_{E3}$: $e_{M\tau_3} \geq 0$ at $\tau_3 = 1970 : 11$. This new restriction changes the baseline results of Ludvigson et al. (2021). We get a strong negative effect on industrial production (Figure D1). We get similar results taking τ_3 =1971:01 in the constraint $\bar{g}_{E3}$ (Figure D2).[16]

[16]Again, the $75th$ percentile value of e_{Mt} at $t = 1971 : 01$ is also negative (-1.07). Therefore, we

In addition, we have noticed that on December 1970, the number of matrices that respect the $\bar{g}_{E3}$ constraint (given the other constraints) is very weak, 169, compared to 596 on November 1970 (196 for January). The fact that less matrices pass the uncertainty threshold is indicative of a rather not uncertain month compared to the other surrounding month in the subset of matrices that satisfy the five other constraints. That is, out of the 1101 matrices that satisfy the five other constraints, most of these exhibit values of macroeconomic uncertainty for the month of December 1970 that do not pass the threshold. Retaining a threshold corresponding to the 75th percentile implies that on average one should retain about 25% of the matrices. However, for this specific month, only 15% of the matrices remain. More, even when lowering the threshold to the 50th percentile (a value of about 1,94), only those 169 matrices remain. And it is still true for a threshold of zero. All this means that the high average level of uncertainty of this month is mainly driven by these 169 matrices since the other matrices that respect the five other constraints exhibit below average uncertainty.

We have already highlighted that the month of December 1970 is an outlier because of the end of the mild recession of 1969-1970 and it now seems that these 169 matrices could be considered as outliers in the outlier. Again, these results show that the choice of 1970:12 is very sensitive and that a rigorous procedure of robustness checks is necessary in the choice of constraints applying the methodology of event constraints.[17] We hope that our work may help improving this promising methodology.

2.4.2 Examining other macroeconomic variables

We examine the effects of macroeconomic uncertainty shocks on other macroeconomics variables that may be related to growth: consumption and unemployment. The choice

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modify the restriction as follows: $\bar{g}_{E3} : e_{M\tau_3} \geq 0$ at $\tau_3 = 1971 : 01$.

[17]The results are qualitatively equivalent applying the real uncertainty index. The results are available upon request

of these variables is determined by the availability of data at a monthly frequency.[18] We apply the personal consumption expenditures (C_t) to examine the effects of macroeconomic uncertainty shocks on consumption. Taking the same set of constraints as Ludvigson et al. (2021), we get a negative effect of macroeconomic uncertainty shocks on consumption (Figure D3) highlighting that households delay their spending and prefer to save (Leland, 1968).

We repeat the procedure by replacing industrial production with the unemployment rate (U_t). However, in this case, we have to modify the constraint $\bar{g}_{E4}$ on the cumulation of real activity shocks during the Great Recession. Indeed, the cumulation of structural real activity shocks: $\sum_{t=\tau_4} e_{Ut}$ for $\tau_4 \in [2007:12, 2009:06]$ must be positive implying that uncertainty will increase unemployment above its average. Our estimates show that indeed macroeconomic uncertainty shocks have a negative effect on the economy with the rise of unemployment after 6 months (Figure D4): we confirm then that firms delay hiring decisions (Bernanke, 1983; Pindyck, 1991).[19] Overall, all these results confirm our previous ones in that the positive effect of macroeconomic uncertainty shocks on economic activity seems not robust when considering other macroeconomic variables.

2.5 Conclusion

In recent years, several empirical studies have tried to investigate the impact of uncertainty shocks on macroeconomic variables. The empirical studies of Ludvigson et al. (2021) and to a lesser extent that of Larsen (2021) have broken the strong consensus on the negative effect of uncertainty applying an innovative method of identification of structural shocks with *event constraints*. The goal of this chapter was to question this striking and controversial conclusion. We find three main shortcomings in Lud-

[18] For instance, to the best of our knowledge, there is no variable approximating investment at a monthly frequency.

[19] The results are qualitatively equivalent applying our constraints on the 09/11 attacks and LTCM.

vigson et al. (2021)'s analysis which prevent to consider their result as robust. Firstly, the choice of the constraint related to Bretton Woods in 1970:12 is questionable. At this date, the level of macroeconomic uncertainty and the level of financial uncertainty do not reach a peak. Furthermore, we have shown in different ways that the positive effect of their macroeconomic uncertainty index on industrial production is linked to this specific constraint only. Removing this restriction, we no longer get their positive effect of macroeconomic uncertainty shocks on industrial production. If we modify this latter constraint by restricting the shock at the date of 1971:08 corresponding to the announcement of the collapse of the Bretton Woods system, we get a negative effect of macroeconomic uncertainty shocks on economic activity. Secondly, we highlight that December 1970 is very specific in that it is the first month following the mild recession of 1969-1970. As a consequence, in this month a catch up has occurred with a strong growth which is by itself a forecast error, a synonym of high uncertainty. Thirdly, if we add new constraints in the model, then we also get the opposite results compared to Ludvigson et al. (2021) ones: a negative effect of a macroeconomic uncertainty shock on industrial production is estimated. These findings show that their results are not robust and are very sensitive to slight modifications of the selected constraints. In other words, academics and practitioners should be very careful with the procedure of identification of uncertainty shocks applying this novel methodology of event constraints. Numerous robustness checks must be employed if researchers want to apply their methodology. We hope that our work will contribute to the improvement of this promising method.

Our main conclusion is then that the controversial result of a positive effect of macroeconomic uncertainty on economic activity does not yet seem to be proven. Whether financial or macroeconomic, uncertainty continues to have a negative impact on industrial production. These results are confirmed by several robustness checks. This negative effect of macroeconomic uncertainty that we have estimated in the chapter still highlights a wait and see behavior (Bernanke, 1983; Pindyck, 1991) meaning firms delay investment decisions and households delay their consumption and increase their savings.

However, the quest for a positive link between uncertainty and the economic activity related to the growth option theories remains stimulating. Recent high-tech innovations like Artificial Intelligence will provide many growth opportunities for firms and the economy in the future. However, there is uncertainty on the final gains and which firms will benefit from them which will encourage investment, research and development. So, the *growth options* theories refer to a new specific nature of uncertainty which is technological uncertainty. Examining the list of time series included in the macroeconomic uncertainty index, we argue that this list is too large to confirm *growth options* and technological uncertainty. An interesting path to test this assumption could be to develop a new measure of uncertainty related to technology applying big data methodologies.

Appendix

A Ludvigson et al. (2021) Regression Results

Table A1: Ludvigson et al. (2021) Regression Results

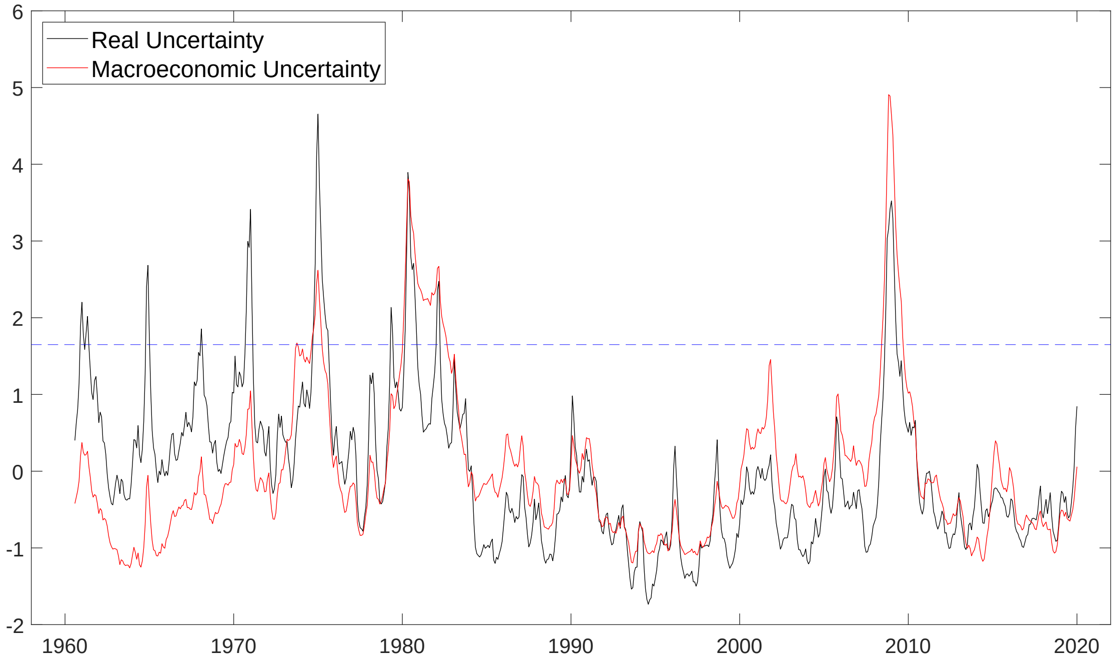
	UM	Y	UF
(Intercept)	0.01	0.02^{***}	0.01
	(0.01)	(0.00)	(0.01)
UM_{t-1}	1.64^{***}	-0.03	0.20
	(0.04)	(0.03)	(0.11)
Y_{t-1}	-0.22^{***}	1.14^{***}	-0.43^{*}
	(0.06)	(0.04)	(0.17)
UF_{t-1}	0.04^{*}	0.01	1.48^{***}
	(0.02)	(0.01)	(0.04)
UM_{t-2}	-0.80^{***}	-0.02	-0.36
	(0.08)	(0.05)	(0.21)
Y_{t-2}	0.36^{***}	-0.06	0.77^{**}
	(0.09)	(0.06)	(0.25)
UF_{t-2}	-0.05	-0.02	-0.50^{***}
	(0.03)	(0.02)	(0.07)
UM_{t-3}	0.20^{*}	0.05	0.28
	(0.08)	(0.05)	(0.23)
Y_{t-3}	-0.17	0.01	-0.10
	(0.10)	(0.06)	(0.26)
UF_{t-3}	0.06^{*}	-0.01	-0.00
	(0.03)	(0.02)	(0.08)
UM_{t-3}	-0.11	-0.05	-0.27
	(0.08)	(0.05)	(0.22)
Y_{t-3}	0.01	-0.03	-0.19
	(0.10)	(0.06)	(0.26)

UF_{t-3}	-0.07^{*}	0.02	0.00
	(0.03)	(0.02)	(0.08)
UM_{t-4}	0.07	0.01	0.31
	(0.08)	(0.05)	(0.21)
Y_{t-4}	0.12	-0.17^{**}	0.03
	(0.10)	(0.06)	(0.26)
UF_{t-4}	0.04	-0.01	-0.02
	(0.03)	(0.02)	(0.07)
UM_{t-5}	-0.01	0.02	-0.13
	(0.04)	(0.03)	(0.11)
Y_{t-5}	-0.11	0.11^{**}	-0.08
	(0.06)	(0.04)	(0.17)
UF_{t-6}	-0.02	0.00	0.01
	(0.02)	(0.01)	(0.04)
R^2	0.99	0.99	0.97
Adj. R^2	0.99	0.99	0.97
Num. obs.	652	652	652

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

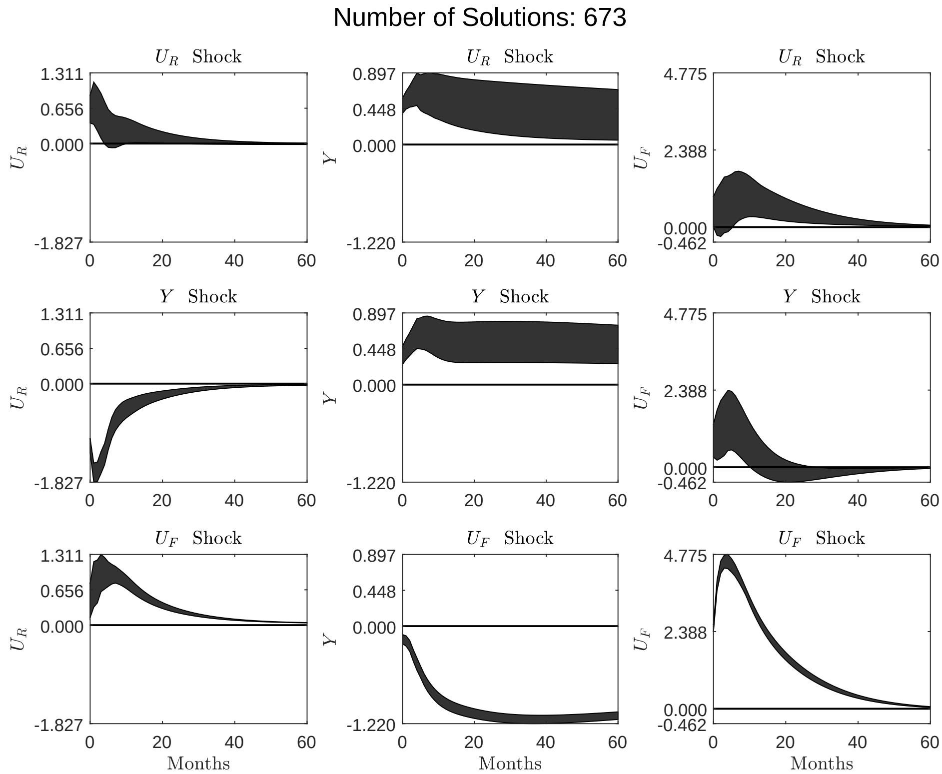
B IRFs using the Real Uncertainty Index

Figure B1: Real Uncertainty Index VS Macroeconomic Uncertainty Index



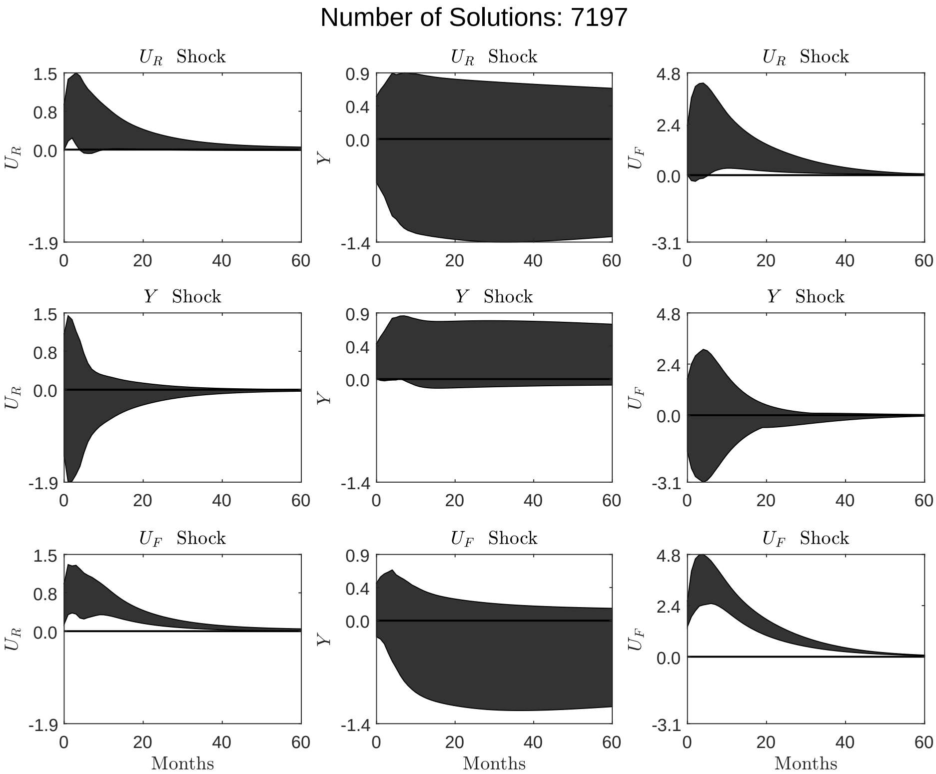
Source: Ludvigson et al. (2021)
Notes: The measures are standardized. The horizontal dashed blue line represents the threshold 1.65. The solid red line corresponds to the macroeconomic uncertainty index of Ludvigson et al. (2021). The solid black line corresponds to the real uncertainty index of Ludvigson et al. (2021).

Figure B2: Impulse Response Functions of Ludvigson et al. (2021)



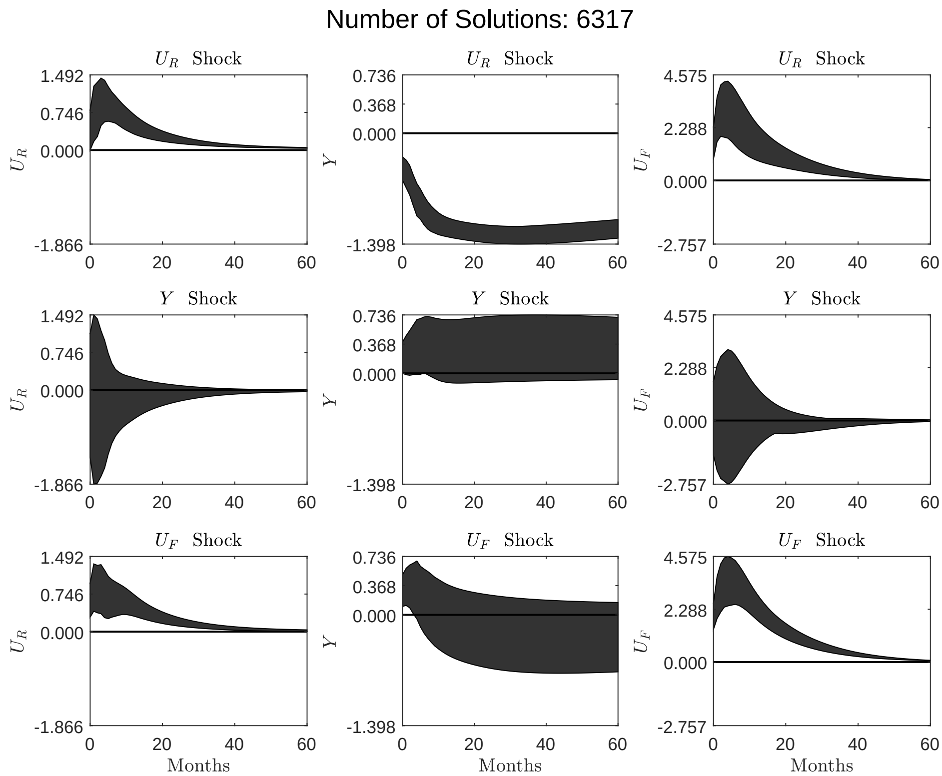
Notes: The figure shows results from the identified set for the system $X_t = (U_{Rt}, Y_t, U_{Ft})'$ using the full set of constraints described in (2.11) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the full set of constraints described in (2.11). The sample spans the period 1960:07 to 2015:04.

Figure B3: Impulse Response Functions removing $\bar{g}_{E3}$



Notes: The figure shows results from the identified set for the system $X_t = (U_{Rt}, Y_t, U_{Ft})'$ using the set of constraints described in (2.11) but removing $\bar{g}_{E3}$ with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of retained constraints. The sample spans the period 1960:07 to 2015:04.

Figure B4: Impulse Response Functions modifying $\bar{g}_{E3}$



Notes: The figure shows results from the identified set for the system $X_t = (U_{Rt}, Y_t, U_{Ft})'$ using the set of constraints described in (2.11) but modifying $\bar{g}_{E3}$ with $\tau_3 = 1971 : 08$. Each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of retained constraints. The sample spans the period 1960:07 to 2015:04.

C Disaggregating the Real Uncertainty Index

This appendix aims at explaining why the real uncertainty index exhibits a peak on 1970:12. To compute their real uncertainty index, Ludvigson et al. (2021) aggregated uncertainty related to 73 time series among the 132 times series applied to get their baseline macroeconomic uncertainty index (Figure B1). These 73 time series are related to the first four groups of the McCracken database corresponding to real activity : output and income, labor market, housing (constructions) and a group related to consumption, orders and inventories.[20]

The goal is to decompose the real uncertainty index to investigate which variables can explain the peak on 1970:12. To achieve it, we must reproduce the real uncertainty of Ludvigson et al. (2021) over the period 1960:07 to 2019:12 to extract its components as the data of these 73 uncertainty indexes are not available for this sample.[21] We research for all variables exhibiting a spike on 1970:12. A high peak is detected on 1970:12 for uncertainty related to industrial production (Figure C1). Other indexes related to industrial production within the first group also reach a strong peak at this date: namely final products and non industrial supplies, final products-market group, consumer goods, durable consumer goods, non durable consumer goods, business equipment, materials, durable materials, manufacturing. These findings show that the variables related to production are a source of the peak of real uncertainty.[22] The measure related to employment (manufacturing) exhibits a spike in 1970:12 (Figure C2). The same peak is detected for other measures of employment: total nonfarm, durable goods, construction, goods-producing industries, average hourly earnings-manufacturing, civilians

[20]A detailed list of the time series is available on the McCracken website.

[21]To get their index, Ludvigson et al. (2021) also applied a set of 147 financial variables in their econometric methodology. Unfortunately, these financial data are not available. However, we were able to reproduce their real uncertainty index without these financial data with a correlation close to 0.995. The correlation is statistically significant with a p-value close to 0. The results are available upon request.

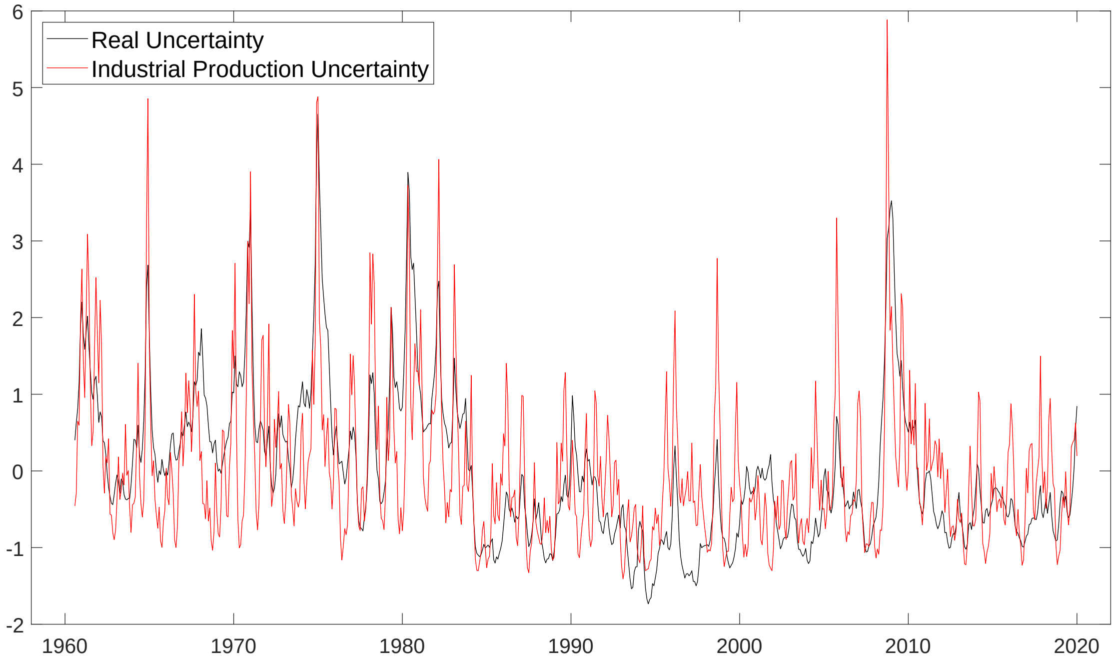
[22]The results are available upon request.

unemployed for 5-14 weeks, civilians unemployed - 15 weeks & over.... The strong uncertainty peak on 1970:12 is not detected for the variables related to housing (third group), consumption, orders and inventories (fourth group).[23] These results show that the high uncertainty peak detected on 1970:12 is mainly generated by variables related to production and employment.

When looking at the different variables that enter the real uncertainty index of Ludvigson et al. (2021), we observe a surge of growth in this specific month of December 1970 which is a catch up after the mild recession of 1969-1970. Hence, just keeping uncertainty peaks for this specific month may artificially associate a high uncertainty to a very specific episode of strong growth. This may explain the positive sign found with the constraint on December 1970. Moreover, we shall remind that the uncertainty measure of Ludvigson et al. (2021) is based on the residuals of econometric specifications, that is the part that is unexplained by the model estimated. As a matter of fact, since the 1969-1970 recession has lasted 11 months, from December 1969 to November 1970, the most probable forecast for the following month was another month of recession which is not what happened. So the strong catch up in growth of December 1970 also constitutes an important forecast error. Therefore, the strong growth and strong uncertainty indeed appeared in December 1970.

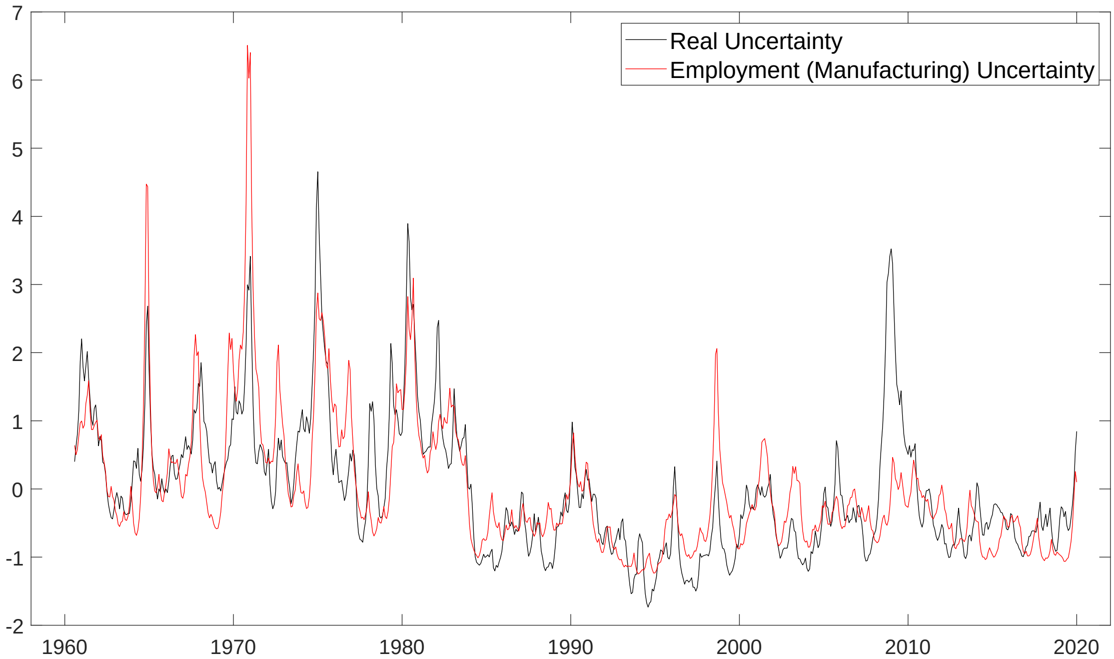
[23]Figure C3 plots uncertainty related to housing starts to illustrate this point on 1970:12.

Figure C1: Real Uncertainty Index VS Industrial Production Uncertainty



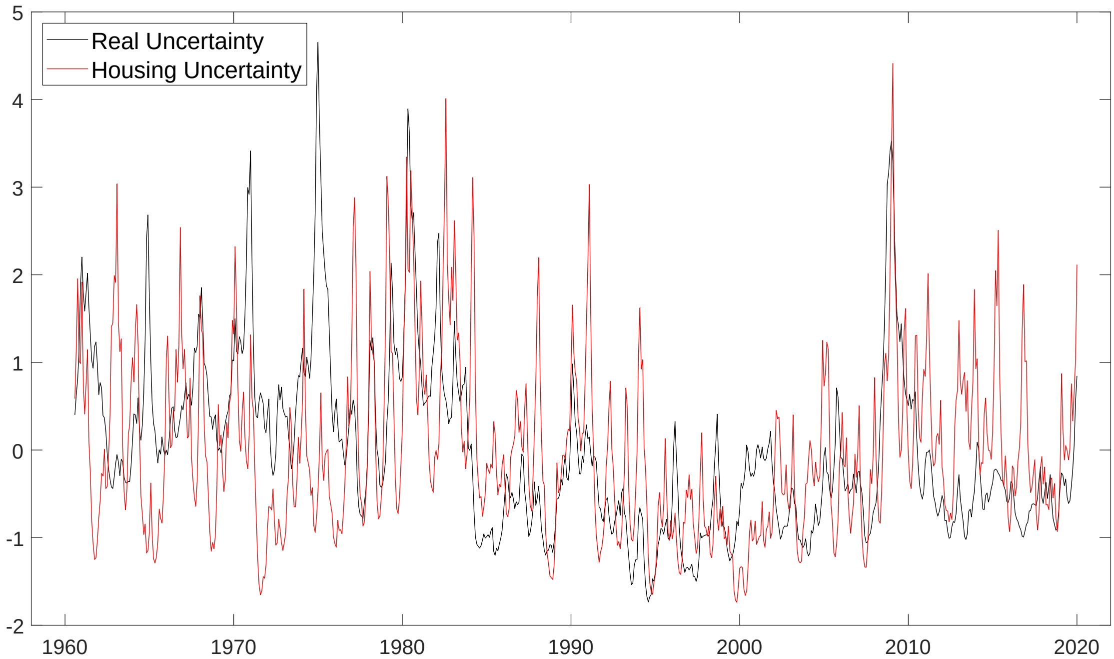
Notes: The measures are standardized. The solid red line corresponds to an uncertainty index related to industrial computed from the Ludvigson et al. (2021)'s framework. The solid black line corresponds to the real uncertainty index of Ludvigson et al. (2021).

Figure C2: Real Uncertainty Index VS Employment Uncertainty



Notes: The measures are standardized. The solid red line corresponds to an uncertainty index related to employment computed from the Ludvigson et al. (2021)'s framework. The solid black line corresponds to the real uncertainty index of Ludvigson et al. (2021).

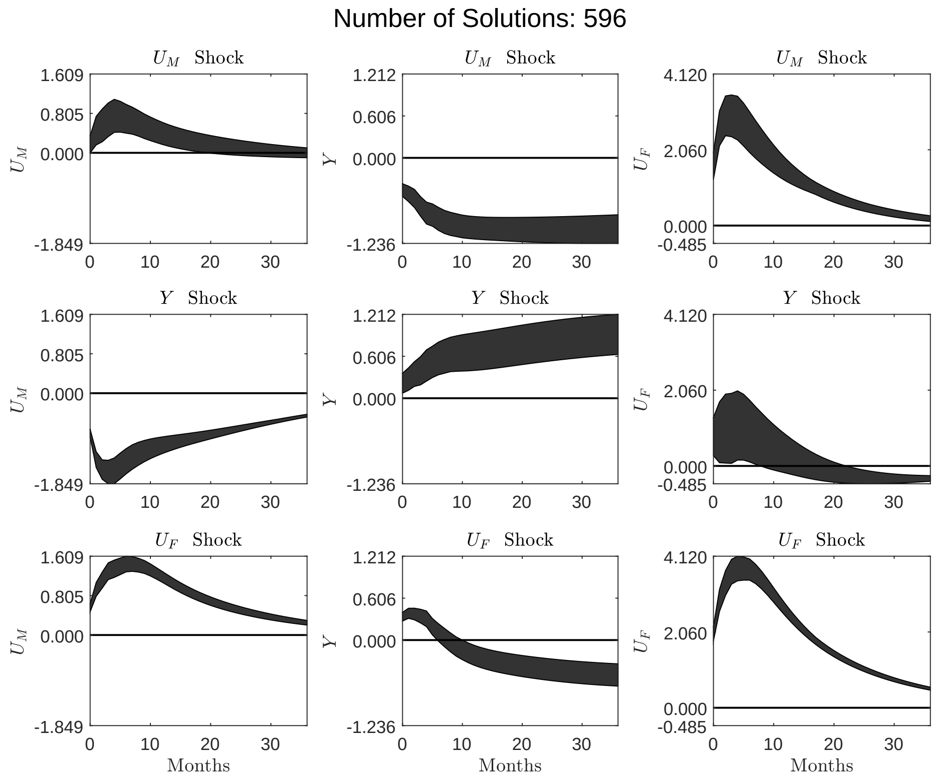
Figure C3: Real Uncertainty Index VS Housing Uncertainty



Notes: The measures are standardized. The solid red line corresponds to an uncertainty index related to housing starts computed from the Ludvigson et al. (2021)'s framework. The solid black line corresponds to the real uncertainty index of Ludvigson et al. (2021).

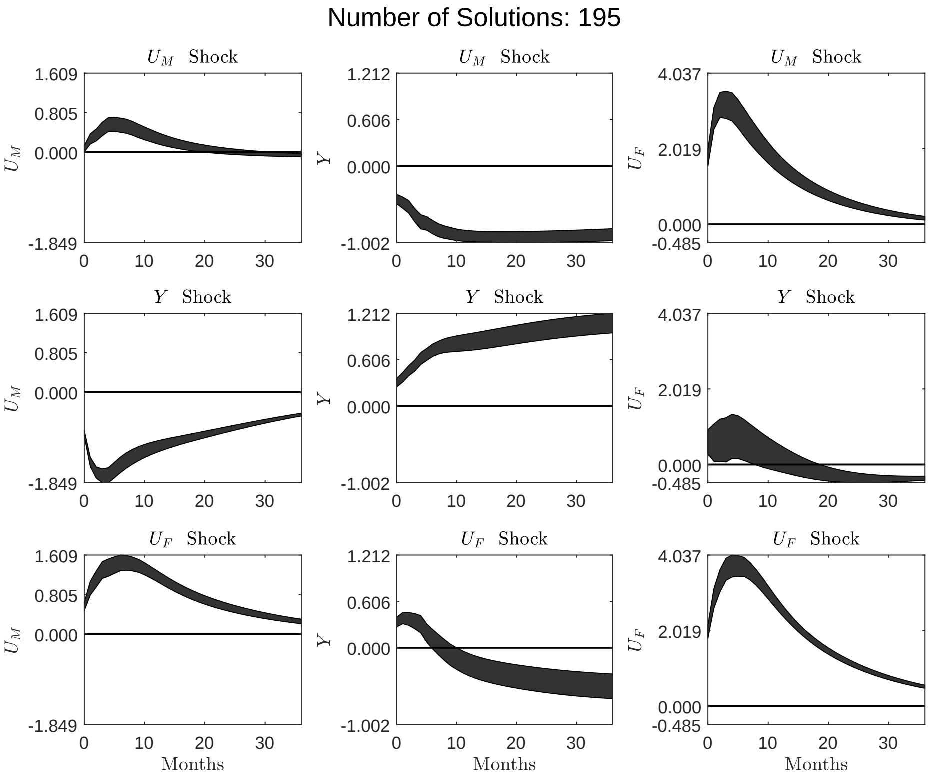
D Robustness Checks

Figure D1: Impulse Response Functions modifying the constraint $\bar{g}_{E3}$ (τ_3 =1970:11)



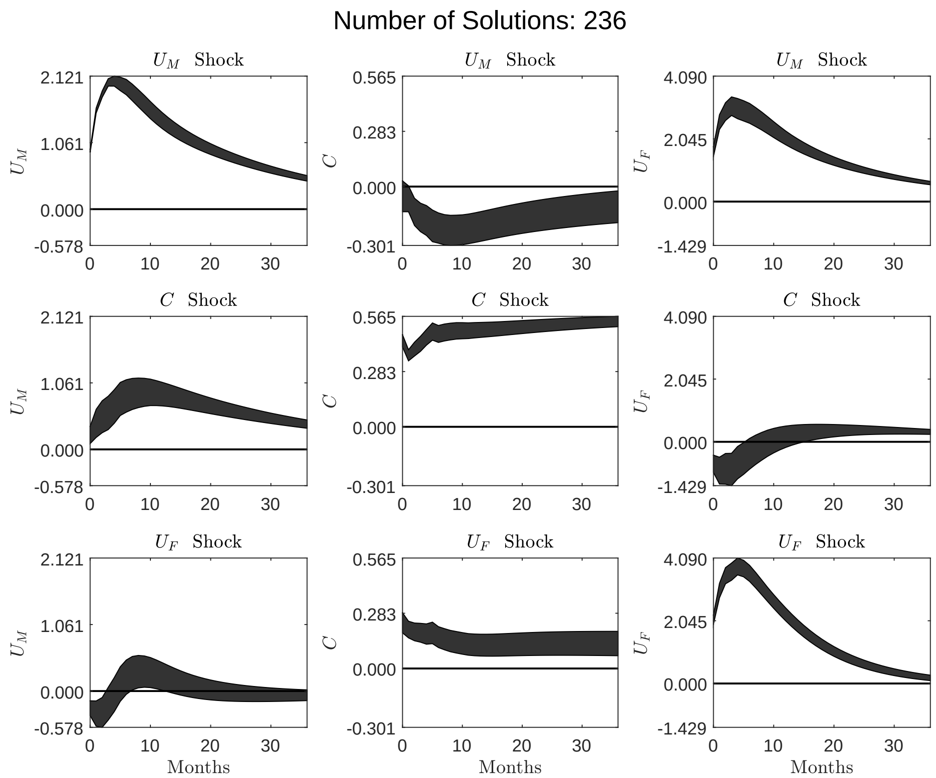
Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the set of constraints. We modify the constraint $\bar{g}_{E3}$ as follows: $\bar{g}_{E3}$: $e_{M\tau_3} \geq 0$ at $\tau_3 = 1970 : 11$. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

Figure D2: Impulse Response Functions modifying the constraint $\bar{g}_{E3}$ (τ_3 =1971:01)



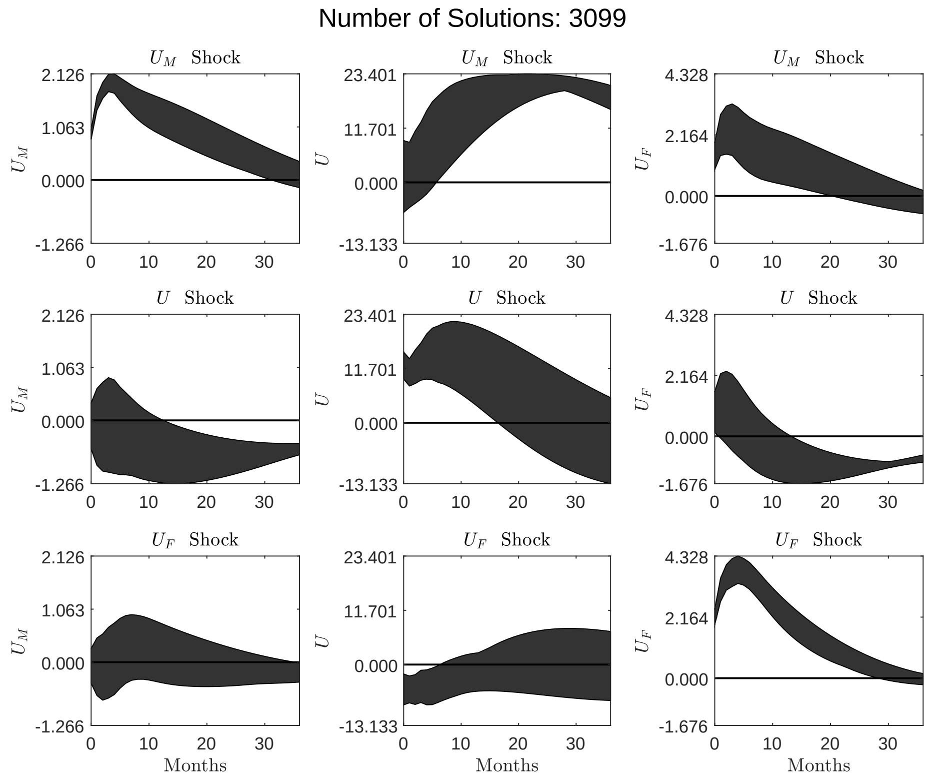
Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the set of constraints. We modify the constraint $\bar{g}_{E3}$ as follows: $\bar{g}_{E3} : e_{M\tau_3} \geq 0$ at $\tau_3 = 1971:01$. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

Figure D3: Impulse Response Functions applying the personal consumption expenditures (C_t)



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, C_t, U_{Ft})'$ using the set of constraints with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

Figure D4: Impulse Response Functions applying the unemployment rate (U_t)



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, U_t, U_{Ft})'$ using the set of constraints with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The constraint $\bar{g}_{E4}$ is modified as follows: $\sum_{t=\tau_4} e_{Ut} \geq 0$ for $\tau_4 \in [2007:12, 2009:06]$. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

Chapter 3

Non-linear Relationship between Uncertainty and Economic Activity: Evidence from quantile regression techniques

"*Thinking nonlinearly is crucial, because not all curves are lines.*" (Ellenberg, 2014)

Introduction

Might uncertainty shocks have non-linear effects on economic activity? In this chapter, we will address this question which became more important for economists and policy-makers during recent years. A growing empirical literature has emerged on the impact of uncertainty on the economy following the seminal paper of Bloom (2009) applying a linear SVAR model (See, among many others, Bloom, 2009; Jurado et al., 2015; Baker et al., 2016, 2020a; Leduc and Liu, 2016, 2020). The main result of these empirical studies is that uncertainty shocks have a negative effect on economic activity with a decline in industrial production and a rise in unemployment. These findings are in line with a theoretical literature where uncertainty leads firms to delay investment and hiring decisions (Bernanke, 1983; Pindyck, 1991). Moreover, uncertainty can lead consumers to rise their savings for precautionary reasons (Leland, 1968). Applying narrative restrictions methodologies in a linear SVAR model, recent works have broken the consensus on the effect of uncertainty in a linear framework finding a positive effect of uncertainty (Ludvigson et al., 2021; Larsen, 2021). The explanation about this positive effect relies on"growth options" theories (Segal et al., 2015). The argument of the "growth options" is based on the fact that the firms will face uncertain situations but there will be no doubt on final massive net gains with high growth opportunities. These high growth opportunities would be generated by new high-tech innovations which could encourage firms to invest boosting economic activity. As an illustration, predicting the industrial achievements of Artificial Intelligence in the future is uncertain but forecasting that the size of the potential profits will be huge is obvious.

However, these previous empirical studies don't take into account the possibility that the effects of uncertainty can be different according to the state of the economy and thus, the non-linear effects of uncertainty. Bloom (2009) opened a way on the non-linear effects of uncertainty focusing on the strongest uncertainty shocks exceeding 1.65 standard deviation above the mean of the uncertainty variable. The underlying assumption is that these strong uncertainty shocks can have different effects than moderate or low uncertainty shocks. The analysis of this chapter is related to a new branch of empirical studies extending these previous studies applying non-linear econometric models. These empirical studies investigated the effects of uncertainty in different regimes of the economy. Adapting the VAR model of the seminal paper of Bloom (2009) to a Smooth Transition VAR (STVAR) model to take into account the non-linearity, Caggiano et al. (2020) show that uncertainty shocks have a stronger negative effect in recessionary phases. In the same line, Caggiano et al. (2014), Caggiano et al. (2017a) and Colombo and Paccagnini (2020) showed that the rise in unemployment generated by uncertainty shocks is higher in recessions in the United States applying a STVAR model. Employing an Interacted-VAR model (IVAR), Caggiano et al. (2021) also showed that the contraction of economic activity after an uncertainty shock is stronger and more persistent during the great recession. These previous empirical studies seem to converge on a consensus with a stronger negative effect of uncertainty shocks on macroeconomic environment in periods of recession. Other non-linear VAR models have been employed to investigate the effects of uncertainty shocks under a different specification of regimes instead of expansions and recessions. Applying a threshold VAR model, Alessandri and Mumtaz (2019) showed that the recessionary effects of uncertainty shocks are larger in a regime of financial stress than in a tranquil financial regime. Applying an alternative approach with a Markov-Switching VAR (MSVAR) model, Lhuissier and Tripier (2021) also got a stronger negative effect of uncertainty shocks in distress regime associated with financial crises. Employing an IVAR model, Caggiano et al. (2017b) studied the effects under a different specification which is related to the state of the monetary policy. The authors showed that the decline in economic activity caused by an uncertainty shock is higher during the zero lower bound period than in times of unconstrained monetary policy.

Several non-linear frameworks can be applied in the investigation of the non-linear effects of uncertainty among which the quantile regression is underexploited on this topic. Applying this methodology, we can investigate to what extent the effects of uncertainty can change across the quantiles of the future US growth. Therefore, we can detect non-linear effects over the business cycles without specification of different regimes contrary to other nonlinear models as TVAR and STVAR which need to check the hypothesis of non-linearity (Linnemann and Winkler, 2016). Moreover, these models need to choose a specification including a sufficient number of observations in each regime contrary to quantile regression models. In the quantile regression, the lower quantiles capture periods of recession corresponding to the lower tail of the distribution while higher quantiles capture periods of expansion corresponding to the upper tail of the distribution. In other words, we can investigate the effects of uncertainty shocks in recessionary periods and expansionary periods applying this framework. This approach has been followed by Jovanovic and Ma (2022) applying the macroeconomic uncertainty index of Ludvigson et al. (2021) for the US and Hengge (2019) for the euro area applying macroeconomic uncertainty indexes computed from the Jurado et al. (2015)'s methodology. The authors got a stronger negative of macroeconomic uncertainty on the lowest quantiles, *i.e.* in recessionary phases. Gupta et al. (2019) have focused on the investigation of the effects of US economic policy uncertainty on the Euro area applying a quantile VAR model. The authors have shown that US uncertainty shocks have a stronger negative effect on the Euro Area during recessions than in expansions.

This chapter aims to contribute to the empirical literature on the non-linear effects of uncertainty applying the quantile regression. We investigate the impact of uncertainty shocks across the percentiles of the future US growth. As a wide range of uncertainty proxies has been developed, we explore the effects of the overall level of uncertainty applying the US general uncertainty index developed by Himounet (2022). This chapter stands out from the other studies by also exploring the non-linear effects of uncertainty shocks according to their nature: non-financial and financial. Previous studies have decomposed the components or the nature of uncertainty shocks as Larsen (2021) for Norway applying machine learning techniques and Ludvigson et al. (2021) applying econometric frameworks. The underlying assumption is that uncertainty shocks can have different effects according to their nature. However, these previous works focused on a linear framework. We extend these previous studies by investigating the effect of the nature of uncertainty in a non-linear framework over the business cycles. To achieve it, we need a methodology decomposing uncertainty shocks according to their nature. Recently, an interesting methodology of decomposition has been proposed by Kang et al. (2021). These authors decomposed a general uncertainty index examining the nature of its highest peaks: financial or non-financial. The advantage is that their methodology of decomposition provides uncertainty variables which are not correlated. However, as this methodology captures only the strongest uncertainty peaks, the number of these peaks can be small. Moreover, it may be difficult to determine what is the real nature associated with these uncertainty shocks. As an example, the collapse of Lehman Brothers appears as an uncertainty peak in most uncertainty indexes: macroeconomic, financial, economic policy. To solve these both problems, we propose to revisit the decomposition between financial uncertainty shocks and non-financial uncertainty shocks proposed by Kang et al. (2021) using a more dynamic approach. We apply the second factor of the PCA of Himounet (2022) distinguishing financial and non-financial uncertainty shocks as the criterion of decomposition. This second factor allows to classify uncertainty shocks associated with finance and uncertainty shocks associated with non-finance in a single variable. Therefore, we are able to identify the nature associated with each uncertainty shock. Applying this factor, our approach differs from the decomposition proposed by Kang et al. (2021) who have manually examined the nature of the strongest uncertainty peaks of their general index. Moreover, our approach captures the strongest uncertainty shocks but also other shocks which are moderate contrary to the methodology of Kang et al. (2021) which focused on the strongest shocks only. Thus, we capture more observations in our procedure of decomposition than in the methodology of these authors.

Two main results can be summarized as follows. Firstly, we get a negative effect of general uncertainty on the percentiles of the future US GDP growth which is stronger on the lower 5*th* percentile capturing recessionary phases highlighting that the *wait and see* behavior is stronger in this kind of scenarios. These findings provide new evidences of non-linear effects of uncertainty over the business cycles. Secondly, decomposing uncertainty shocks, we find a negative effect of financial uncertainty on the percentiles. The striking result we get is that non-financial uncertainty shocks have a positive effect on the lower 5*th* percentile corresponding to economic crisis situations breaking the empirical consensus on the negative effect of uncertainty in recessions. We show that uncertainty can have a positive when its nature is non-financial and during recessions This positive effect of non-financial uncertainty can be explained by the theoretical works of Gabaix (2014, 2020). Generally, these economic crisis scenarios are associated with high uncertainty periods exacerbating the myopia described by Gabaix (2014, 2020). The myopia suppresses the ability of individuals to predict the future perfectly and restores the effectiveness of an economic stimulus that will generate a positive effect on economic activity.

The rest of this chapter is organized as follows. Section 1 presents the methodology and data. Section 2 presents the results of the empirical application and the decomposition of uncertainty shocks. Section 3 presents the robustness checks. The last section presents conclusions.

3.1 Methodology and Data

3.1.1 Quantile Regression

Traditionally, policymakers focus on the conditional mean applying the standard ordinary least squares (OLS) approach. These models allows to capture the effect of a change of an explanatory variable x on the conditional mean of a variable of interest y. However, this approach provides an incomplete scheme of the effect of this change on the whole distribution of y which may be different (Koenker, 2005; Cecchetti and Li, 2008). The solution to this problem relies on Koenker and Bassett (1978) who extended the regression model introducing the concept of quantile regression: :

$$y_t = x_t \beta_\tau + \epsilon_t \tag{3.1}$$

where $\tau \in]0,1[$ denotes the quantile of interest. This methodology provides an analysis of a change of the explanatory variable on the τ^{th} quantile of the distribution of the dependent variable. The coefficient β_τ associated with x answers to the following question: what is the effect of a one-unit change in the variable x on the τ^{th} quantile of the conditional distribution of y ? As an illustration, if policymakers decide to adopt measures in order to improve the purchasing power of the households, the OLS approach can provide a non-significant effect on the conditional mean of the purchasing power of the households meaning that these measures are not effective. Applying quantile regressions, policymakers could investigate the effectiveness of their measures on the lowest quantile (ex: $\tau = 5\%$) of the distribution of the purchasing power of households, i.e, on the part of households having the lowest purchasing power. In this case, the effect can be more significant and different meaning that the effects of these measures can be effective on this specific part of households. Thus, the quantile regression methodology provides a much richer set of information than OLS regressions which focus on the average trajectory only.

Applying this methodology, Cecchetti (2006) and Cecchetti and Li (2008) introduced the concept of *GDP at risk* investigating the impact of asset price boom focusing on the effect of the lowest quantiles of the distribution of future growth, i.e, in the worst possible outcomes of growth corresponding to economic crisis situations. Adrian et al. (2022) popularized these previous studies on the worst possible outcomes of growth. The authors investigated to what extent the quantiles of the distribution of the US GDP growth at h-months ahead are influenced by the current economic and financial conditions:

$$y_{t+t} = x_t\beta'_\tau + \epsilon_t \qquad h = 1, \ldots, H \tag{3.2}$$

where y_{t+h} denotes the average growth rate between t and $t+h$ and x_t denotes a vector of conditioning variables representing the current and financial economic conditions with a constant. Instead of minimizing the sum of squared errors as in the OLS approach, the estimation of a quantile model is based on the asymmetric minimization of the weighted absolute errors. In the quantile regression of y_{t+h} on x_t, the regression slope β_τ is chosen to minimize the quantile weighted absolute value of errors (Koenker and Bassett, 1978; Koenker and Portnoy, 1997):

$$\widehat{\beta_\tau} = \underset{\beta_\tau}{argmin} \sum_{t=0}^{T-h} \rho_t(y_{t+h} - x_t\beta'_\tau) \tag{3.3}$$

where $\rho_t(.)$ denotes the loss function such that:

$$\rho_t(y_{t+h} - x_t\beta'_\tau) = \begin{cases} \tau|y_{t+h} - x_t\beta'_\tau| & if \quad y_{t+h} - x_t\beta'_\tau \geq 0 \\ (1-\tau)|y_{t+h} - x_t\beta'_\tau| & if \quad y_{t+h} - x_t\beta'_\tau < 0 \end{cases} \tag{3.4}$$

There is no formal solution contrary to the OLS approach. Assuming that the error term ϵ_t satisfies the restriction $Q_\tau(\epsilon_t|x_t) = 0$, the predicted value from the regression is the quantile of y_{t+h} conditional on x_t and is computed as follows:

$$\widehat{Q}_\tau(y_{t+h}|x_t) = x_t\widehat{\beta}_\tau{}' \tag{3.5}$$

Koenker and Bassett (1978) have shown that $\widehat{Q}_\tau(y_{t+h}|x_t)$ is a consistent estimator of the quantile function of y_{t+h} conditional on x_t. Thus, $\widehat{Q}_\tau(y_{t+h}|x_t)$ provides an estimation of the τ^{th} quantile of the growth at h months in the future.

For a low value of τ,we capture the expected growth at the lower end of the GDP growth distribution associated with economic crisis scenarios. Thus, for a low value of τ, we can investigate the effects of explanatory variables as an uncertainty index in economic crisis scenarios or in recessionary phases. Inversely, for a high value of τ, we capture to what extent the explanatory variables can influence the future growth in the best scenarios like boom phases. Unlike to other regime-switching models, the great advantage of this method is that quantile models do not rely on an *ex ante* specification of different regimes (Linnemann and Winkler, 2016).

In this chapter, we follow Adrian et al. (2019, 2022) linking the future GDP growth distribution with a set of variables x_t representing the current economic and financial conditions but adding an uncertainty variable in the quantile regression:

$$y_{t+h} = x_t\beta'_\tau + \zeta_\tau Uncertainty_t + \epsilon_t \qquad h = 1, \ldots, H \tag{3.6}$$

To track how uncertainty can affect the conditional distribution of GDP growth over time, we follow the approach of Adrian et al. (2022) running the equation (3.6) for $h = 1, ..., H$. For each percentile τ of interest, a series of estimated coefficients ζ_τ associated with the uncertainty variable can be collected.[1] These estimated coefficients correspond to the evolution of the marginal effect of uncertainty on the different percentiles of the

[1]This approach has been followed by Hengge (2019); Jovanovic and Ma (2022) applying macroeconomic uncertainty indexes computed from the Jurado et al. (2015)'s methodology.

expected future growth over time.[2]

3.1.2 Variables and Data

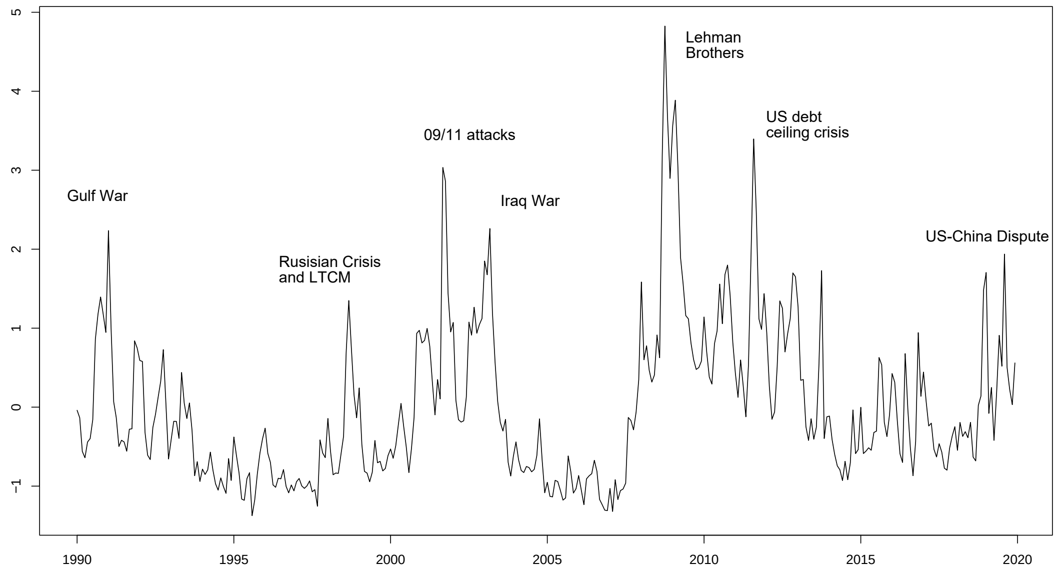
Data are at a monthly frequency spanning the period 1990-2019. To approximate the GDP growth at a monthly frequency, we apply the industrial production index in log difference as it is usually used in the empirical studies. To investigate the effect of uncertainty shocks, we need one variable approximating uncertainty. A booming economic research has proposed several proxies but providing different information (financial, macroeconomic, policy, geopolitical,...).[3] To take into account this wide range of information contained by those uncertainty indexes, we apply the US general uncertainty index developed by Himounet (2022) with a principal component analysis (Figure 3.1). This index identifies many uncertainty shocks over the period 1990-2019: the Gulf War, the 09/11 attacks, the Iraq War, the US debt ceiling crisis, the collapse of Lehman Brothers.

As conditioning variable, Adrian et al. (2019) have used the current GDP growth only to approximate economic conditions in order to predict the future distribution of GDP growth. However, taking the current GDP growth only isn't sufficient. The current economic conditions are influenced by other variables like fiscal and monetary policy,... Moreover, other aspects don't have taken into account in current economic conditions as the international dimension. Geopolitical foreign shocks could have an influence on the future distribution of GDP growth. To represent current economic conditions, we use the current GDP growth (y_t) and we add the other aspects mentioned above. We add the effective federal fed funds rate as a proxy for the monetary policy instrument (Fed). We take the monthly price of crude oil (West Texas Intermediate) deflated by the consumer

[2]This chapter focuses on the effects of uncertainty on the quantiles of future growth. It will not estimate the entire predictive density of future growth at specific points in time applying the skewed t-distribution of Azzalini and Capitanio (2003) in a second step as in Adrian et al. (2022) to quantify the tail risk of the growth over the full sample.

[3]See Himounet (2022) for an overview.

Figure 3.1: US General Uncertainty Index of Himounet (2022)



Note: The figure plots the general uncertainty developed by Himounet (2022). The index is standardized over the period 1990-2019.

price index and also in log difference (Oil) to represent the international dimension.[4] As explained previously, it aims to capture possible geopolitical foreign influences on the US economy. We apply the monthly outlays of the United States (G) that we collected on the US department of the treasury website as a proxy of government spending at a monthly frequency.

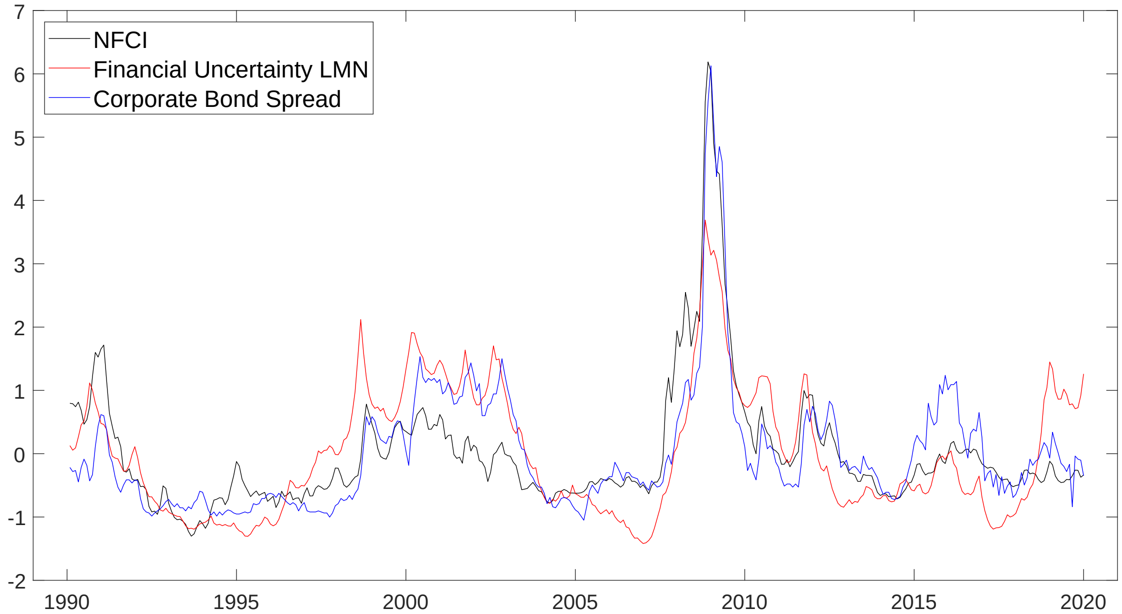
To represent the current financial conditions, Adrian et al. (2019) have used the National Financial Conditions Index (NFCI) of the Chicago Federal Reserve to approximate financial conditions.[5] When the NFCI is positive, it means that financial conditions

[4]The data are downloaded from FRED database on the Federal Reserve Bank of St. Louis' website.

[5]This index provides an estimate of US financial conditions in money markets, debt and equity markets, and the traditional and shadow banking systems. The index is a weighted average of 105 measures of financial activity.

are tighter than average. Caldara et al. (2016) have pointed out that a financial environment more stressful than average can induce financial conditions tighter than average and hence, may reflect financial uncertainty. To measure financial uncertainty and the degree of stress on financial markets, Bachmann et al. (2013) have used the corporate bond spread defined as the difference between the yield of Baa-rated corporate bonds and the 30-year Treasury yield. A rise of this index is a sign of tension on the financial markets. Therefore, the interpretation of the NFCI and the corporate bond spreads can be similar. We note many similarities comparing the NFCI and the corporate bond spread (Figure 3.2) with a high level of correlation: 0.89.[6] We can also note many similarities with the financial uncertainty index of Ludvigson et al. (2021). In front of

Figure 3.2: Financial Uncertainty indexes VS NFCI



Note: The figure represents the comparison between the national financial conditions index (NFCI) and financial uncertainty indexes. The black line represents the NCFI. The red line represents the financial uncertainty index of Ludvigson et al. (2021). The blue line represents the corporate bond spread. Indexes are standardized.

[6]The correlation is statistically significant with a p-value close to 0.

these similarities, we can consider that the NFCI could represent financial uncertainty. However, since we are using a general uncertainty index which incorporates financial uncertainty, we can't apply the NFCI in the model.[7] We take the log difference of the S&P 500 index ($SP500$) that we collected on Yahoo! Finance to take into account financial and broader economic conditions instead of the NFCI. The list of variables and their sources can be summarized as follows:

Applying the variables mentioned above, we consider our model as follows:

$$y_{t+h} = \alpha_\tau + \beta_{1,\tau} y_t + \beta_{2,\tau} Oil_t + \beta_{3,\tau} SP500_t + \beta_{4,\tau} Fed_t + \beta_{5,\tau} G_t + \zeta_\tau GU_t + \epsilon_t \quad (3.7)$$

3.2 Empirical Application

3.2.1 Baseline Results

We track how uncertainty can affect the conditional distribution of GDP growth over time following Adrian et al. (2022).[8] For each horizon $h = 1, \ldots, 24$, the estimated coefficients ζ_τ associated with the general uncertainty measure for the lower $5th$ percentile ($\tau = 0.05$), the median ($\tau = 0.5$) and the $95th$ percentile ($\tau = 0.95$) are shown on the upper panel, the middle panel and the lower panel respectively (Figure 3.3). They correspond to the effect of uncertainty shocks over time in high recessionary phases, in normal situations and in boom phases respectively. On all percentiles, we get a negative effect of general uncertainty in the near-term months. It means that the effect of general uncertainty is to significantly reduce expected growth and therefore, increases downside risk to growth.[9] The negative effect of general uncertainty is in line with previous works

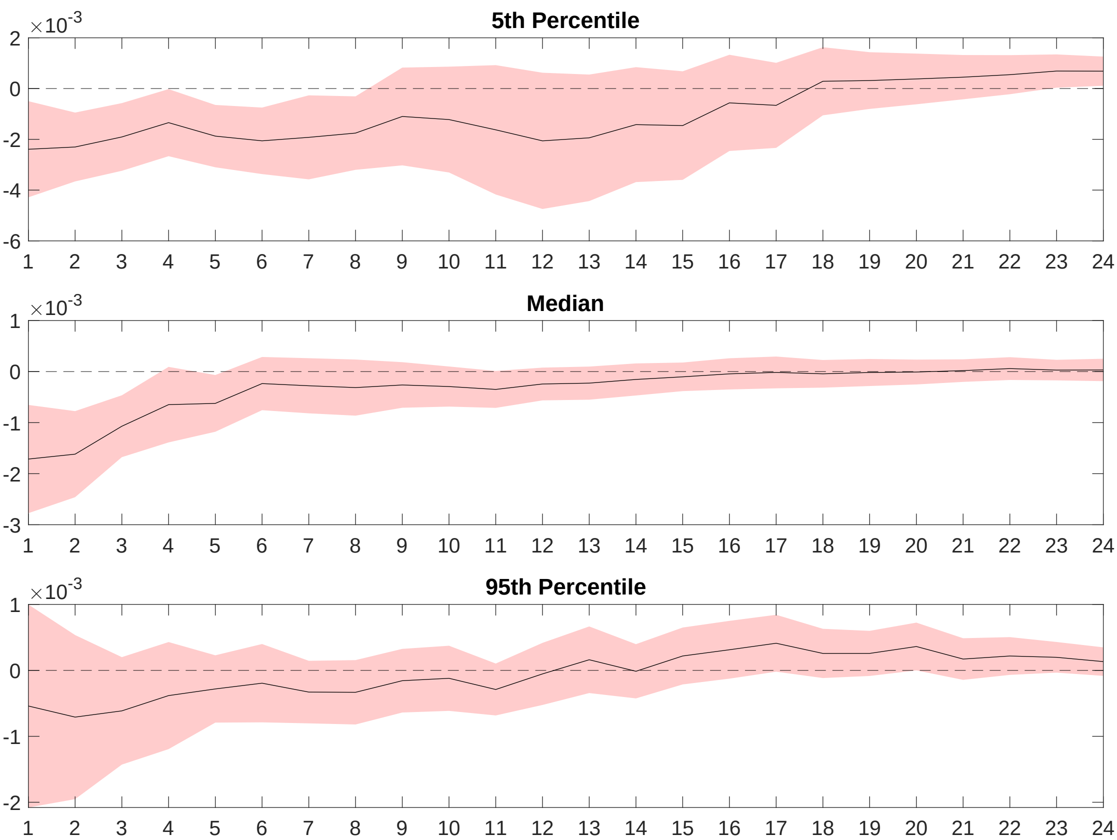
[7]We also get some similarities between the NFCI index and the general uncertainty index of Himounet (2022) with a correlation equal to 0.68 and a p-value close to 0.

[8]The approach of Adrian et al. (2022) has also been followed by several works on the topic of macroeconomic tail risk (See, among many others, Aikman et al., 2019; Loria et al., 2019; O'Brien and Wosser, 2021; Ferrara et al., 2022b).

[9]The effects are significant at the 5% percent level. To compute confidence intervals of the marginal effects for each horizon h, we use the xy-pair method (Kocherginsky, 2003). The xy-pair method has

and highlights a *wait and see* behaviour (Bernanke, 1983; Pindyck, 1991) where firms delay investment decisions and households delay their consumption and save. Interestingly, our findings highlight that the negative effect of general uncertainty is stronger and more significant over time on the lower 5*th* percentile than on the other percentiles. Indeed, the negative effect on the median is significant during 5 consecutive months against 8 months on the lower 5*th* percentile. Examining the upper 95*th* percentile, the negative effect is not significant.

Figure 3.3: Marginal Effects of General Uncertainty



Notes: The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

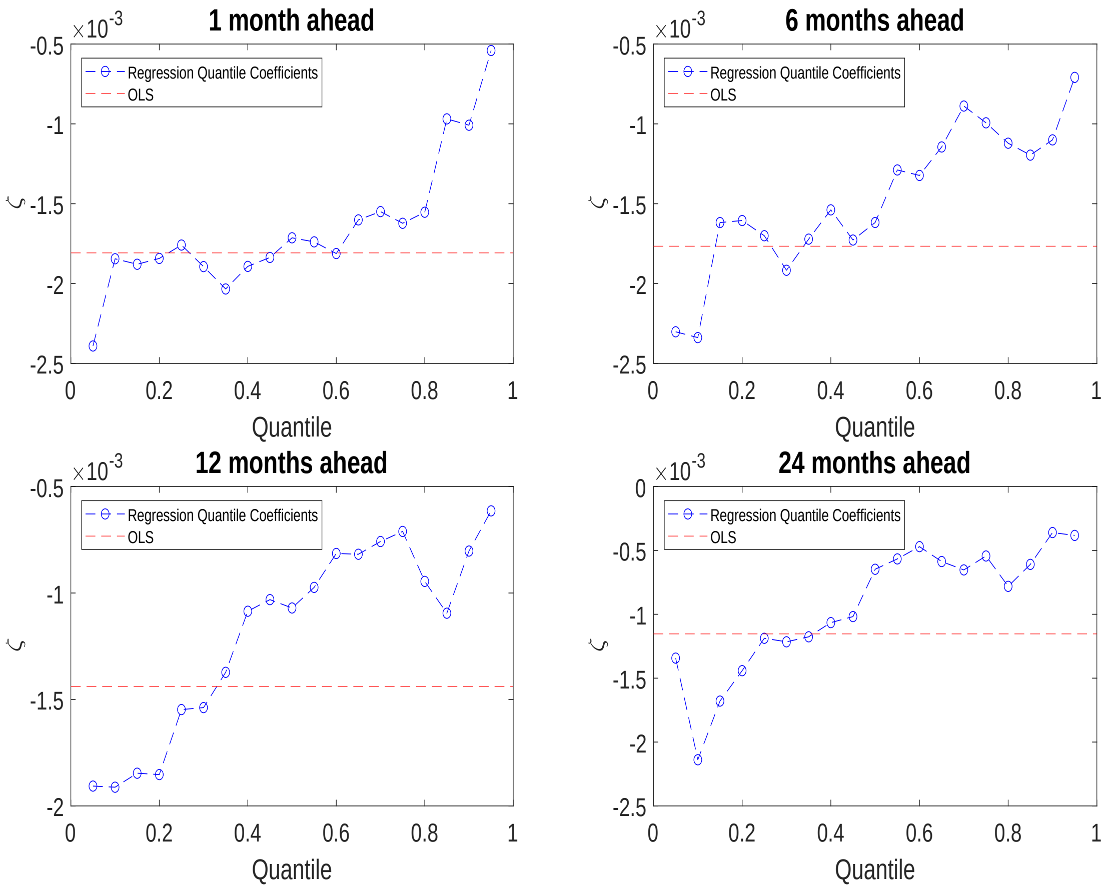
been shown to provide accurate estimates, even in the presence of heteroskedasticity (Vistocco et al., 2014).

Figure 3.4 displays the coefficients for more quantiles at different horizons adding the OLS slope. For the one month ahead (upper left panel), the coefficients for the extreme quantiles (lower and upper) are different from the OLS slope contrary to other quantiles which closer. Over the medium term examining the results for the 6 month ahead (upper right panel), the upper quantiles (greater than the median) differ from the OLS slope. After one year, all quantiles differ from the OLS coeffcient. The coefficients associated with the lowest quantiles are more negative than the coefficients associated with the upper showing that the effects of uncertainty are different according to the percentile of the future growth and over time providing a much richer set of information than OLS regressions and highlighting non-linear effects.

All these results highlight that the *wait and see* behaviour is stronger and more persistent in strong economic crisis situations. These findings are consistent with previous empirical studies showing that uncertainty shocks have a stronger negative effect in recessionary periods (Caggiano et al., 2014, 2021; Fontaine et al., 2018). For example, it is obvious that households save more in economic crisis situations because of their anticipations of a decrease in their income (Blanchard, 1993). These results provide new evidences of non-linear effects of general uncertainty on economic activity over the business cycles.

Examining the other variables (Figure A1), there is no significant effect of oil prices on the distribution of future GDP growth. The increase of the fed funds rate has a significant negative effect on the lower 5*th* percentile from the 12-month-ahead contrary to on the median (normal situations) which is not significant. Thus, if the Fed decides to lower its rate, this policy will boost the economy in economic crisis situations. Jannsen et al. (2019) have shown that the monetary policy is more effective during financial crises than in normal situations. We can note that the effect takes longer to be significant as it was the case following the 2007-2008 financial crisis with interest rates close to the zero lower bound. This result is in line with Caggiano et al. (2020) who have pointed

Figure 3.4: Marginal Effects of General Uncertainty



Notes: The figure shows the estimated coefficients in the quantile regression for different horizons.

out that firms cut their capital demand waiting until uncertainty in these economic crises situations vanishes before a return to their normal level of production. Examining the proxy of financial conditions with the S&P500 index, we find that a boom in stock market stimulates the future GDP growth in the near-term. This result is in line with Adrian et al. (2022) who have shown that credit booms and looser financial conditions can stimulate the future growth in the short run before increasing downside risk to growth because of financial vulnerabilities generated.

Our analysis highlights the non-linear effect of general uncertainty over the business cycles with a stronger negative effect in recessions. Previous empirical studies investigated the effect of the nature of uncertainty shocks in a linear framework assuming that the effect can be different according their nature (Kang et al., 2021; Larsen, 2021; Ludvigson et al., 2021). The next step of this chapter extends these previous empirical studies investigating to what extent the effect of the nature of uncertainty shocks can differ over the business cycles.

3.2.2 Investigation of the effect of the nature of uncertainty: Decomposition of Ludvigson et al. (2021)

In this subsection, we investigate the effect of the nature of uncertainty shocks applying the macroeconomic uncertainty index ($MUlmn$) and the financial uncertainty index ($FUlmn$) provided by the decomposition of uncertainty shocks of Ludvigson et al. (2021):

$$y_{t+h} = \alpha_\tau + \beta_{1,\tau} y_t + \beta_{2,\tau} Oil_t + \beta_{3,\tau} SP500_t + \beta_{4,\tau} Fed_t + \beta_{5,\tau} G_t + \zeta_{1,\tau} MUlmn_t + \zeta_{2,\tau} FUlmn_t + \epsilon_t \tag{3.8}$$

The sign of the coefficients of the macroeconomic uncertainty index is negative and significant on the lower $5th$ percentile and on the median (Figure 3.5). The coefficients are positive but not significant on the upper $95th$ percentile. Concerning the financial uncertainty index, the coefficients are negative on the median on the upper percentile. However, we find an unconventional result with a significant and positive effect on the lower $5th$ percentile over the long term. In the best of our knowledge, no theoretical argument can explain this result. Applying a PCA, Himounet (2022) has underlined the limits of the decomposition of uncertainty shocks of Ludvigson et al. (2021) between macroeconomic and financial uncertainty. Indeed, the macroeconomic uncertainty index of these authors seems more linked to finance and presents many similarities with their financial uncertainty index. These similarities can explain the troubling result on the effect of financial uncertainty because we would have inserted two equivalent measures in the same model and therefore, we generate incorrect results.

To check this assumption, we run our model by inserting these variables separately in two different regressions:

$$y_{t+h} = \alpha_\tau + \beta_{1,\tau} y_t + \beta_{2,\tau} Oil_t + \beta_{3,\tau} SP500_t + \beta_{4,\tau} Fed_t + \beta_{5,\tau} G_t + \zeta_{1,\tau} MUlmn_t + \epsilon_t \quad (3.9)$$

$$y_{t+h} = \alpha_\tau + \beta_{1,\tau} y_t + \beta_{2,\tau} Oil_t + \beta_{3,\tau} SP500_t + \beta_{4,\tau} Fed_t + \beta_{5,\tau} G_t + \zeta_{2,\tau} FUlmn_t + \epsilon_t \quad (3.10)$$

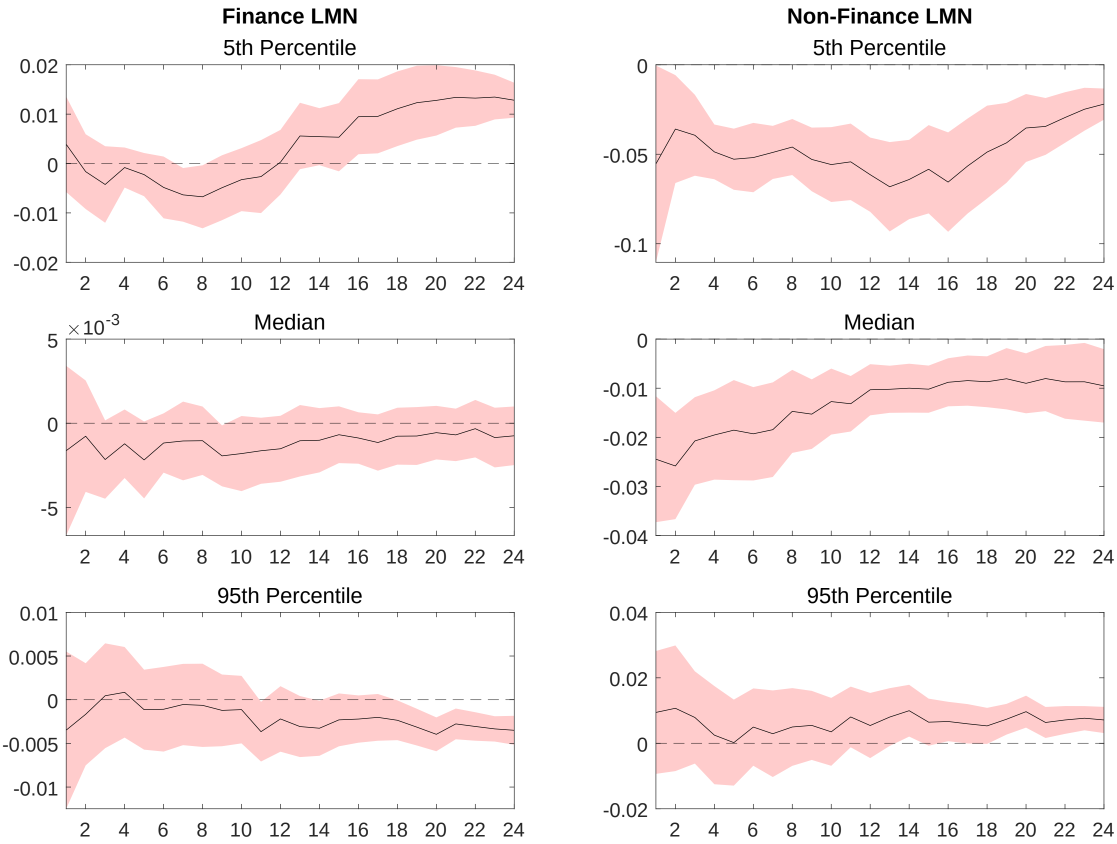
We keep the negative effect of their macroeconomic uncertainty index on the percentiles (Figure 3.6). However, the financial uncertainty index has a significant and negative effect on the lower $5th$ percentile over the medium term if we run the model without the macroeconomic uncertainty index of these authors. These results also show the weaknesses of the decomposition of Ludvigson et al. (2021) as their uncertainty indexes seem to have many similarities. Inserting both uncertainty indexes in a same model, we could have wrong results ans conclusions concerning the effects of these indexes because of their strong similarities.

The previous results underline that it is necessary that the decomposition of uncertainty shocks must provide measures which are not correlated. Recently, Kang et al. (2021) have proposed an interesting methodology to decompose uncertainty shocks.

3.2.3 Investigation of the effect of the nature of uncertainty: Decomposition of Kang et al. (2021)

We propose to revisit the decomposition of uncertainty shocks between non-financial uncertainty shocks and financial uncertainty shocks proposed by Kang et al. (2021) providing indexes less correlated. These authors have proposed a simpler methodology to

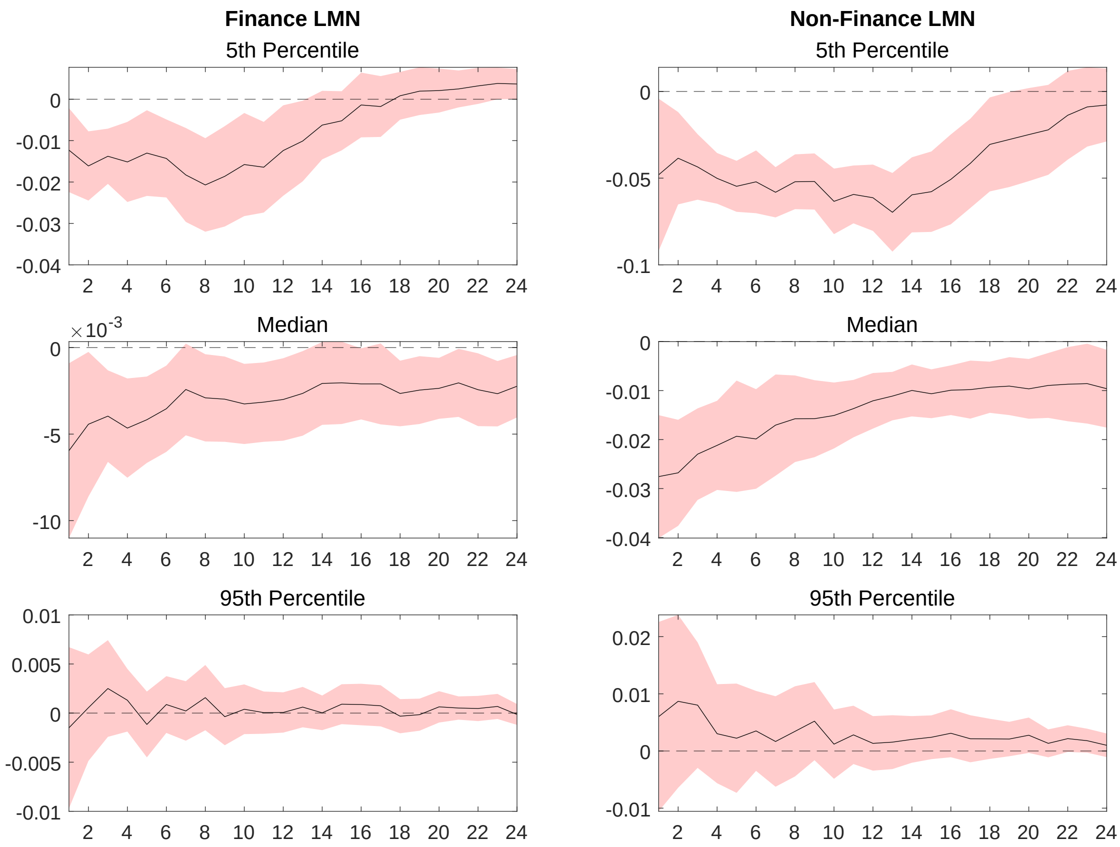
Figure 3.5: Marginal Effects of uncertainty indexes of Ludvigson et al. (2021)



Notes: The left panel represents the effects of the financial uncertainty index of Ludvigson et al. (2021). The right panel represents the effects of the macroeconomic uncertainty index of Ludvigson et al. (2021). The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

decompose uncertainty shocks disaggregating a global index between these both natures of uncertainty shocks by building two dummy variables. The first dummy variable is related to non-financial uncertainty taking the value of 1 if the shocks exceed 1.65 standard deviation above the mean of their global index and the corresponding uncertainty shock must be related to non-finance. The threshold of 1.65 corresponds to a significant threshold at a 5% level (Bloom, 2009) allowing to capture the strongest uncertainty shocks. The second dummy variable is related to financial uncertainty taking the value

Figure 3.6: Marginal Effects of uncertainty indexes of Ludvigson et al. (2021) with two regressions



Notes: The left panel represents the effects of the financial uncertainty index of Ludvigson et al. (2021). The right panel represents the effects of the macroeconomic uncertainty index of Ludvigson et al. (2021). Uncertainty indexes have been separately inserted in two different regressions. The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

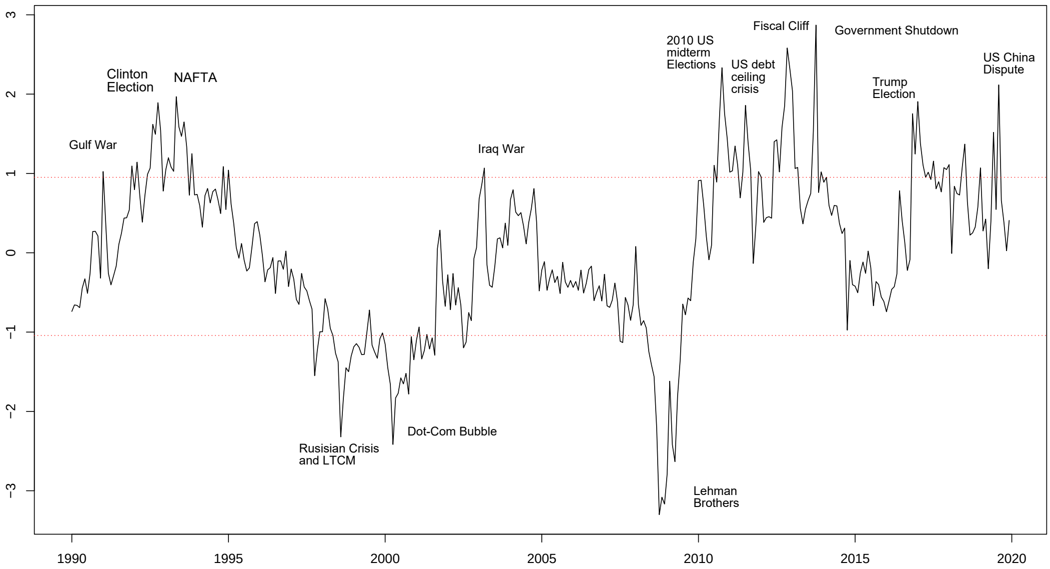
of 1 if the shocks exceed the threshold of 1.65 but the corresponding shock must be related to finance. However, even if the methodology proposed by Kang et al. (2021) is very interesting to decompose uncertainty shocks, we can highlight two weaknesses. The first is that the number of uncertainty shocks exceeding the threshold of 1.65 can be small. As an illustration, Bloom (2009) identified 17 uncertainty peaks applying this threshold to the VIX over the sample 1962-2009. Kang et al. (2021) identified 5 uncertainty peaks with their global index over the sample 1981-2018. The second is to determine the nature associated with each identified uncertainty shock. Indeed, some uncertainty peaks as the Gulf War or the collapse of Lehman Brothers are represented both in a non-financial uncertainty measure and in a financial uncertainty index provided by the literature. For example, the VIX proposed by Bloom (2009) and the economic policy uncertainty index of Baker et al. (2016) reach a peak at the collapse of Lehman Brothers and the Gulf War. However, these both uncertainty indexes measure two different types of uncertainty: financial and economic policy. It means that the collapse of Lehman Brothers can be associated with these both types of uncertainty. In front of this observation, it may be difficult to affirm what is the real nature associated with uncertainty peaks. Kang et al. (2021) have associated the nature examining the event associated with the peak. For example, the peak corresponding to the collapse of Lehman Brothers is associated with financial uncertainty.

To remedy both weaknesses described above, we decompose uncertainty shocks applying the second factor of the PCA of Himounet (2022). This factor distinguishes non-financial uncertainty shocks and financial uncertainty shocks in a single variable (Figure 3.7).

When this factor is high, the nature of uncertainty shocks is associated with macroeconomics or non-finance (Gulf War, Iraq War, Government Shutdown,...). Inversely, when it is low, the nature of uncertainty shocks is financial (LTCM, Dot-Com bubble, Lehman Brothers). We label this variable $Nature$ to emphasize that this variable associates uncertainty shocks with their real nature.[10] Therefore, we can use this variable as a criterion of decomposition of a general uncertainty index. Relying on the approach of Kang et al. (2021) but applying the variable $Nature$ as the criterion of decomposition, we build our dummy variables as follows:

[10]This variable also shows asymmetric effects over the percentile of the future growth (Figure A2).

Figure 3.7: Factor 2 of Himounet (2022): Nature of Uncertainty Shocks



Notes: The dashed red lines correspond to the estimated threshold values ($\gamma_1 = 0.9511116$ and $\gamma_2 = -1.042606$). Below the lower dashed red line, the nature of uncertainty shocks is linked to finance. Above the upper dashed red line, the nature of uncertainty shocks is linked to non-finance.

$$NFU_t = \begin{cases} 1, & \text{if } Nature_t > \gamma_1 \\ 0, & \text{otherwise} \end{cases} \quad (3.11) \qquad FU_t = \begin{cases} 1, & \text{if } Nature_t < \gamma_2 \\ 0, & \text{otherwise} \end{cases} \quad (3.12)$$

where NFU denotes the non-financial uncertainty shocks and FU denotes the financial uncertainty shocks. γ_1 and γ_2 are two thresholds with $\gamma_1 > \gamma_2$. Below the lower threshold γ_2, the nature of uncertainty shocks will be related to finance according to the interpretation of the variable $Nature$. Inversely, above the upper threshold γ_1 which is greater than γ_2, the nature of uncertainty shocks will be related to non-finance. This procedure allows to capture more observations than the methodology of Kang et al. (2021). Moreover, we more generalize their approach in the determination of the nature of uncertainty shocks instead of determining manually the nature associated with each uncertainty peak. We can't use the threshold of 1.65 for the variable $Nature$ in this case. Above the threshold of 1.65, the nature of uncertainty shocks is always associated with non-finance. However, all observations under 1.65 could be classified as financial uncertainty shocks. Applying one threshold, we assume that we pass from a non-financial uncertainty regime to a financial uncertainty regime instantaneously. That's why, the estimation of two thresholds instead of one seems a good choice and allows to get an intermediate zone between γ_1 and γ_2. This zone means that we do not necessarily pass instantly from a non-financial uncertainty regime to a financial uncertainty regime and inversely.

The threshold values γ_1 and γ_2 are extracted from a threshold VAR model (TVAR) applying $Nature$ as the threshold variable with the following set of endogenous variables: GDP, $SP500$, Oil, Fed ,G and GU. The likelihood ratio test rejects the hypothesis of linearity (Table 3.1). On the Figure 3.7, above the upper red line ($\gamma_1 = 0.9511116$), we capture events associated with non-finance. Below the lower red line ($\gamma_2 = -1.042606$), we capture events associated with finance. As explained previously, we capture more observations for both dummies than in the methodology of Kang et al. (2021). We capture uncertainty shocks which are moderate according to the general uncertainty index as the Russian financial crisis and LTCM in the case of financial uncertainty.

Table 3.1: TVAR: Likelihood-Ratio (LR) test

	Linearity VS Three Regimes
Threshold Variable	$Nature$
LR statistic	524.6135
p-value	0.000
Estimated threshold	-1.042606 ; 0.9511116

Source: Author's own calculations.
Notes: The LR test rejects the hypothesis of linearity with a $p - value$ equal to 0 for the VAR: GDP, $SP500$, Oil, Fed ,G and GU. The estimated threshold values are -1.042606 and 0.9511116.

As these dummy variables concern the nature of uncertainty shocks, their marginal effects cannot be very meaningful. As highlighted by Kang et al. (2021), the dummy variable introduced by Bloom (2009) does not capture the magnitude of the uncertainty shocks. To gain in meaningfulness, following Kang et al. (2021), we multiply both dummy variables by the general uncertainty index: $NFU \times GU$ and $FU \times GU$. These interacted variables capture both a qualitative and a quantitative dimension. Taking only the dummy variable may assume that retained uncertainty shocks can have the same level. Interacting the dummies with the general uncertainty index, we capture the nature associated with uncertainty shocks and their overall level which can be different. The variable $NFU \times GU$ is high when uncertainty is high and the nature is associated with non-financial uncertainty. Similarly, the variable $FU \times GU$ is high when uncertainty is high and the nature is associated with financial uncertainty. Both variables are not correlated as their correlation (-0.03) is not significant with a p-value equal to 0.53. We introduce these new variables in the model:

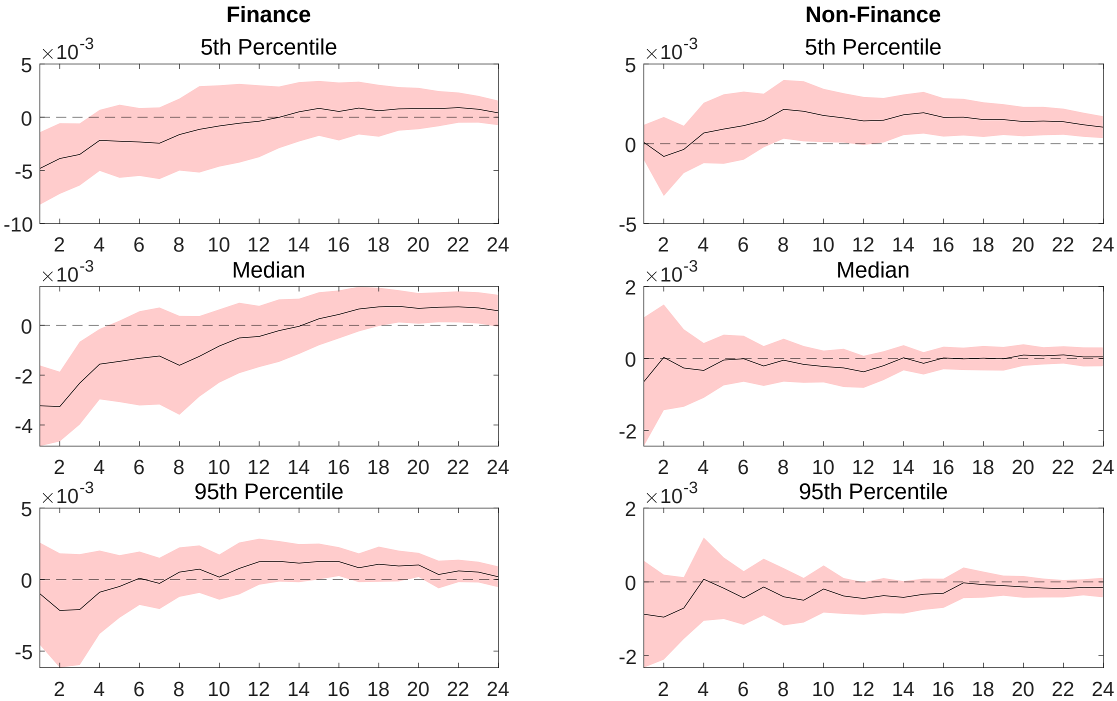
$$\begin{aligned} y_{t+h} = \alpha_\tau + \beta_{1,\tau} y_t + \beta_{2,\tau} Oil_t + \beta_{3,\tau} SP500_t + \beta_{4,\tau} Fed_t + \beta_{5,\tau} G_t \\ + \zeta_{1,\tau}(NFU_t \times GU_t) + \zeta_{2,\tau}(FU_t \times GU_t) + \epsilon_t \end{aligned} \tag{3.13}$$

We get negative coefficients associated with financial uncertainty on the lower $5th$ percentile and the median translating a negative effect on the different quantiles of the future US growth (Figure 3.8). The negative effect is significant for the first quarter on the lower $5th$ percentile making the worst events even worse and therefore, increasing downside risk to growth. Investors require higher compensation to lend to households or firms, and similarly for equity or other investments in companies meaning that the cost of borrow is more expensive increasing the risk premia (Christiano et al., 2014). We don't find any significant effects on the $95th$ percentile. Examining the non-financial uncertainty variable, the estimated coefficients are negative but not significant on the median and the upper $95th$ percentile. However, we get positive and significant coefficients on the lower $5th$ percentile (recessionary phases) over the medium term. The striking result we obtain is that non-financial uncertainty shocks improve economic activity in recessions breaking the empirical consensus on the negative effect of uncertainty in recessions.[11] We find equivalents results if we separately insert these variables in two different regressions (Figure 3.9). Thus, applying the decomposition of this chapter, the results are qualitatively equivalent whether by inserting our non-financial uncertainty variable and our financial uncertainty variable separately in two regressions or by inserting them in the same model. As the decomposition of this chapter provides uncertainty variables which are very less correlated, the results of this chapter are more stable than applying uncertainty indexes provided by the decomposition of Ludvigson et al. (2021). The results are also robust adding the general uncertainty index in the regression 3.13.

The finding of a positive effect of uncertainty is recent in the empirical literature. In a linear framework, Larsen (2021) and Ludvigson et al. (2021) found a positive effect of a non-financial uncertainty shock explaining it by a technological uncertainty associated with "growth options" theories (Segal et al., 2015). The recent developments in artificial intelligence (AI) seems to be a good example to illustrate "growth options". It is obvious that AI will provide many growth opportunities that will benefit firms and the economy in the future. However, predicting the future industrial achievements that will result from research and development spending in AI is uncertain while predicting that the potential future benefits of these innovations will be huge seems quite obvious. Moreover, there is uncertainty on which firms and by how much. This uncertainty about the size of the future profits could encourage research and development spending in AI boosting economic activity. Atanassov and Leng (2018) showed that firms react to an increase in political uncertainty by investing more in R&D during election periods but in a preventive way. Stein and Stone (2013) also showed that uncertainty over firms'

[11] There are no major changes about coefficients associated with the other explanatory variables.

Figure 3.8: Marginal Effects of the Nature of Uncertainty



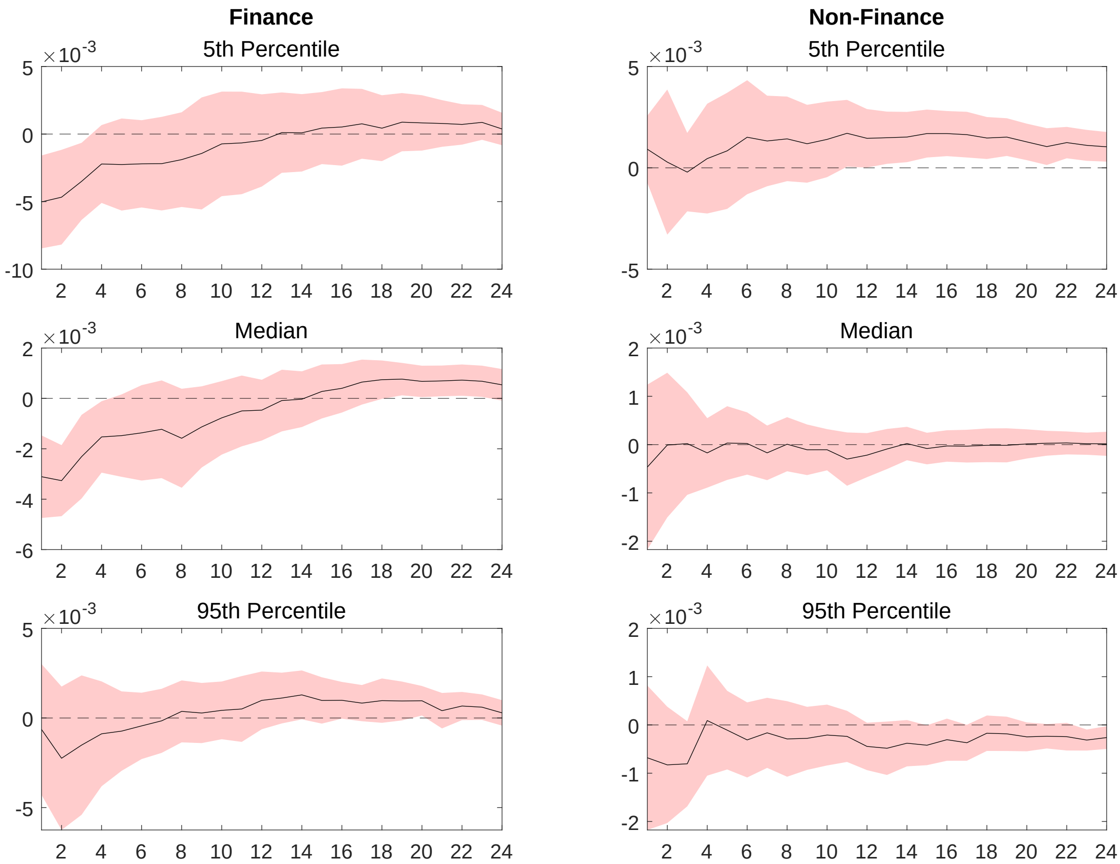
Notes: The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

business conditions can encourage R&D.

Figure 3.10 shows the evolution of the stock market SP500 index and the NASDAQ index. The NASDAQ is considered as an index related to high-tech innovations because to the companies in this sector which are mainly taken into account in the calculation of this index. This index exhibits a more important increase during the dot-com bubble than the SP500 where *growth options* have been the explanation to this phenomenon. The graph also underlines that the upward trend of both indexes is exacerbated for the NASDAQ underlying enthusiasm about the outlook for technology profits.

Even if this argument is interesting to explain our results, we don't find any mentions about the state of the economy. Our results highlight a positive effect of non-financial uncertainty only in recessions while "growth options" theory may work in every state of

Figure 3.9: Marginal Effects of the Nature of Uncertainty with two regressions

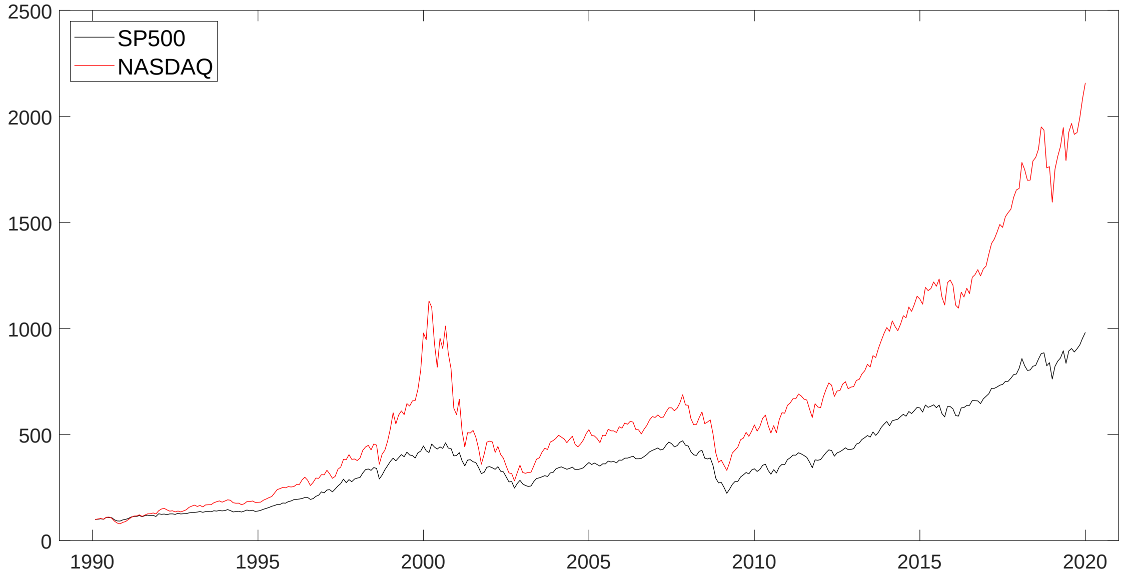


Notes: The left panel represents the effects of financial uncertainty. The right panel represents the effects of non-financial uncertainty. Uncertainty indexes have been separately inserted in two different regressions. The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

the economy according to its explanation.

Another argument can explain this result which is related to the theoretical works of Gabaix (2014, 2020) showing that individuals are myopic when a lot of information is available given that they can't analyse this large quantity of information. This myopia makes individuals unable to predict that an economic stimulus will induce taxes to rise in the future removing the Ricardian equivalence. In other words, this large quantity of information available removes the Ricardian equivalence suppressing agents' ability to

Figure 3.10: Comparison between SP500 and NASDAQ



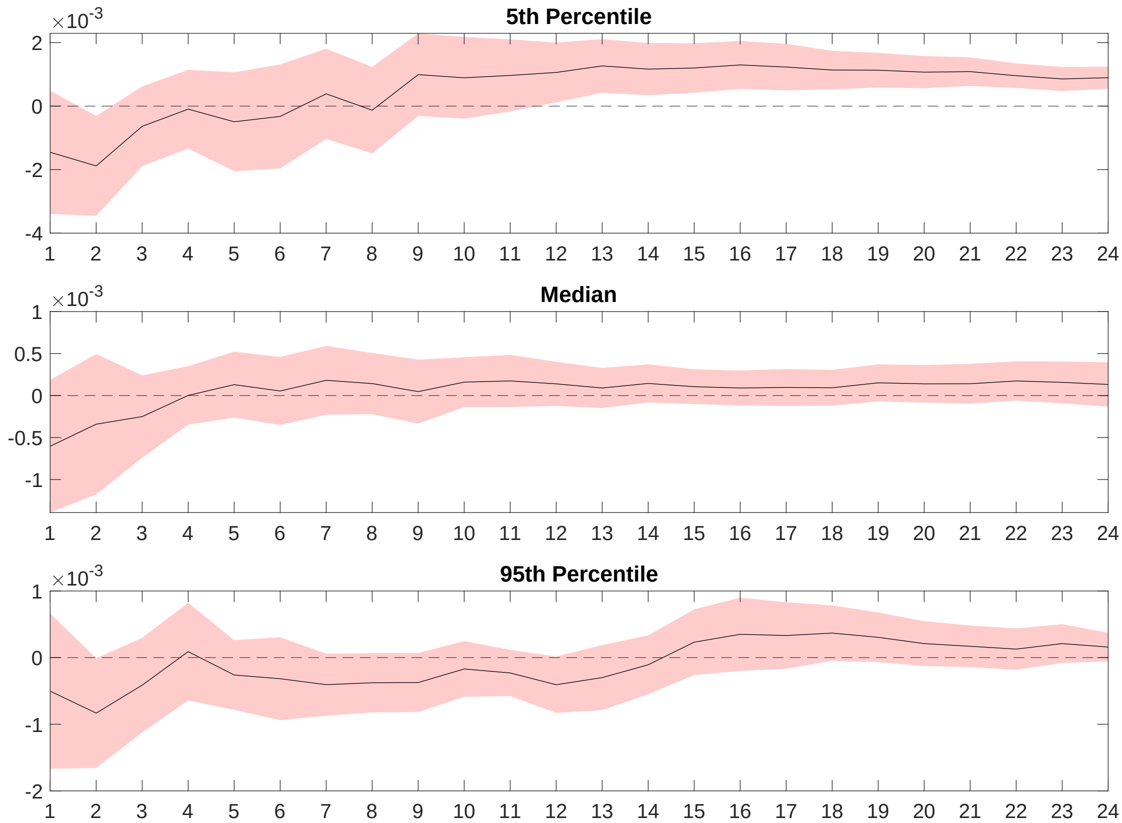
Notes: The indexes are transformed with 1990 as the base (=100).

anticipate the future perfectly. We can infer that myopia is exacerbated when uncertainty is strong (Himounet et al., 2021). In our model, the $5th$ lower percentile represents the worst-case scenario GDP growth which are associated with economic crisis situations. Generally, the overall level of uncertainty is high during this kind of scenarios according to the countercyclical hypothesis of Bloom (2009). Thus, from Gabaix's arguments, non-financial uncertainty shocks can have a positive effect in these situations. However, these non-financial uncertainty shocks must be related to fiscal policy according to Gabaix's arguments. Examining the non-financial uncertainty shocks highlighted by the second factor of Himounet (2022), we have many uncertainty shocks which are linked to fiscal policy and government spending as the Gulf War, the Iraq War, the 2011 US debt ceiling crisis and the Fiscal Cliff. Moreover, there has been a large economic stimulus following the financial crisis with the American Recovery and Reinvestment Act of Barack Obama in 2009. From these arguments and our results, we can refer more to this second explanation than the previous one without asserting that the assumption related to artificial intelligence is false. Uncertainty related to technology can have a positive effect in both economic crisis situations associated with a strong general uncertainty and economic boom situations associated with a low general uncertainty. It may not depend on current economic conditions contrary to Gabaix's theory which only works if myopia is strong. The fact that the positive effect of non-financial uncertainty shocks is significant over the medium term can be due to the situation of severe recessions in which this kind of shock occur. As the damages on economic activity are already presents on the lower $5th$ percentile corresponding to strong recessions, the stimulus can take longer to be effective. As the theoretical arguments of Gabaix (2014, 2020) rely on fiscal policy, we run our baseline model replacing the general uncertainty index with the fiscal policy uncertainty index (Figure A3) of Baker et al. (2016). This index is based on textual analysis of newspaper counting the occurrence of key words related to uncertainty, economy and fiscal policy. By its construction, a shock on this variable indicates that there are more information and news on fiscal policy for agents to analyze. We get a significant positive effect on the lower $5th$ percentile of the future growth after one year (Figure 3.11). These results could constitute a beginning of empirical evidence of the theoretical arguments of Gabaix (2014, 2020). However, we need to decompose the fiscal policy uncertainty index by isolating peaks that were followed by an increase in government spending afterwards.

3.3 Robustness Checks

In this section, we will check the robustness of our results in three ways. Firstly, we insert the dummy variables NFU and FU in the regression, *i.e.* , by not interacting with the overall level of uncertainty shocks GU. In his seminal paper, Bloom (2009) has investigated the effects of uncertainty shocks applying a dummy variable taking the value of 1 if the VIX index exceeds 1.65 standard deviation above the mean. Despite

Figure 3.11: Marginal Effects of Fiscal Policy Uncertainty



Notes: The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

the weaknesses highlighted about this dummy which don't take into account the overall level of the shocks, we run the following model:

$$y_{t+h} = \alpha_\tau + \beta_{1,\tau} y_t + \beta_{2,\tau} Oil_t + \beta_{3,\tau} SP500_t + \beta_{4,\tau} Fed_t + \beta_{5,\tau} G_t + \zeta_{1,\tau} NFU_t + \zeta_{2,\tau} FU_t + \epsilon_t \quad (3.14)$$

We get negative coefficients associated with the financial uncertainty dummy variable on the lower $5th$ percentile and the median translating a negative effect on the different quantiles of the future US growth (Figure B1) as in our baseline results. We don't find any significant effects on the $95th$ percentile. Examining the non-financial uncertainty dummy variable, the estimated coefficients are always positive and significant on the lower $5th$ percentile for many months.[12]

Secondly, we apply the same method of decomposition proposed by Kang et al. (2021). We capture the strongest uncertainty peaks exceeding the threshold of 1.65 of the general uncertainty index associating each peak with their nature: non-financial or financial. This decomposition of the general uncertainty index (GU) between non-financial uncertainty shocks (NFU) and financial uncertainty shocks (FU) can be summarized as follows:

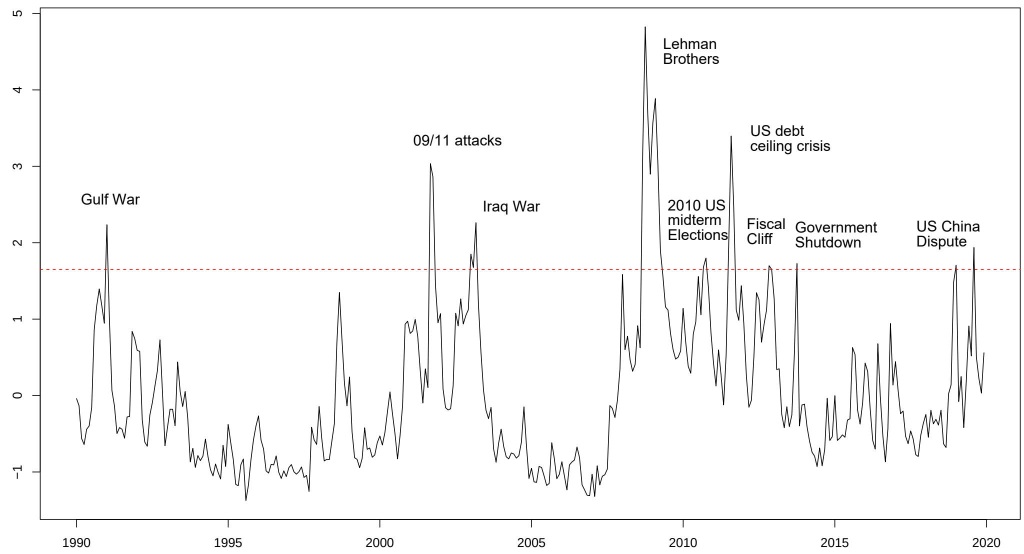
$$NFU_t = \begin{cases} 1, & \text{if } GU_t > 1.65 \text{ standard deviations AND if the shock is linked to non-finance} \\ 0, & \text{otherwise} \end{cases} \tag{3.15}$$

$$FU_t = \begin{cases} 1, & \text{if } GU_t > 1.65 \text{ standard deviations AND if the shock is linked to finance} \\ 0, & \text{otherwise} \end{cases} \tag{3.16}$$

The non-financial uncertainty shocks matching the criteria are related to the 1990 Gulf War, the 09/11 attacks, the 2003 Iraq War, the US-debt ceiling crisis in 2011, the fiscal cliff, the 2013 Government Shutdown, the US-China dispute in 2019 (Figure 3.12). The financial uncertainty shocks are related to the 2007-2009 financial crisis with the collapse of Lehman Brothers. As highlighted previously, the number of observations is very limited following the methodology of Kang et al. (2021). Then, we multiply these dummy variables by the general uncertainty index like previously allowing to associate these strongest uncertainty shocks with their overall level. There is a significant negative effect of the financial uncertainty variable during the first months on the percentiles. Interestingly, the negative effect becomes significant on the $95th$ per-

[12] We find equivalents results if we separately insert these dummy variables in two different regressions.

Figure 3.12: General Uncertainty Shocks



Notes: The index is standardized over the period 1990-2019. The horizontal dashed red line indicates 1.65 standard deviations above the mean.

centile over the short term showing that the highest financial uncertainty shocks have a stronger effect on the percentiles. On the lower 5*th* percentile, we keep the positive effect of the non-financial uncertainty variable associated with the strongest non-financial uncertainty shocks (Figure C1). These findings highlight that our non-linear framework provides a much richer set of results than Kang et al. (2021) who only found a negative effect of non-financial uncertainty shocks applying a linear framework. The results are robust taking the dummy variables only (Figure C2).

3.4 Conclusion

We have investigated the effects of uncertainty on the future GDP growth applying quantile regression techniques. We find that general uncertainty has a negative effect on the different percentiles highlighting a *wait and see* behaviour. However, the negative effect is more significant on the lower 5*th* percentile than on the median and the 95*th* percentile. These results show a non-linear effect according to the state of the economy. These findings suggest that the *wait and see* behaviour is stronger in the worst-case GDP growth scenarios which are associated with economic crisis situations.

Decomposing uncertainty shocks between non-financial uncertainty shocks and financial uncertainty shocks. We find that financial uncertainty has a negative effect on the percentiles increasing the downside risk to growth. These results could help policymakers to conceive macroprudential policies in order to reduce the probability of this downside risk. We also provide an evidence that uncertainty may be positive when its nature is non-financial during economic crisis situations. The explanation about this positive effect can rely on the arguments of Gabaix (2014, 2020) where a strong myopia restores the effectiveness of an economic stimulus. Reinterpreting his results, myopia removes the Ricardian equivalence allowing a strong efficiency of an economic stimulus when uncertainty and therefore, the myopia are strong. These arguments refer to uncertainty related to fiscal policy. To better test the assumption of Gabaix (2014, 2020), an extension to this work could consist in the investigation of the effects of fiscal policy uncertainty indexes developed by Baker et al. (2016) on economic activity applying a non-linear framework but by isolating peaks that were followed by an increase in government spending afterwards. The results of this chapter and these future works could have policy implications about fiscal policy making in economic crisis situations taking into account this unexplored aspect of uncertainty.

Appendix

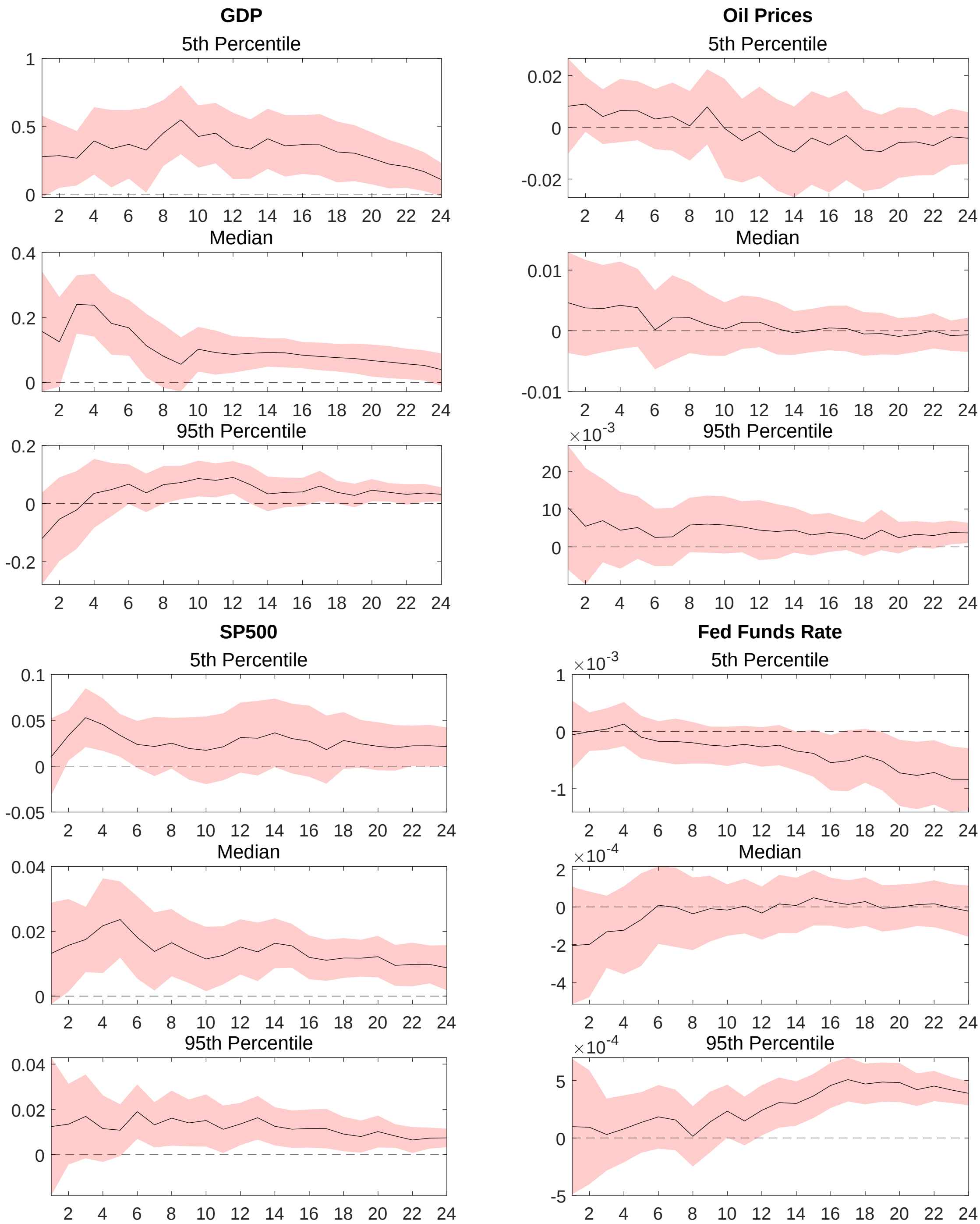
A Data and Results

Table A1: Variables and Data

Variables	Acronym	Source
Industrial Production (log difference)	y	FRED
Oil prices deflated by the CPI (log difference)	Oil	FRED
S&P 500 Index (log difference)	$SP500$	Yahoo Finance
Effective Fed Funds Rate	Fed	FRED
US Outlays	G	US department of the treasury website
General Uncertainty Index	GU	Himounet (2022)
Factor 2	$Nature$	Himounet (2022)
Macroeconomic Uncertainty Index	$MUlmn$	Ludvigson et al. (2021)
Financial Uncertainty Index	$FUlmn$	Ludvigson et al. (2021)
Fiscal Policy Uncertainty	FPU	Baker et al. (2016)

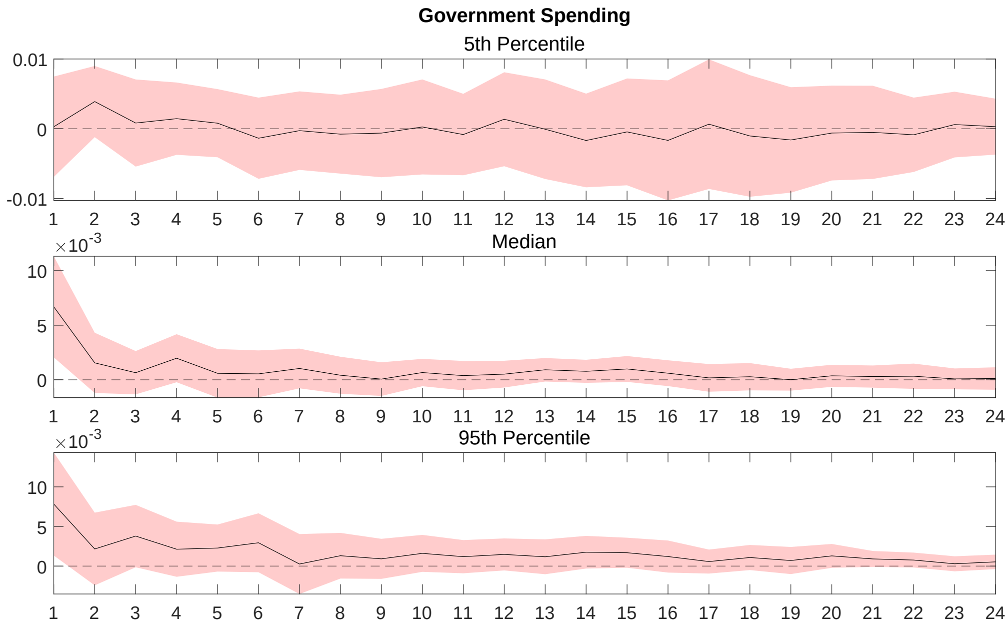
Note: The sample spans the period 1990M1-2019M12.

Figure A1: Marginal effects of other variables



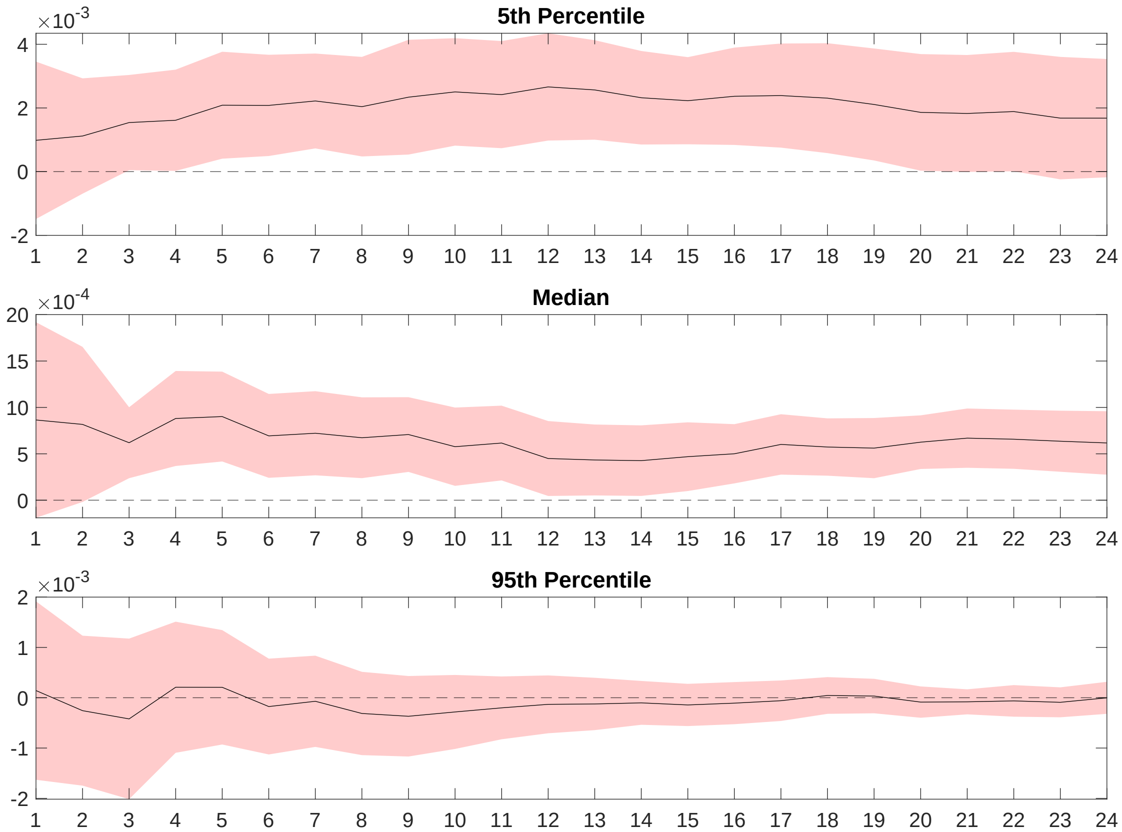
Notes: The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

Figure A1: Marginal effects of other variables (continued)



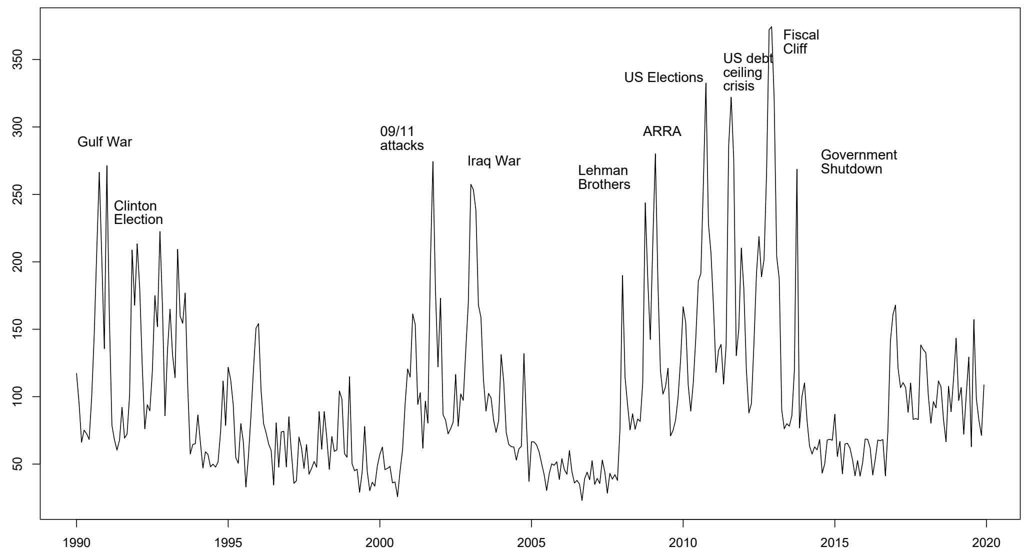
Notes: The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

Figure A2: Marginal Effects of $Nature$



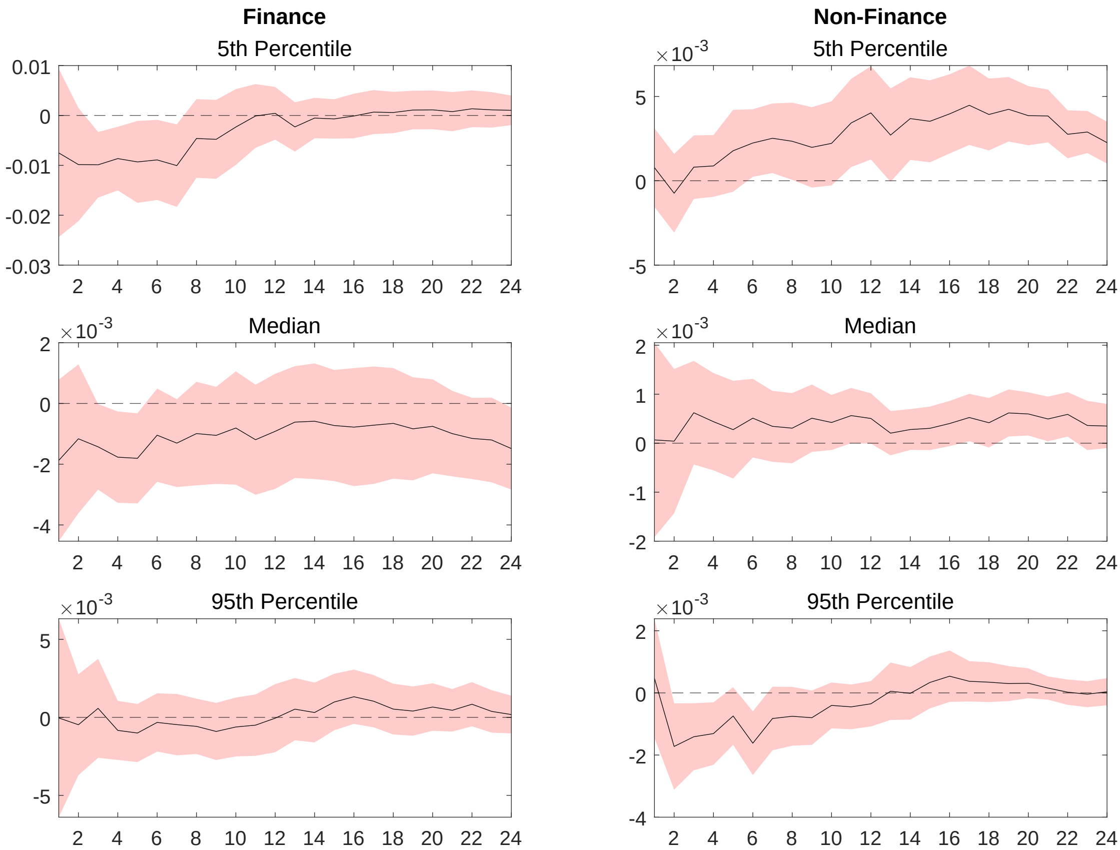
Notes: The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

Figure A3: Fiscal Policy Uncertainty index of Baker et al. (2016)



B Robustness Check: Nature of Uncertainty using dummy variables

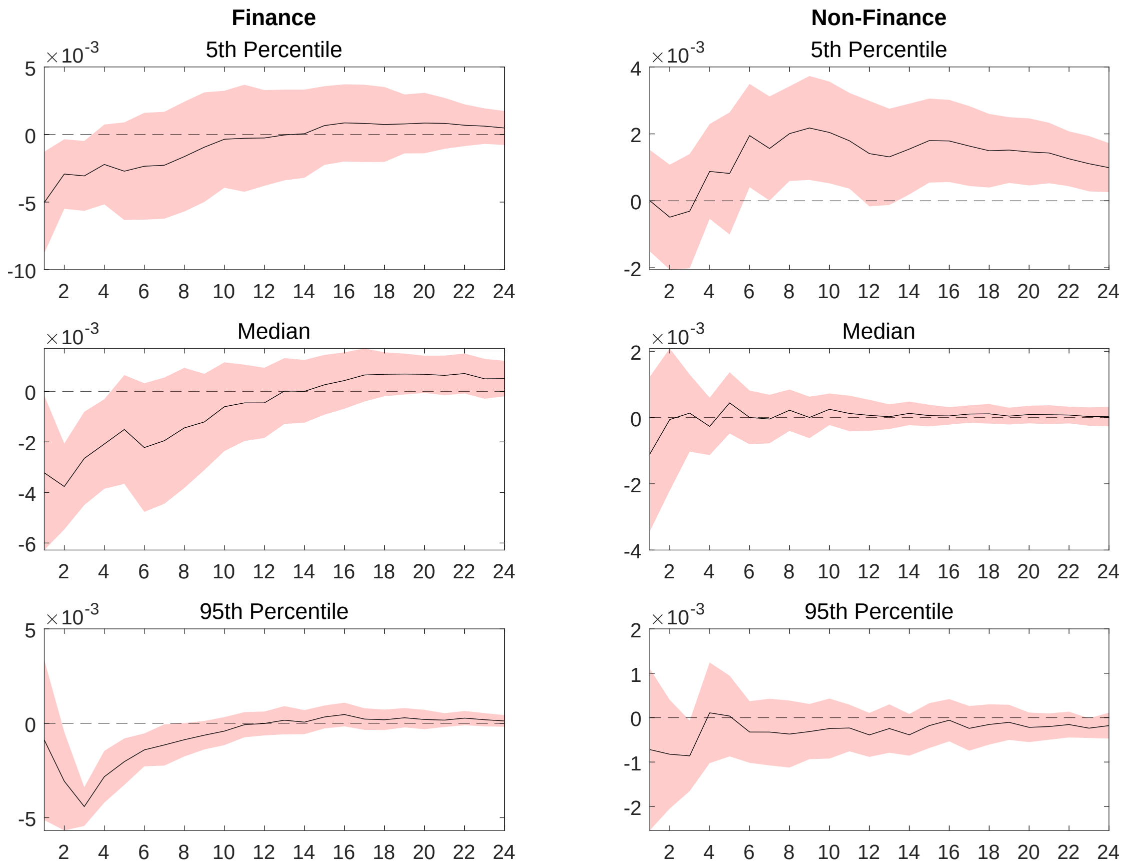
Figure B1: Marginal Effects of the Nature of Uncertainty



Notes: The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

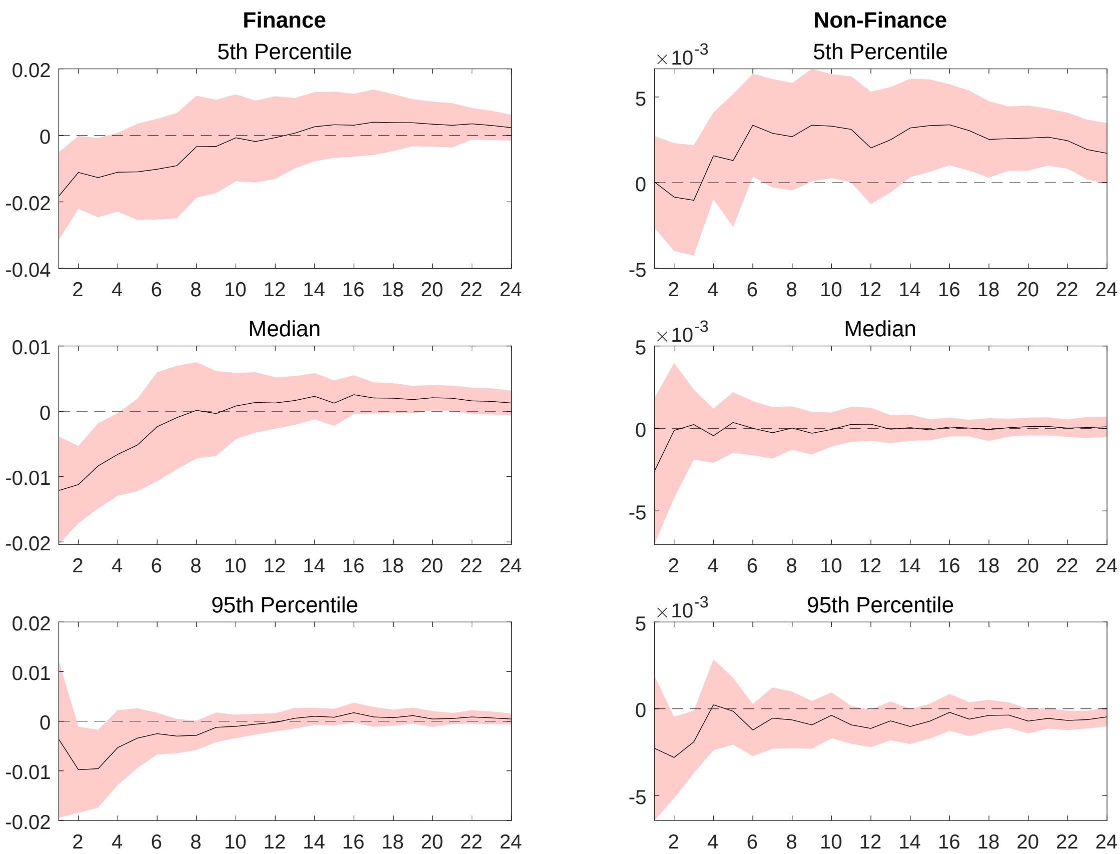
C Robustness Check: Decomposition of Kang et al. (2021)

Figure C1: Marginal Effects of the Nature of Uncertainty



Notes: The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

Figure C2: Marginal Effects of the Nature of Uncertainty using Dummy Variables



Notes: The solid black lines correspond to the estimated coefficients. The shaded area denotes the 95% confidence interval. Confidence intervals are computed using bootstrapping techniques.

Chapter 4

Uncertainty is Bad for Business. Really? [‡]

[‡]An older version of this chapter is available as a Working Paper on the International Network for Economic Research (INFER) website (co-written with Francisco Serranito and Julien Vauday).

Introduction

The common wisdom about uncertainty is that it is negative. The last financial crisis and the following surge of papers in the literature that study the effects of uncertainty were perceived as an empirical validation of this consensus. However, since the middle of the last decade some papers have started to consider the possibility that some forms of uncertainty may instead have a positive impact on the economy.

This recent and still rare literature has started with a paper by Segal et al. (2015) that states uncertainty may also be about positive growth perspectives. For instance one may think to recent developments on Artificial Intelligence (AI). Despite forecasting what will be the industrial achievements due to AI in ten years is highly uncertain, predicting that these achievements will generate very large profits is a safe bet. Some authors refer to this theory as the "growth option" theory. They postulate that uncertainty may be good or bad, they develop a theoretical model in which they introduce good and bad shocks and study the effect of uncertainty surrounding those shocks. They show theoretically that good uncertainty may have a positive effect on various variables when there is a channel through which uncertainty influences future growth. They then confirm this empirically.

Another paper that highlights a positive effect of uncertainty is the one by Ludvigson et al. (2021). They use an index of macroeconomic uncertainty (developed in a previous paper, Jurado et al. (2015)) and an index of financial uncertainty which is newly built for this work. They have various results but focusing on a possible positive effect of uncertainty, they find that a shock on the macroeconomic uncertainty generally has a positive effect on industrial production on the short term that turns negative in the long-run. They argue that the positive effect they identify confirms the "growth option" theory.

One last paper that finds a positive effect of uncertainty is Larsen (2021). He uses machine learning techniques that autonomously identify some types of uncertainty by analyzing many Norwegian business press articles. Then the author uses these various types in SVAR's and it appears that some of them, especially those related to business (e.g. Mergers & acquisitions), have a positive effect.

This paper is in line with this very recent literature in that it is about finding under which conditions uncertainty may have a positive effect. Despite very rare, previous empirical results highlight that positive uncertainty may come from industrial prospects or be more broadly macroeconomic. Arguably, industrial perspectives are a subset of the macroeconomic context. To the contrary, uncertainty is not positive when it is about finance. The three papers above as well as the other works analyzing the effects of uncertainty starting with the seminal paper of Bloom (2009) do all conclude that uncertainty related to financial variables has a clear negative impact. So we first propose a mean to empirically distinguish endogenously financial uncertainty from non financial one. Second, we show that non financial uncertainty may have a positive effect under some conditions. Contrary to previous works that find a positive effect of uncertainty, we provide a more general approach that allows to identify a positive effect of uncertainty.

Come back to the theoretical mechanisms that may explain a positive effect of uncertainty. Segal et al. (2015) proposes a model based on the intuition that when it concerns industrial prospects, uncertainty may be good. Ludvigson et al. (2021) refer to this mechanism as the "growth option" theory and connect it to several old papers (Oi, 1961; Hartman, 1972; Tisdell, 1978; Abel, 1983) that in fact are not really directly about growth (Larsen, 2021, does a distinction). They rather show that because firms are not risk averse, they prefer price instability because the better uncertain issues generate very large profits. It is not exactly the same than writing that future industrial perspectives may generate very large profits in the future despite the fact that increased investment that follows an increase in output or factor prices uncertainty should lead to more growth in the future. Nevertheless, they all relate to industry inasmuch firms are at the center of these mechanisms. We want to add to these possible mechanisms another one that is inferred from recent works by Gabaix (2014, 2020) on behavioral new Keynesian models. The second article shows that agents, because they are partly myopic, fail to perfectly anticipate future taxes after a stimulus is enacted. This implies that Ricardian equivalence does not hold. The first article as for it explains how agents decide what degree of attention to bring to each existing information in order to process an action aimed at optimizing its utility. We believe that conditions under which increased uncertainty may lead to a reduced mean attention do exist. As a consequence, by increasing agent's myopia, uncertainty may lead stimuli to have a stronger (positive) effect. This leads us to believe that uncertainty may have a positive effect not only when it concerns industrial aspects but more generally when it is non-financial.

Uncertainty is an unobservable phenomenon and measuring it is clearly a challenge. In recent years a booming economic research has emerged to take up this challenge and to propose how to quantify uncertainty. Ferrara et al. (2017) review all the different methodologies to measure uncertainty and their impact on macroeconomic variables. In this paper, we contribute to this growing empirical literature and we propose three new improvements. Firstly, using a new measure of general uncertainty (See Himounet, 2022), we provide an empirical analysis in order to identify not only changes in the overall level of uncertainty in the US but also the determinants of an uncertainty shock (financial, macroeconomic policy, news index, geopolitical risks, ...). Secondly, we identify the conditions under which uncertainty could have a positive effect on the economy by testing an intuition in a linear VAR model. Thirdly, we validate this intuition using a non linear VAR model.

Himounet (2022) applies a principal component analysis (PCA) in order to build-up a global measure of uncertainty for the US using new measures recently developed in the literature. In particular, if as expected the first factor can be interpreted as a measure of the general level of uncertainty, the second one of this PCA is more about the nature of uncertainty. This second factor is high when uncertainty is industrial/macroeconomic and low when it is financial. We use these factors to study the impact of uncertainty shocks using local projection methods (Jordá, 2005) on US data on the period 1990-2019.

Our US global uncertainty variable (Factor 1) is shown to have a negative and significant effect on all the macroeconomic variables used in the estimations as the literature generally does. Then, we conduct the same analysis using the factor that discriminates financial and non-financial uncertainty (Factor 2) and find no significant effect. Strikingly, using a nonlinear framework, we obtain a positive and significant effect of this second dimension of uncertainty on industrial production and a negative one on the unemployment when the general level of uncertainty is high. In order to confirm that our result is robust, we redo the same estimations on a reduced 1990-2006 subsample. On the one hand, by doing so we suppress the financial crisis during which uncertainty unambiguously has had a negative effect and on the other hand we suppress all the high-tech innovations of the 2007-2019 decade and the quite massive stimulus of 2009 that according to us has had a positive effect.[1] It turns out that the effect becomes negative thus supporting our view that the 2007-2019 decade has witnessed radical innovations in high tech that has generated an uncertainty that appears to be positive and that uncertainty around macroeconomic prospects has allowed the stimulus of 2009 to have a positive effect on the economy.

The rest of this chapter is organized as follows. In section 1, we present a brief literature review on the positive effect of uncertainty. In section 2, we use local projection methods to investigate the dynamics between uncertainty and economic activity in a linear and a non linear framework. In section 3, we present robustness checks. The last section presents our conclusions and directions for future research.

[1]For example, we are thinking of the internet revolution in the new millennium with the impact of the FAANG stocks (Facebook, Amazon, Apple, Netflix and Alphabet Google) on the overall economy.

4.1 Positive effect of uncertainty: Literature review and theoretical discussion

A recent literature has emerged proposing different measures of uncertainty based on various methodologies making the task of establishing a consensus on how to measure uncertainty very hard, if not impossible. This section presents the papers that have put forward a positive effect of uncertainty and then discusses the possible theoretical arguments for this positive effect. For those interested, Himounet (2022) proposes a very detailed literature review of all the papers that develops some measures of uncertainty with the aim of improving the Ferrara et al. (2017)'s classification and uncertainty approximation with new measures and approaches.

4.1.1 Positive effect in the data

Segal et al. (2015) is the first paper to break the consensus about the negative effect of uncertainty. They start from a conjecture: uncertainty may be good for business activities when considering future industrial perspectives. They give the example of the high tech revolution of the 1990s during which it was hard to guess what would be the concrete achievements for the business. However, many business analysts and specialists were almost certain that many firms would benefit from these new technologies. Arguably, it was true. Then, they first develop a theoretical model in which both kind of uncertainty shocks exist, negative and positive. These shocks affect consumption growth as well as consumption expectation. This last effect allows uncertainty to have opposed effects. The authors confirm empirically the existence of a positive component of uncertainty using a VAR. Their methodology implies that positive shocks are by nature positive since they correspond to positive semivariances of industrial production. Then they use the predictable component of this measure to capture ex-ante uncertainty.

It results that shocks on good uncertainty have lasting effects on several key macro variables and that it dampens the negative effects of bad shocks. In the same way, Forni et al. (2021) decomposed uncertainty between two components relying on the methodology of Adrian et al. (2022): downside uncertainty and upside uncertainty. Downside uncertainty is considered as uncertainty on the future decrease of growth while upside uncertainty is considered as uncertainty on the future increase of growth.[2] As expected, the authors get a negative of downside uncertainty and a slightly positive effect of uncertainty. Their results seems to underline that the negative component of uncertainty dominates the positive component in uncertainty data explaining the fact that most studies have got a negative effect.

The other papers that find a positive effect of uncertainty are empirical. Ludvigson et al. (2021) have decomposed uncertainty between macroeconomic uncertainty and financial uncertainty. According to them, financial uncertainty could be very linked to recessions, both as a cause and as a propagating mechanism. Macroeconomic uncertainty and financial uncertainty are computed using Jurado et al. (2015)'s methodology. Jurado et al. (2015) have constructed a measure of macroeconomic uncertainty using a panel of macroeconomic and financial time series (industrial production, real income, hours, unemployment, prices, stock market indexes, ...). According to Jurado et al. (2015), volatility measures are partly predictable. So, in order to get a "true" measure of uncertainty, the predictable component of each series must be removed. Using this methodology, Ludvigson et al. (2021) have developed a financial uncertainty index from a panel of 148 monthly financial indicators (Treasury bill yields, price-earnings ratio, risk factors of Fama and French (1992), ...).

Then, they propose a new method to estimate a SVAR model with several event constraints. One of their side result, this was not the objective of their paper to show

[2] Forni et al. (2021) defined downside uncertainty as the difference between the forecast of the median and the 5th percentile of the future growth. Upside uncertainty is defined as the difference between the forecast of the 95th percentile and the median of the future growth.

this, is to find a positive effect of uncertainty. In the second chapter, we have showed that this result is at best to be considered very carefully. Indeed, it appears that the positive effect of uncertainty is fully explained by one constraint. This constraint is supposedly related to the end of Bretton-Woods but we show that it is also related to the end of a one year recession. Hence the positive effect of uncertainty would be in fact the surge of growth that followed the recession.

Larsen (2021) relies on a different approach to measure uncertainty since he uses machine learning techniques to analyse Norvegian business articles published in a daily newspaper. In a first step, the author uses an unsupervised learning algorithm that will both classify by topic the articles and quantify the degree of uncertainty. Each of the 80 topics may vary in time according to the degree of uncertainty that is related to it. For instance, the measure linked to the topic on *Oil price* varies whether events related to this topic generate more or less uncertainty. Then he runs SVAR with narrative sign restrictions *à la* Antolín-Díaz and Rubio-Ramírez (2018). Some topics exhibit the usual pattern of uncertainty as more uncertainty results in a decrease in variables used to evaluate the health of an economy. However, it appears that the opposite is true for the topic on *Mergers & acquisitions* which for uncertainty has a positive effect on the economy.

To sum up this brief literature review, one of the result that identifies a positive effect of uncertainty is fragile whereas the others highlight a very specific component of uncertainty related to business activities.

4.1.2 Positive effect in the theory

Among the papers referred to above, the last two do not develop a theoretical explanation of the positive effect of uncertainty. They instead refer to two old papers by Oi (1961) and Hartman (1972) to which Larsen (2021) adds Tisdell (1978). Oi (1961) show that competitive firms that maximize short term profits always prefer price instability, hence uncertainty, over price stability. Tisdell (1978) extends the results of Oi (1961) to factors' price instability which is also preferred by competitive firms under the same conditions and shows that both output price instability and factors price instability are simultaneously preferred by competitive firms. Hartman (1972) shows that optimal investment of firms increases or remains unchanged with increased uncertainty in future output prices and/or wage rates and that it is invariant to uncertainty in future investment costs. Using a mean preserving uncertainty, he shows that this result holds quite generally except that it requires the production function to be homogeneous of degree 1. Without going too far in analyzing these results, they mostly lay on the fact firms are risk-neutral. The explanation of Oi (1961) and Hartman (1972) is based on the assumptions of perfect competition. Caballero (1991) shows that if the assumptions of perfect competition are relaxed, firms' investments may fall when uncertainty increases but this relationship could also remain positive if firms have increasing returns to scale under imperfect competition.

As already written above, in Segal et al. (2015) the authors develop a theoretical model in which uncertainty shocks may either be positive or negative. As in Hartman (1972), the two shocks are mean zero. Both consumption shocks have time varying volatilities that depend on two state variables that represent good and bad macroeconomic uncertainties. They allow a feedback effect of the macro volatilities in that they also affect expected consumption. This means that good and bad macro uncertainties have direct effects on future economic growth as well as on the shocks. As the authors put it, they do not provide a *"primitive micro-foundation for this channel*, [but they] *show direct empirical evidence to support our volatility feedback specification"*. One important aspect is that agents may dislike uncertainty be it good or bad which implies that the overall effects of uncertainty will be skewed towards bad uncertainty. That is, good uncertainty has a negative component because it implies volatility. As a consequence, the equity risk premium the authors obtain exhibit a second order moment that is positive, i.e the risk premium increases, whereas the third order moment may be either positive or negative, i.e the risk premium increases or decreases.

These two first theoretical channels are rather related to industrial prospects that may have positive effect on future growth. Here we want to suggest another mechanism that would explain a positive effect of uncertainty. This mechanism is related to recent works by Gabaix (Gabaix, 2014, 2020). In the first of these two articles Gabaix proposes the sparse max operator in which agents do not observe all the information available at time t. In order to decide which action to undertake they will first have to allocate for each available information x_i an amount m_i of attention for $i = 1, \ldots, N$. Consequently, the agent does not take into account most of the information available because it is costly to analyze it. The agent observes $x_i^s := m_i x_i$ instead of x_i and there may have a lot of null m_i depending on some parameters.

In the second article, Gabaix develops a behavioral new Keynesian model that is built on a simplified version of Gabaix (2014) as he mostly uses a macroeconomic attention parameter $\bar{m}$ which somehow represent the mean of the above m_i. Similarly, this means that agent are partly myopic since they only observe $\bar{m}x_i$. As a consequence, $\mathbb{E}_t^{BR}[z(X_{t+k})] = \bar{m}^k \mathbb{E}_t[z(X_{t+k})]$ where the left hand side (LHS) is the expected value of the behavioral agent at time t of the vector of variable X_t in k periods and the last term of the right hand side (RHS) is the expectation of a rational agent that corresponds to $\bar{m} = 1$ coefficiented by $\bar{m}^k$ which indicates that myopia is increasing with distance to the future.

One of the (many) insights of Gabaix (2020) is that with behavioral agents, Ricardian equivalence does not hold anymore. Proposition 7 of this paper is about fiscal policy and concerns a situation with a public deficit $d_t := \mathcal{T}_t + \frac{r}{R} B_t$ financed with debt in order to allow a lump-sum transfer $\mathcal{T}$ to the agents. The value of the government debt evolves as $B_{t+1} = B_t + Rd_t$. This proposition establishes that the new IS curve becomes

$$x_t = M\mathbb{E}_t[x_{t+1}] + b_d d_t - \sigma(i_t - \mathbb{E}_t[\pi_{t+1}] - r_t^{n0}) \tag{4.1}$$

We want to focus here on the second term of the RHS: $b_d d_t$. It measures the sensitivity to deficits of the agent. It is null if $\bar{m} = 1$ (agents are rational) but it is positive otherwise and decreasing in $\bar{m}$. As exposed in the appendix of Gabaix (2020), this part of the paper requires an additional state vector $\mathbf{Z}_\tau$ that complements the original vector X_τ. The agent has then to observe now some additional information that concern precisely deficits. The perceived future taxes are then given by

$$\mathbb{E}_t^{BR}[\mathcal{T}(Z_\tau)] = -\frac{r}{R}B_t + \bar{m}^{\tau-t}\mathbb{E}_t\left[d_\tau - r\sum_{u=t}^{\tau-1} d_u\right] \tag{4.2}$$

The first term of the RHS reflects a Ricardian behavior: If debt was to remain at its level in t, namely B_t, then the behavioral agent correctly anticipates that the debt will have to be repaid. The second term reflects the myopia of the behavioral agent that fails to precisely taking into account of future deficits and their fiscal consequences on its revenues, i.e futures taxes implied by the future deficits.

Now come back to Gabaix (2014) that explains how an agent chooses the degree of attention it will bring to each available information. Proposition 1 of this paper establishes the behavior of a behavioral agent that uses the sparse max procedure to choose which x_i he will consider and with which degree of attention. The consequences of proposition 1 are that (i) many x_i are eliminated, (ii) more attention is paid to more variable x_i, (iii) more attention is paid to x_i that matter more for the action the agent considers to undertake, (iv) more attention is paid to x_i that may generate great losses and (v) more attention is paid generally if the cost of attention is low.

Where do we see uncertainty in this model? One could argue that this is the variance of x_i. If this is so, then proposition 1 establishes that more attention is paid to an information that varies more. However, what if the number of x_i increases temporarily? What if the number of more variable x_i^s increases temporarily? We believe that these two possibilities better reflect the idea of a general uncertainty. In order to answer intuitively to these questions, let see how the attention vector is chosen by a behavioral agent (Definition 1 in Gabaix (2014)):

$$\underset{m\in[0,1]^n}{argmin}\frac{1}{2}\sum_{i,j=1..n}(1-m_i)\Lambda_{ij}(1-m_j)+\kappa\sum_{i=1..n}m_i^{\alpha} \tag{4.3}$$

where $\Lambda_{ij} = -\sigma_{ij}a_{x_i}u_{aa}a_{x_j}$. σ_{ij} is the covariance of x_i and x_j, a_{x_i} is the marginal effect of x_i on the optimal action of the agent and u_{aa} is the second derivative of the utility function with respect to a, the action. κ and α parameterize the psychological cost of paying attention to any variable, the first part is the quadratic loss associated to the fact of not taking the right action because the agent observes $m_i x_i$ instead of x_i.

Assume as Gabaix mostly does that the agent considers the variables as uncorrelated. Consider first the possibility of an increase of the number of variables. If one assumes that the initial total psychological cost paid by the agent before the increase in the number of variables is the maximum the agent can bear[3], then adding any new variable implies that the mean attention vector is reduced, even when $\alpha = 1$, the value recommended by Gabaix. Indeed, the agent has to allocate the same total cost on $n+1$ variables instead on n.

Consider now the second possibility of more variable x_i^s. Under the same hypothesis on the total psychological cost then, if $\alpha > 1$, increasing attention on variable x_j if m_j was already positive may necessitate to reduce at least one m_i such that $\Delta m_j < -\Delta m_i$. Consequently, the mean attention is also reduced. If m_j was null before its importance increased, then it is when $\alpha < 1$ that the same could happen. When $\alpha = 1$, then nothing happens since $\Delta m_j = -\Delta m_i$.

[3]It is admittedly a strong assumption but it reflects the more general idea that an agent may be constrained by a maximal psychological cost he can bear.

We may add that even without the assumption on the total psychological cost those effects should exist under some conditions. The characterization of those conditions is let for future work.

Finally, if one considers that variables are correlated as in 4.3. Note first that an increase of a_{x_j} implies that more attention should be paid to variable x_j. But as it is clear in 4.3, this increase will also affect the choice of the optimal m_i. There is no reason to consider that this relationship could not imply a reduction of m_i. This being true whatever the values of κ and α.

To conclude, there are a lot of reasons to believe that uncertainty may result in a decrease of $\bar{m}$ in 4.1. As a consequence, increased uncertainty would increase myopia of the agents if they are behavioral and then would reinforce the effect of the stimulus enacted by the government. It is important to be aware that the three theoretical explanations are complementary.

4.2 Uncertainty and Macroeconomy: a local projection approach

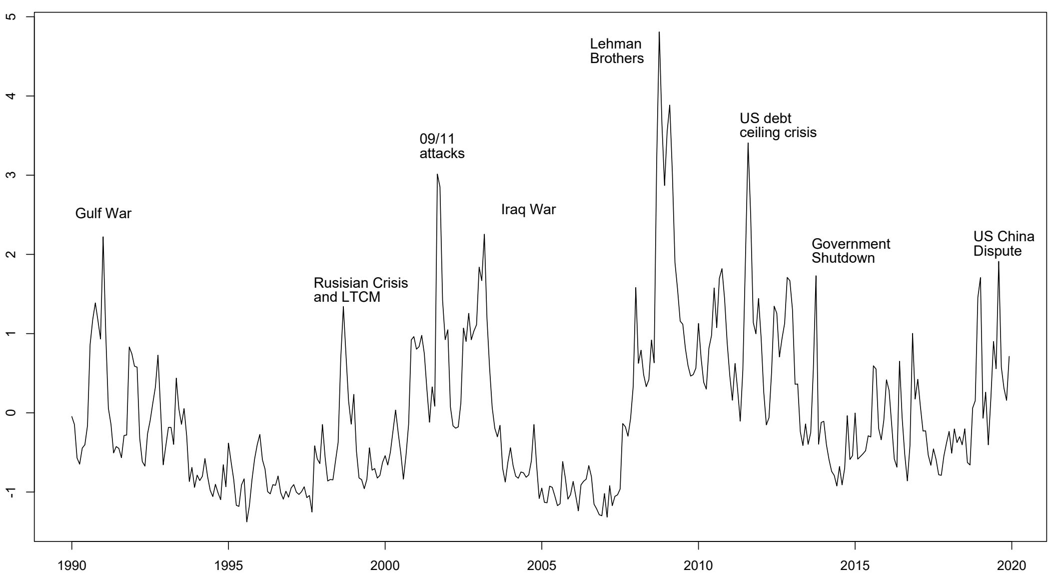
4.2.1 Uncertainty Data

To investigate the impact of uncertainty shocks on economic activity, many measures of uncertainty have been developed from different methodologies. However, many measures represent just one dimension of uncertainty: financial, economic policy, geopolitical,... As these indexes are provided from different methodologies, they provide different information. To take into account this heterogeneity, some works have developed composite indexes. Haddow et al. (2013) have constructed a global indicator of uncertainty for the United Kingdom based on a principal component analysis (PCA) with several indicators measuring uncertainty in the United Kingdom. Charles et al. (2018)

have developed a global measure for the United States applying a dynamic factor model.

We are going to apply the measure estimated in Himounet (2022) from a PCA on the period January 1990 to December 2019. Figure 4.1 represents this synthetic or general measure over this sample. It can identify different uncertainty peaks corresponding to well identified events like the Gulf War, the Russian financial crisis and Long-Term Capital Management in 1998, the 9/11 attacks, the collapse of Lehman Brothers or the US debt-ceiling dispute in 2011. These are shocks (financial, macroeconomic, geopolitical, policy,...) that increase the general uncertainty.

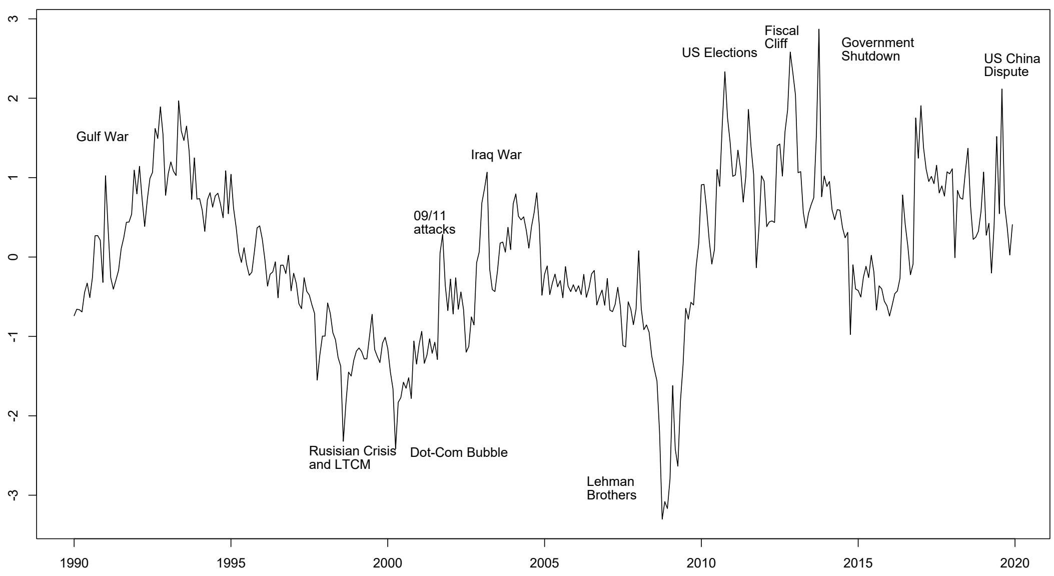
Figure 4.1: General Uncertainty Index



Note: The index is standardized over the period 1990-2019.

The second factor ($Factor2$) of the PCA of Himounet (2022) concerns the nature of uncertainty shocks (Figure 4.2). This variable discriminates two types of uncertainty shocks: non-financial and financial. The interpretation of this variable is that when this factor is high, the nature of uncertainty shocks is associated with macroeconomics or non-finance (Gulf War, Iraq War, Government Shutdown,...). Inversely, when this variable is low, the nature of uncertainty shocks is financial (LTCM, Dot-Com bubble, Lehman Brothers). We will use this variable to investigate the nature of uncertainty shocks. As both variables are provided by the same PCA, they are orthogonal by construction.

Figure 4.2: Factor 2



Note: The index is standardized over the period 1990-2019.

4.2.2 Linear Framework

To investigate the dynamics between macroeconomy and uncertainty, vector autoregressive (VAR) models developed by Sims (1980) have been traditionally used in the empirical literature to construct impulse responses. Based on the conventional reduced form VAR model, the notation for the impulse response function is based on the difference between two forecasts (Hamilton, 1994):

$$IR(t, s, d_i) = E\left(y_{t+s}|v_t = d_i; X_t\right) - E\left(y_{t+s}|v_t = \mathbf{0}; X_t\right) \quad s = 0, 1, ... \tag{4.4}$$

where $E(.|.)$ denotes the best mean squared error predictor, y_t is a $n \times 1$ vector, X_t denotes the lags of y_t (y_{t-1}, y_{t-2}, y_{t-3},...), **0** is a $n \times 1$ vector containing 0, v_t denotes a vector of reduced-form disturbances, and D is an $n \times n$ matrix, whose columns d_i contain the relevant experimental shocks.

Jordá (2005) has pointed out that this methodology is not optimal if the VAR does not coincide with the underlying data generating process and has developed a popular alternative approach to impulse responses from VAR: local projection methods. This methodology consists in running a series of predictive regressions of our variable of interest. The impulse responses are computed using regression coefficients. According to the author this method has many advantages. Local projections can be estimated by one equation, they are more robust to misspecification of the data generating process and can easily be adapted to a nonlinear framework. Jordá (2005) has demonstrated that impulse responses from a VAR and local projection are equivalent if the VAR coincides with the true data generating process. Montiel Olea and Plagborg-Møller (2021) and Plagborg-Møller and Wolf (2021) have showed that local projections are more robust than the SVAR methodology. Both methodologies lead to the same median impulse responses in the short and medium term.

Applying the local projections of Jordá (2005), we run the following regressions:

$$y_{t+s} = \alpha_s + B_1^{s+1} y_{t-1} + B_2^{s+1} y_{t-2} + ... + B_p^{s+1} y_{t-p} + u_{t+s}^s \tag{4.5}$$
$$s = 0, 1, ..., h$$

where y_t is a vector of endogenous variables including our synthetic measure of uncertainty and a set of monthly macroeconomic variables:[4] industrial production, unemployment rate, inflation, oil prices, the S&P500 index and the fed funds rate. Impulse responses are computed according to:

$$\hat{IR}(t, s, d_i) = \hat{B}_1^s d_i \qquad (4.6)$$
$$s = 0, 1, ..., h$$

where d_i corresponds to the i^{th} column of the experimental matrix D and the identified structural shock. We construct this matrix following the suggestion of Jordá (2005), which essentially follows methodologies applied in the traditional VAR literature and begins by estimating a SVAR with a Cholesky decomposition as identification scheme. If the shock is already identified and/or considered as exogenous, there is no need to apply a VAR model and the Cholesky decomposition:[5]

$$x_{t+h} = a^h + b^h shock_t + \gamma z_t + \epsilon_{t+h} \qquad (4.7)$$

x_t represents the variable of interest, z_t a vector of control variables and $shock_t$ represents the identified or exogenous shock. The impulse response of $shock_t$ on x_t will correspond to the series of coefficients b^h for each horizon h.

We apply a Cholesky decomposition as many works which have used VAR models to identify our shocks (See, among many others, Bloom, 2009; Colombo, 2013; Jurado et al., 2015; Baker et al., 2016; Leduc and Liu, 2016, 2020). Therefore, to compute the impulse response functions, we have to determine the contemporaneous impact ma-

[4] The data used for the analysis are downloaded from FRED database on the Federal Reserve Bank of St. Louis' website.

[5] Other identification scheme can be applied with local projections: long-run restrictions, identification with external instruments (Jordá, 2005; Stock and Watson, 2018; Plagborg-Møller and Wolf, 2021).

trix with a VAR model applying Cholesky decomposition to identify structural shocks. d_i denotes the i^{th} column of the Cholesky decomposition and therefore represents the structural shock to the i^{th} element in y_t. A crucial point is to estimate the contemporaneous impact matrix applying the Cholesky decomposition. The impact of shocks can differ with the ordering of our variables. We order our variables such that:

$$y = \begin{bmatrix} \text{SP500} \\ \text{OIL} \\ \text{GU} \\ \text{Inflation} \\ \text{Unemployment rate} \\ \text{Fed funds rate} \\ \Delta\text{log(Industrial production)} \end{bmatrix}$$

where GU denotes our measure of general uncertainty. We use $\Delta\log(\text{Industrial Production})$ to have a stationary variable (IPI). We order our measure of uncertainty third under the assumption that uncertainty shocks will have an immediate impact on the macroeconomic variables. $SP500$ is the $\Delta\log(\text{Stock market index})$, it is usually placed first in the literature. We collected this variable on Yahoo! Finance. The second one is OIL, the monthly price of crude oil (West Texas Intermediate) deflated by the consumer price index and also in log difference to have a stationary variable. It is aimed at capturing possible geopolitical foreign influence on US economics contrary to previous works that who did not take it into account. We order these both variables before uncertainty index under the assumption that these variables are unaffected by the uncertainty shock to take into account expectations and identify an unanticipated uncertainty shock. Inversely, the macroeconomic variables will not have an immediate impact on uncertainty. This is a common choice in the empirical literature (See, among others, Bloom, 2009; Baker et al., 2016; Caggiano et al., 2014; Istrefi and Mouabbi, 2018). The idea is that agents do not have information about the current macroeconomic conditions (Leduc and Liu, 2016) because data are not yet available. $Inflation$ (I) is ranked fourth since price may react quickly after a shock. We place the fed funds rate (Fed) after the unemployment rate (U) under the assumption that the Federal Reserve will react instantly to an unemployment shock. Indeed, one objective of the Federal Reserve is a low level of unemployment.[6] The results reported in Figure A.1.1 demonstrate that no unit root lies outside the unit root circle, indicating the stationarity of the VAR. The estimated coefficients of each equation are display in Table A.1.1. A result which can be surprising is the value of the R^2 for the unemployment and the Fed funds rate which is close to 0.99 even if we have shown the stationarity of the VAR.[7] These results could be due to the fact that their past values are statistically significant contrary to other variables meaning that these variables are strongly linked to their past values.[8]

Examining the impulse response functions from the local projections, the impact of uncertainty on macroeconomic variables, we find a statistically negative impact on economic activity as almost all works.[9] We get a negative effect on employment during the months following the uncertainty shock with an increase in unemployment (Figure 4.3). These results highlight a *wait and see* behavior where firms delay investment and hiring decisions. We get a slightly negative effect on industrial production in the near term. The Fed decreases its rate in order to boost the economy.

We run the same exercise with $Factor2$ as uncertainty variable to investigate the effect of the nature of uncertainty shocks. We replace the general uncertainty index by the second factor ($Factor2$) in the model. According to its interpretation, a positive shock to this second factor indicates more non-financial uncertainty. We find that a

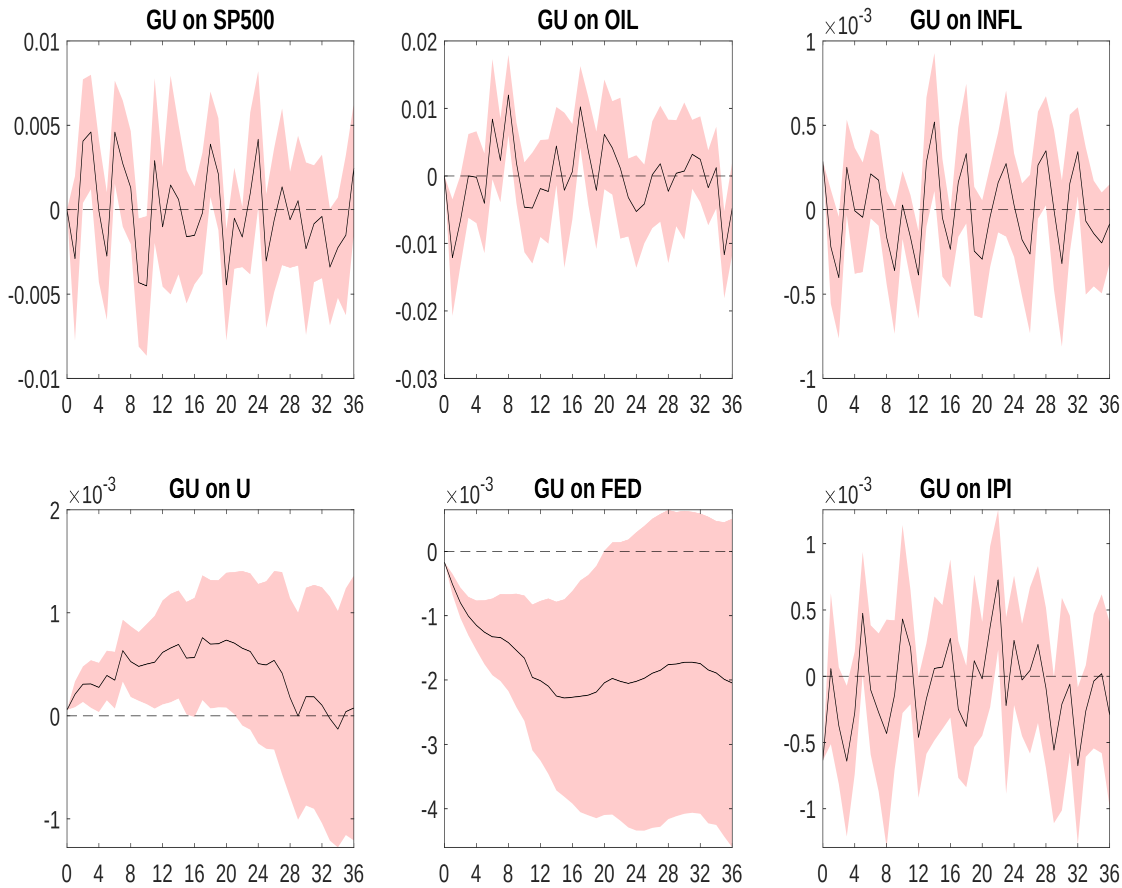
[6]To determine the number of lags, we apply the Akaike information criteria (AIC).

[7]Moreover, both variables do not have a unit root applying the Elliott-Rothenberg-Stock (ERS) test.

[8]We get the same results if we apply the Hodrick-Prescott filter in robustness checks. The VAR of the seminal paper of Bloom (2009) also presents high values of the R^2.

[9]The effect is significant at the 5% level. Applying local projections, the residuals u^t_{t+s} are a moving average of the forecast errors. To correct heteroskedasticity, we compute error bands applying the Newey and West (1987) method.

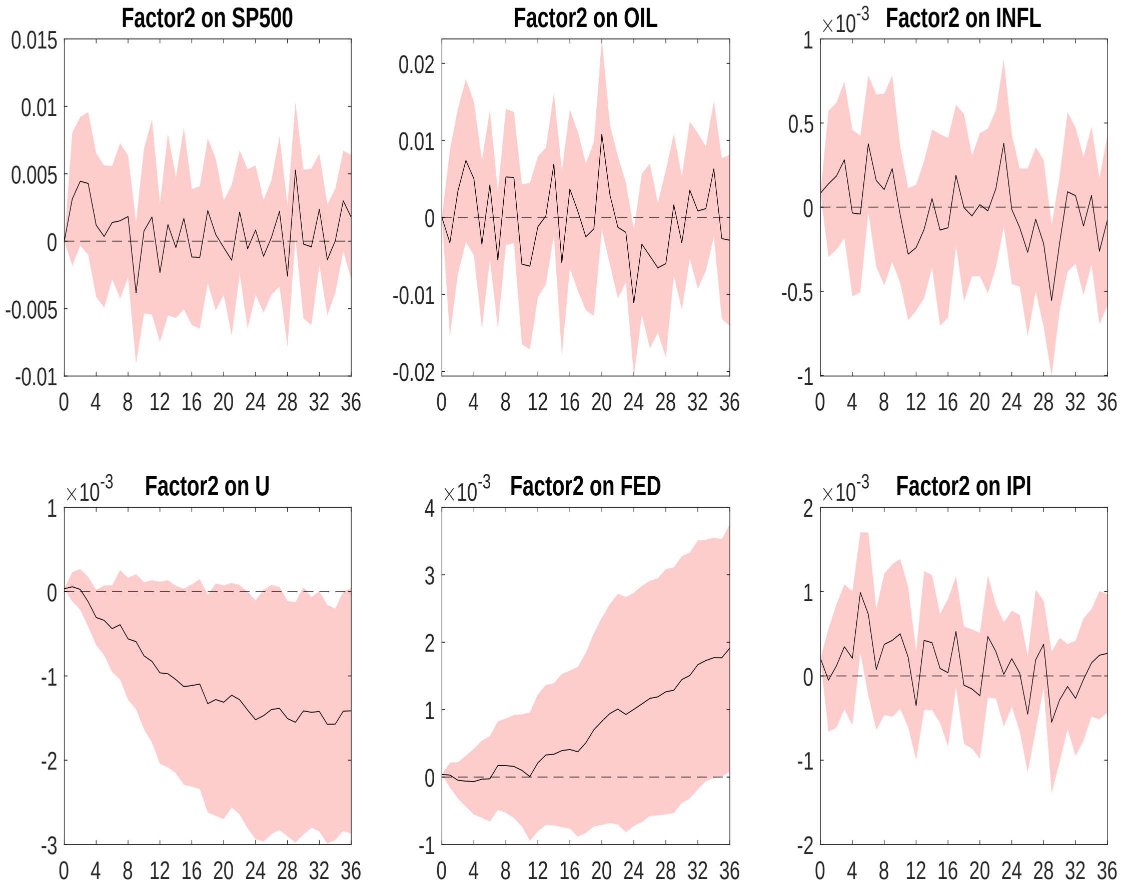
Figure 4.3: Impulse Response Functions



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

non-financial uncertainty shock has no significant effects on industrial production and unemployment during the months following the shock (Figure 4.4). We run a VAR but we introduce the product of both factors ($GU * Factor2$) instead of each factor alone. It is worth noticing that no caution is needed when introducing this product since these two factors present the quality of being independent from each other by construction from the PCA. Hence this variable is high when both factors are high, i.e when uncertainty is high and non-financial. Remind here that both theoretical frameworks that, according to us, may explain why uncertainty could be positive rely on non financial uncertainty. Growth option theory relies on an industrial uncertainty whereas Gabaix's theory relies on a general macroeconomic uncertainty.

Figure 4.4: Impulse Response Functions



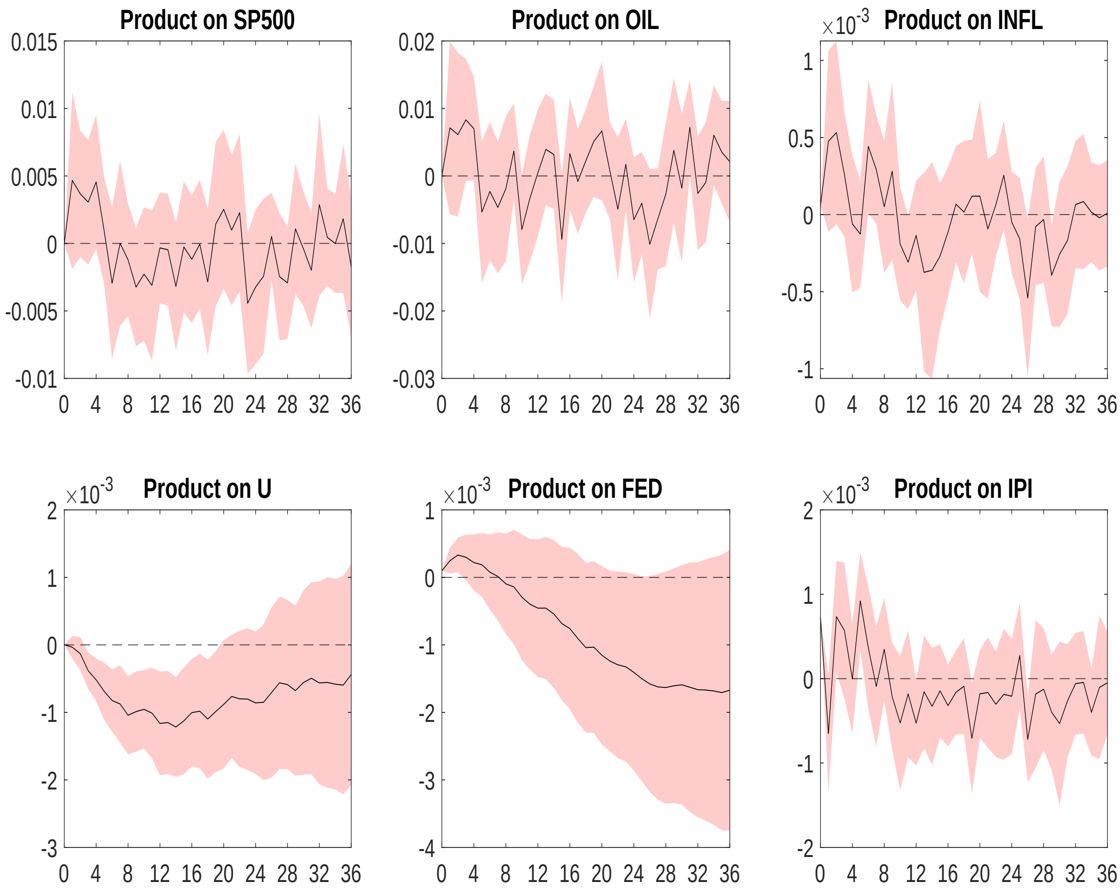
Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

The striking result we obtain is that when the product is shocked it has a short positive and significant impact on industrial production and a lasting negative and significant effect on unemployment (Figure 4.5). These results show that the variable $Factor2$ representing the nature of uncertainty does not have a significant effect but its interaction with the overall level of uncertainty can provide a much richer set of results. Hence, as we hypothesized, uncertainty can have a positive effect on the economy. More specifically, uncertainty has a positive effect when it is non financial interacting it with the overall level of uncertainty. However, we do not know exactly what happens in the product $GU * Factor2$. For instance, the product of both factors may be as high when uncertainty is high and the nature of uncertainty is indeterminate as when the nature of uncertainty is non-financial and uncertainty is moderate. This result is rather a confirming intuition than a robust proof. In order to check whether this intuition is correct using a proper estimation method, we turn to a non linear framework.

4.2.3 Non linear framework

In the linear framework, we have found that a shock of the nature of uncertainty doesn't have a significant effect whereas uncertainty does have an effect. However, the nature may have an effect depending on the general level of uncertainty or uncertainty may have a different impact depending on the nature of uncertainty. This is what suggests the previous intuitive test using the product of both factors. A non linear framework allows to study the effect of a shock on a variable conditioned to the level of another variable. This intuition comes from the theoretical model of Gabaix (2020) assuming that agents are partly myopic. Therefore, they fail to perfectly anticipate future taxes after a stimulus generating an effective stimulus. A corollary of these results is that myopia is exacerbated when uncertainty is high. Following these theoretical arguments, taking the second factor of the PCA of Himounet (2022) distinguishing non-financial uncertainty from financial uncertainty as a threshold variable makes no sense given its non cardinal nature. Therefore, we are going to use the measure of general uncertainty representing the overall level of uncertainty as the threshold variable. Concretely, we aim at studying the effect of a shock on the nature of uncertainty conditioned to various levels of the general uncertainty. This strategy allows to examine the interaction between

Figure 4.5: Impulse Response Functions



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

both measures in another way.

High, moderate and low uncertainty regimes

A great advantage of the local projection methodology is that it can easily be adapted to a nonlinear framework. Many works have applied local projections to study non linear effects, threshold effects (See, among many others, Owyang et al., 2013; Ramey and Zubairy, 2018; Ahmed and Cassou, 2021). We apply local projection methods to investigate the impact of the nature of uncertainty shocks in different regimes estimating the state-dependent impulse response functions. We have decided to use a three regimes set-up as our preferred specification in order to properly distinguish the high uncertainty regime from the low uncertainty regime, thus implying that a moderate uncertainty regime also exists.[10]

We consider the extension of our baseline model with threshold effects:

$$y_t = I(z_{t-1} < \gamma_1)\Pi_L(L)y_{t-1} + I(\gamma_1 \leq z_{t-1} < \gamma_2)\Pi_M y_{t-1} + I(z_{t-1} > \gamma_2)\Pi_H y_{t-1} + \mu_t$$

where y_t is a vector of endogenous variables including our measure of the nature of uncertainty and the set of monthly macroeconomic variables that we have used in the linear framework. z_t is the switching variable which is the measure of general uncertainty. I denotes an indicator function which takes the value of 1 alternatively if the first factor is above the threshold value γ_2 (high uncertainty regime, H), or between the two threshold values γ_2 and γ_1 (moderate uncertainty regime, M), or below γ_1 (low uncertainty regime, L). $\Pi_H(L)$ is a lag-polynomial of matrices in the high uncertainty regime. $\Pi_M(L)$ is a lag-polynomial of matrices in the moderate uncertainty regime. $\Pi_L(L)$ is a lag-polynomial of matrices in the low uncertainty regime. The threshold values are estimated applying a TVAR model. The threshold values of the switching variable are determined endogenously by a grid search over possible values of the switching variable. The grid is constructed such that the grid is trimmed at a lower and upper bound to ensure a minimal percentage of observations in each regime. In practice, the level is chosen arbitrary. It doesn't exist a general guideline. However, a level around 20% of observations in each regime has often been used. The estimation of the threshold value corresponds to the model with the smallest determinant of the covariance matrix of the error terms μ_t.

We apply the Likelihood Ratio (LR) test to test the linearity (Table A.2.1). The LR

[10]We extent the R code of the package *lpirfs* of Adämmer (2019) to add the third regime.

test rejects the null hypothesis of linearity. A nonlinear framework is more appropriate to study the impact of shocks. Moreover, the LR test rejects the null hypothesis of two regimes against three regimes. It means that three regimes are more appropriate to study the effect of the non linear effects of the nature of the shocks instead of two regimes. As in the linear framework, we apply local projection that we adapt to a non linear framework such that:

$$y_{t+s} = I(z_{t-1} < \gamma_1)\Pi_L^{s+1}(L)y_{t-1} + I(\gamma_1 \leq z_{t-1} \leq \gamma_2)\Pi_M^{s+1}y_{t-1} + I(z_{t-1} > \gamma_2)\Pi_H^{s+1}y_{t-1} + \mu_{t+s}^s$$

Impulse responses in a high uncertainty regime are computed according to:

$$\hat{IR}(t,s,d_i) = \hat{\Pi}_{1,H}^s d_i \qquad (4.8)$$
$$s = 0, 1, ..., h$$

Similarly, impulse responses in a low uncertainty regime are computed according to:

$$\hat{IR}(t,s,d_i) = \hat{\Pi}_{1,L}^s d_i \qquad (4.9)$$
$$s = 0, 1, ..., h$$

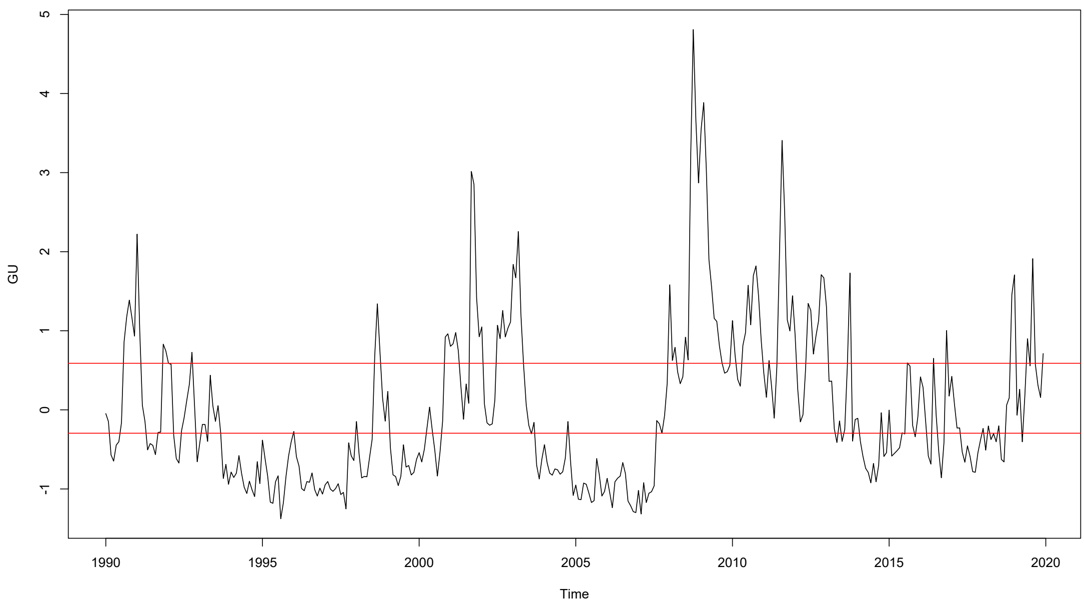
And for the moderate uncertainty regime:

$$\hat{IR}(t,s,d_i) = \hat{\Pi}_{1,M}^s d_i \qquad (4.10)$$
$$s = 0, 1, ..., h$$

where d_i is the i^{th} column of the Cholesky decomposition as in the linear framework.

The estimated threshold values of -0.2953414 and 0.5885597 allow to separate shocks of the last two decades as the following graph highlights.

Figure 4.6: Two thresholds of general uncertainty

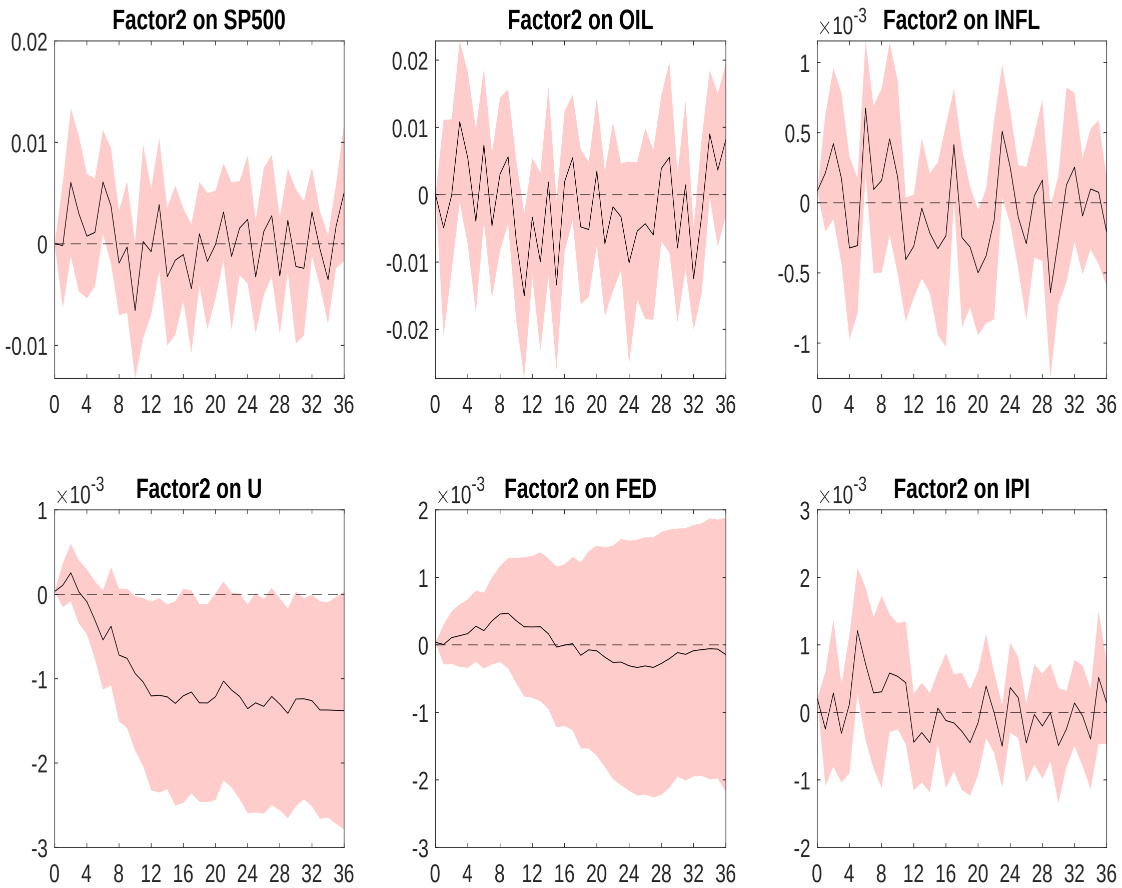


Source: Author's own calculations.
Notes: The horizontal red lines correspond to the estimated threshold values (-0.2953414 and 0.5885597)

The results for the three different regimes are provided in Figure 4.7, Figure 4.8 and Figure 4.9. As for the linear framework, we do not have any significant effect of the nature of uncertainty under the low uncertainty regime and there is a very short negative effect on industrial production. However, it turns out that under both the moderate and the high uncertainty regimes, the nature of uncertainty has a positive significant and lasting effect on unemployment. There is a short (a quarter) positive effect on production industrial production under the moderate regime. One should note that the effect on unemployment is stronger in the moderate uncertainty regime whereas it lasts longer in the high uncertainty regime.[11]

[11] We get results which are qualitatively equivalent for the moderate and high uncertainty regimes extending the regression 4.7 to our non-linear specification even if they are less significant (Figure A.2.1). $Factor2$ is considered as the identified shock and the vector of control variables contains the lags of

Figure 4.7: Impulse Response Functions in a high uncertainty regime

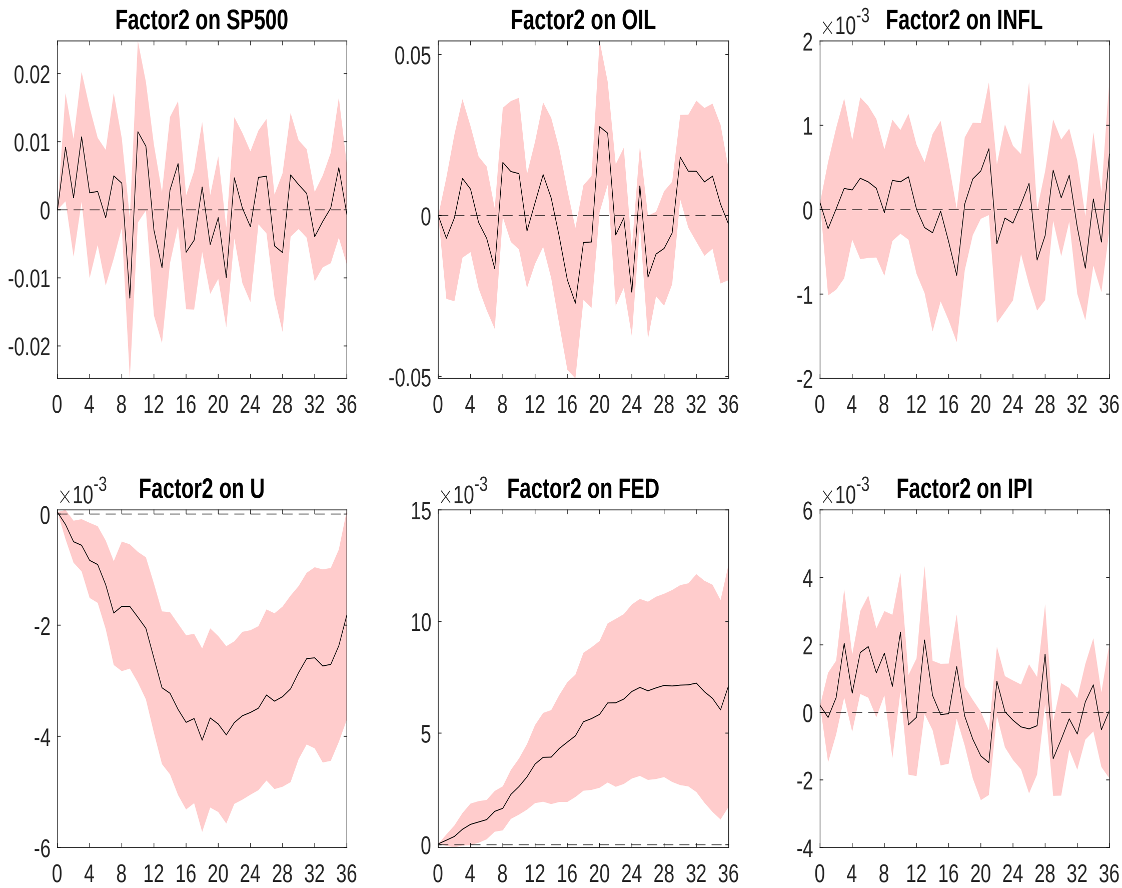


Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

In the theoretical literature, "growth options" theories argue that some forms of uncertainty can have a positive effect on economic activity. This theory refers more specifically to macroeconomic uncertainty related to technology. During the last decade, many technological advances have appeared and other advances are developing. We can take the example of the rapid development of artificial intelligence (AI). AI will provide growth opportunities that will benefit firms and the economy in the future. However, we

$Factor2$ and the lags of other macroeconomic variables of our baseline model.

Figure 4.8: Impulse Response Functions in an intermediate uncertainty regime

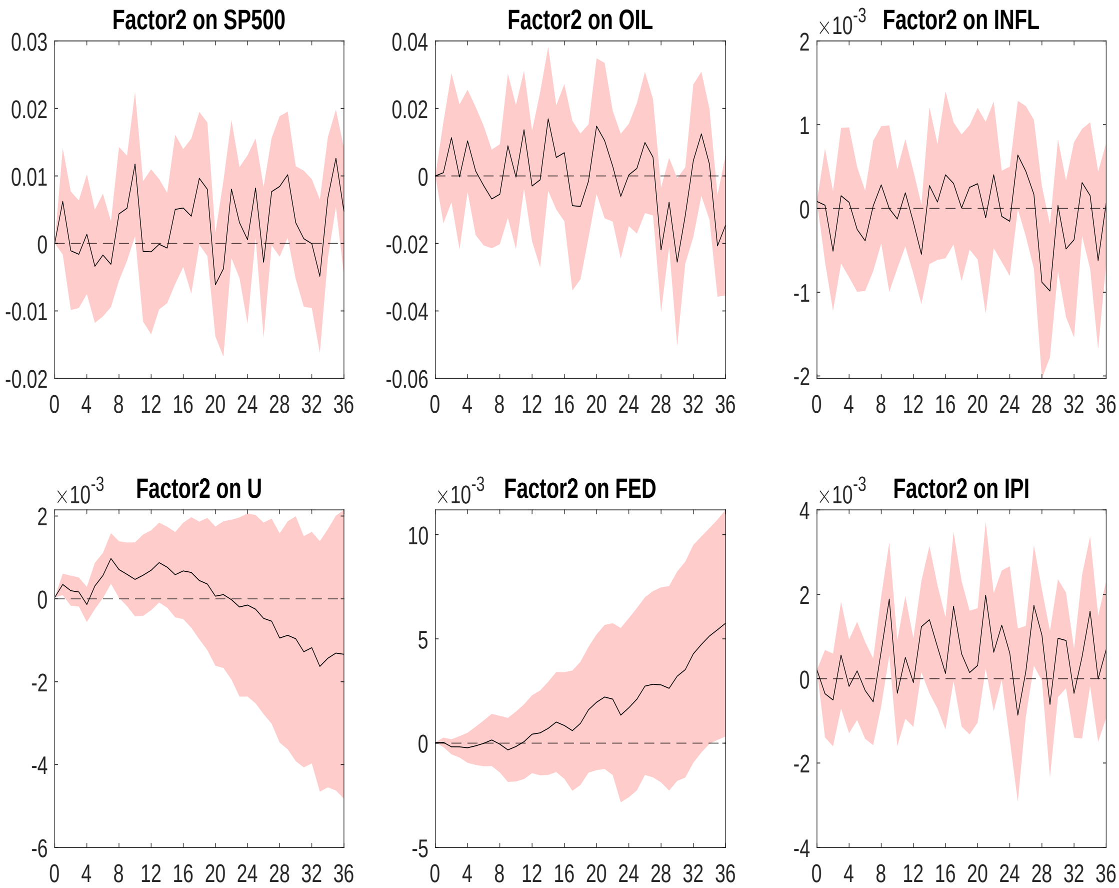


Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

do not know which firms and by how much. That is why, there isn't a consequent gain when we examine the response of industrial production since most of the work firms do on AI is R & D.

Another explanation which is not exclusive of the previous one is as follows. Gabaix (2014, 2020) has shown that when a lot of information is available then individuals have to choose which information to analyze and by how much they will do so. It results that when a lot of information is available, individuals are not able to anticipate that an

Figure 4.9: Impulse Response Functions in a low uncertainty regime



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

economic stimulus will certainly induces taxes to rise in a quite near future and hence, accordingly, to save money thus suppressing the positive expected effect of the stimulus. In other words, the quantity of available information shuts down the ricardian equivalence. Importantly, this effect works on the theoretical set-up of Gabaix uniquely when myopia is strong. So, behind this second factor, we could have a distinction between a "positive" macroeconomic uncertainty that could refer to technological progress and a "negative" uncertainty which is financial.

The fact the effect on unemployment is stronger in the moderate regime may seem counter-intuitive. We argue however that, concerning the growth theory explanation, the technical uncertainty it involves is not surging as a peak but is rather a lasting phenomenon that corresponds quite well with a moderate uncertainty regime. As for the Gabaix explanation, we argue that under the high uncertainty regime, the negative financial uncertainty is also often there. The negative effect of financial uncertainty on unemployment may attenuate the positive effect induced by the increased myopia of the agents. In other words, the remedy is working but the illness it has to cure is very damaging.

To add an additional evidence to validate these assumptions, we redo our procedure on a subsample as a robustness check: 1990-2006. By doing so we suppress the financial crisis during which uncertainty unambiguously has had a massive negative effect. We redo the PCA of Himounet (2022) applying the same set of uncertainty indexes on this subsample. We do not observe major changes concerning the first two factors of this new PCA (Figure B.1.1). The first factor represents the overall level of uncertainty and the second factor also represents the distinction between non-financial and financial uncertainty shocks. A shock of non-financial uncertainty in a low uncertainty regime has no significant effects on macroeconomic variables (Figure B.1.5) as in a high uncertainty regime (Figure B.1.3). However, in the intermediate uncertainty regime, there is a significant positive effect on unemployment and a significant negative effect on the industrial production in the short term (Figure B.1.4).

Several explanations may hold. By suppressing the 2007-2019 period, we originally aimed at reinforcing the positive effect we have highlighted by removing the negative effect of the financial crisis. It appears that we obtain the opposite result: uncertainty is again negative. In fact we have also removed all the positive effect of the industrial uncertainty, i.e all the high-tech innovations of the 2007-2019 decade that according to our “growth option” explanation have had a positive effect. Another relies on the theoretical result of Gabaix (2014, 2020) that we interpret simply as the fact that uncertainty restores its efficiency to economic stimulus. As a matter of fact, there has been a large stimulus in the US during the period 2007-2019 that we have also suppressed by shortening the sample.

This additional exercise does not help us to disentangle between both explanations but confirms that they can be convincing. In addition, note that both explanations are not mutually exclusive and may therefore be both valid. We nevertheless can notice that the effect of the nature of uncertainty on the fed's rate is in line with the Gabaix's explanation since the rate increases as usually happens after a stimulus in order to avoid an overheated economy. In order to better test our assumption linked to high-tech innovations, we should construct a measure of uncertainty related to technology. We let this task for future works.

4.3 Robustness Check

4.3.1 Non linear framework with two regimes

We try here to do the same exercise than before but with two regimes instead of three. The VAR is then the following:

$$y_t = (1 - I(z_{t-1} > \gamma))\, \Pi_L(L) y_{t-1} + I(z_{t-1} > \gamma) \Pi_H y_{t-1} + \mu_t$$

As we proceed in the whole paper, we use local projections that we adapt to the non–linear framework:

$$y_{t+s} = (1 - I(z_{t-1} > \gamma))\, \Pi_L^{s+1}(L) y_{t-1} + I(z_{t-1} > \gamma) \Pi_H^{s+1} y_{t-1} + \mu_{t+s}^s$$

Impulse responses in a high uncertainty regime are computed according to:

$$\hat{IR}(t, s, d_i) = \hat{\Pi}^s_{1,H} d_i \tag{4.11}$$
$$s = 0, 1, ..., h$$

Similarly, impulse responses in a low uncertainty regime are computed according to:

$$\hat{IR}(t, s, d_i) = \hat{\Pi}^s_{1,L} d_i \tag{4.12}$$
$$s = 0, 1, ..., h$$

The estimated threshold value is equal to 0.5938924 (Table A.2.1) It means that when we are above this threshold, the situation is very more uncertain than the average. Here, we investigate the impact of the nature of shocks when we are in a high uncertainty regime and a low uncertainty regime. We find that a non-financial uncertainty shock doesn't have significant effects when we are in the low uncertainty regime (Figure B.2.2). However, we a negative and significant effect on unemployment when we are in the high uncertainty regime (Figure B.2.1). The decrease of unemployment is persistent for many months. Consequently, the results are qualitatively the same than with three regimes. Note that by construction under two regimes, these are the moderate and the low regimes that are merged into one regime. It is interesting that when doing so, the results of the low regimes "dominate" those of the moderate regime.

4.3.2 Alternative ordering

Uncertainty has been ordered third in the VAR. However, uncertainty has been ordered last by some authors (See, among others, Colombo, 2013; Jurado et al., 2015; Charles et al., 2018). Uncertainty has been ordered last to remove the measure of uncertainty of the contemporaneous movements of the macroeconomic variables (Colombo, 2013).

There is no consensus on how to order the measure of uncertainty in the vector of endogenous variables. We redo local projections and a SVAR model with a Cholesky Decomposition to identify shocks in ordering our measure of uncertainty in last. This novel ordering implies that all shocks of the system can have a contemporaneously impact on our measure of uncertainty. This alternative ordering could change the dynamic of the system. However, our results are very similar.[12] We have a short-term negative impact on industrial production with our general uncertainty using local projections. There is an effect which isn't statistically different from zero with the second factor. Applying this ordering in our nonlinear framework, the results are qualitatively identical.

4.3.3 Hodrick Prescott Filter

Following the seminal paper of Bloom (2009), we detrend the variables that are applied in the VAR model applying the Hodrick-Prescott filter except the uncertainty variable. Following Ravn and Uhlig (2002), we take the smoothing parameter $\lambda = 129600$ for monthly data. The results are qualitatively equivalent with a negative effect of a general uncertainty shock (Figure B.3.1) on economic activity with the decline in industrial production and the rise in unemployment. Applying our non linear framework with the general uncertainty as threshold variable, a positive shock on the second has a negative effect on economic activity in a low uncertainty regime (Figure B.3.4). We keep the positive effect in an intermediate uncertainty regime (Figure B.3.5). In the high uncertainty regime, we have a decrease in unemployment and an increase in industrial production which are not significant a 5% level (Figure B.3.6).[13]

[12] The results and figures are available upon request.
[13] These results are more significant at a 10% level.

4.3.4 VAR-8

In this subsection, we run local projections with our non-linear specification applying the eight-variable VAR model of Bloom (2009); Jurado et al. (2015); Charles et al. (2018) ordered as follows: the S&P 500 stock index, the manufacturing production (IPI), the level of employment (EMP), the average hours worked in manufacturing, the wage in manufacturing, the log aggregate CPI, the Federal Funds rate, and uncertainty. The measure of uncertainty is ordered at the end. We identify the shocks with a Cholesky decomposition as previously. The results are less significant but we keep a slightly positive effect of $Factor2$ on the industrial production and the employment under the high and the moderate regime of uncertainty (Figure B.4.1).

4.4 Conclusion

This chapter has investigated the effects of uncertainty applying a local projection approach in a linear and a non linear framework. We apply the second factor of the PCA of Himounet (2022) distinguishing financial uncertainty from non-financial uncertainty, hence it is about the nature of uncertainty. In the linear framework, this variable doesn't have a significant effect but its interaction with the overall level of uncertainty provides a significant positive effect. Applying a nonlinear framework to measure the interaction of this variable with the overall of uncertainty in another way, the estimation of a positive effect of the second factor when general uncertainty is above its mean confirms that uncertainty may indeed have a positive effect. Uncertainty associated with this second dimension can refer to macroeconomic uncertainty related to technological progress. Firms don't doubt that technological progress is a source of value creation. However, there is uncertainty on the final gain only. This uncertainty can lead firms to invest and hire. The estimation of a negative effect on the subsample 1990-2006 seems to be another sign of our assumption of technological progress. Another explanation relies on the theoretical works of Gabaix (2014, 2020). He shows that when agents are strongly myopic, economic stimuli regain in effectiveness. The simple interpretation that we make of his results is that by increasing myopia, uncertainty suppresses the Ricardian equivalence. Therefore, an increased uncertainty restores the effectiveness of an economic stimulus. Again, the results with the subsample 1990-2006 seem to confirm this hypothesis since the large economic stimulus that followed the 2007-2008 crisis disappears from the sample.

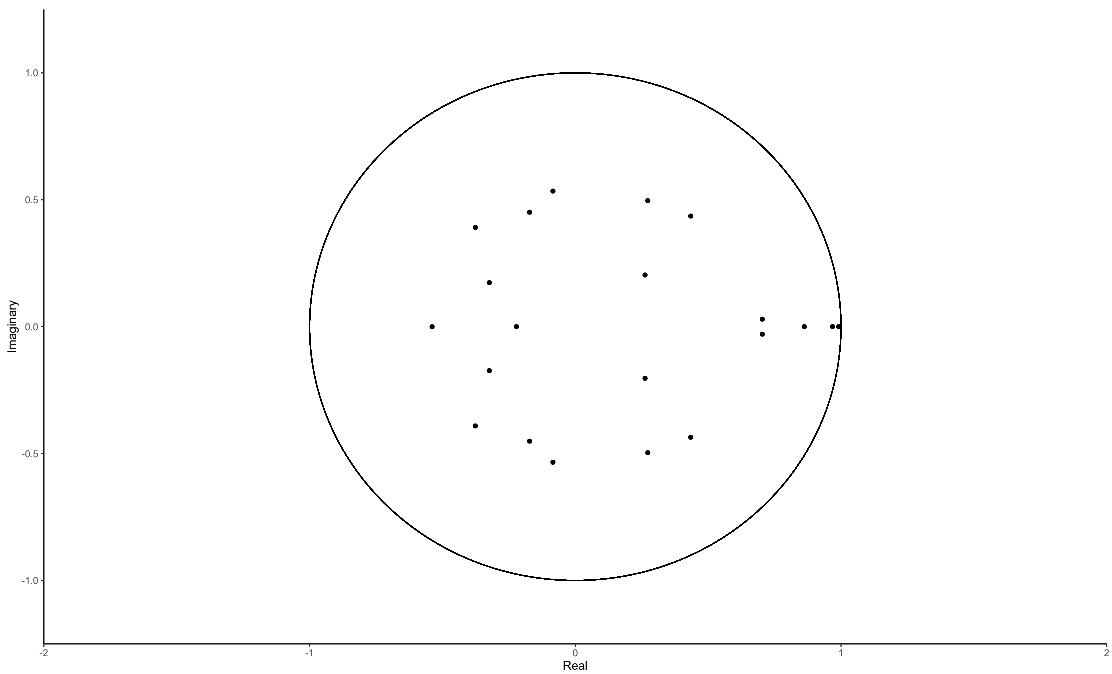
All in all, we have showed that uncertainty may indeed be positive when it is non-financial and strong. We have proposed two explanations on this positive effect which both are credible and not exclusive of each other. In order to test whether one is more valid one should construct a measure of technological uncertainty which represents another quite challenging perspective.

Appendix

A Local Projections: Impulse response functions

A.1 Linear Model

Figure A.1.1: Inverse roots of AR characteristic polynomial



Source: Author's own calculations.
Note: The VAR is specified with 3 lags.

Table A.1.1: Linear Model Results: GU as Uncertainty variable

	SP500	OIL	GU	Infl	U	FED	IPI
(Intercept)	0.00	0.01	-0.19	0.00	-0.00	0.00	-0.00
	(0.01)	(0.02)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
SP500_{t-1}	-0.03	-0.02	-3.69^{***}	0.00	-0.00	0.00	0.01
	(0.06)	(0.12)	(0.72)	(0.01)	(0.00)	(0.00)	(0.01)
OIL_{t-1}	0.01	0.24^{***}	-0.27	0.01^{***}	-0.00	0.00	0.01
	(0.03)	(0.06)	(0.35)	(0.00)	(0.00)	(0.00)	(0.00)
GU_{t-1}	-0.00	-0.02^{*}	0.73^{***}	-0.00	0.00	-0.00^{**}	0.00
	(0.01)	(0.01)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-1}	-0.35	-0.31	7.02	0.34^{***}	-0.01	-0.04	0.00
	(0.69)	(1.33)	(8.24)	(0.06)	(0.02)	(0.02)	(0.09)
U_{t-1}	-0.78	6.91^{*}	17.44	0.16	0.85^{***}	0.01	-0.43^{*}
	(1.63)	(3.14)	(19.40)	(0.14)	(0.05)	(0.05)	(0.22)
FED_{t-1}	1.59	4.34	-30.89	0.10	-0.07	1.39^{***}	0.25
	(1.78)	(3.44)	(21.29)	(0.15)	(0.06)	(0.05)	(0.24)
IPI_{t-1}	1.16^{**}	1.49	-13.74^{**}	0.01	-0.04^{**}	0.05^{***}	-0.03
	(0.40)	(0.78)	(4.81)	(0.03)	(0.01)	(0.01)	(0.05)
SP500_{t-2}	0.01	-0.06	-1.05	-0.00	-0.00	0.00	0.03^{**}
	(0.06)	(0.12)	(0.74)	(0.01)	(0.00)	(0.00)	(0.01)
OIL_{t-2}	0.04	0.01	-0.31	-0.00	-0.00	-0.00	0.00
	(0.03)	(0.06)	(0.36)	(0.00)	(0.00)	(0.00)	(0.00)
GU_{t-2}	0.02^{*}	0.01	-0.13	0.00	-0.00	0.00	-0.00
	(0.01)	(0.01)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-2}	-0.77	0.60	1.07	-0.17^{**}	-0.00	0.04	-0.05
	(0.72)	(1.38)	(8.56)	(0.06)	(0.02)	(0.02)	(0.10)
U_{t-2}	-1.02	-11.07^{**}	5.93	-0.15	0.15^{*}	0.03	0.56^{*}
	(2.11)	(4.06)	(25.12)	(0.18)	(0.07)	(0.06)	(0.28)
FED_{t-2}	0.01	-2.46	39.93	-0.31	0.10	-0.24^{*}	-0.22
	(3.07)	(5.92)	(36.62)	(0.26)	(0.10)	(0.09)	(0.41)
IPI_{t-2}	1.03^{*}	0.16	-7.53	0.09^{**}	-0.03^{*}	0.00	0.07
	(0.42)	(0.80)	(4.96)	(0.03)	(0.01)	(0.01)	(0.06)
SP500_{t-3}	0.07	0.19	-1.23	0.01	-0.00	-0.00	0.04^{***}
	(0.06)	(0.11)	(0.68)	(0.00)	(0.00)	(0.00)	(0.01)
OIL_{t-3}	0.01	-0.10	0.99^{**}	0.00	0.00^{*}	-0.00	-0.00
	(0.03)	(0.06)	(0.35)	(0.00)	(0.00)	(0.00)	(0.00)
GU_{t-3}	0.00	0.02^{*}	0.11	0.00	0.00	0.00	-0.00
	(0.00)	(0.01)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-3}	0.11	0.02	3.68	-0.06	-0.03	-0.03	0.11
	(0.65)	(1.26)	(7.78)	(0.05)	(0.02)	(0.02)	(0.09)
U_{t-3}	1.70	3.90	-18.43	-0.02	-0.00	-0.04	-0.08
	(1.64)	(3.17)	(19.58)	(0.14)	(0.06)	(0.05)	(0.22)
FED_{t-3}	-1.44	-1.77	-10.13	0.20	-0.01	-0.17^{**}	-0.01
	(1.77)	(3.42)	(21.15)	(0.15)	(0.06)	(0.05)	(0.24)
IPI_{t-3}	-0.22	1.24	-0.55	0.07^{*}	-0.04^{**}	0.01	0.17^{**}
	(0.41)	(0.79)	(4.86)	(0.03)	(0.01)	(0.01)	(0.05)
R^2	0.11	0.18	0.78	0.29	0.98	0.99	0.32
Adj. R^2	0.05	0.12	0.77	0.25	0.98	0.99	0.28
Num. obs.	357	357	357	357	357	357	357

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.1.2: Linear Model Results: Factor2 as Uncertainty variable

	SP500	OIL	Factor2	Infl	U	FED	IPI
(Intercept)	-0.00	-0.00	-0.22	0.00	-0.00	0.00	-0.00
	(0.01)	(0.02)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
SP500_{t-1}	-0.00	0.16	-1.01	0.01	-0.00	0.00^{*}	0.01
	(0.06)	(0.11)	(0.58)	(0.00)	(0.00)	(0.00)	(0.01)
OIL_{t-1}	0.01	0.26^{***}	0.76^{*}	0.01^{***}	-0.00	0.00	0.01
	(0.03)	(0.06)	(0.32)	(0.00)	(0.00)	(0.00)	(0.00)
Factor2_{t-1}	0.01	-0.01	0.72^{***}	0.00	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-1}	-0.67	-0.75	-0.70	0.33^{***}	-0.01	-0.04	0.01
	(0.70)	(1.35)	(7.37)	(0.06)	(0.02)	(0.02)	(0.09)
U_{t-1}	0.48	6.98^{*}	-11.75	0.13	0.84^{***}	-0.02	-0.45^{*}
	(1.65)	(3.19)	(17.45)	(0.14)	(0.05)	(0.05)	(0.22)
FED_{t-1}	0.73	4.77	-19.70	0.13	-0.12^{*}	1.43^{***}	0.30
	(1.76)	(3.41)	(18.64)	(0.15)	(0.06)	(0.05)	(0.23)
IPI_{t-1}	0.98^{*}	1.47	4.88	0.01	-0.04^{**}	0.06^{***}	-0.02
	(0.40)	(0.78)	(4.26)	(0.03)	(0.01)	(0.01)	(0.05)
SP500_{t-2}	-0.02	0.06	0.09	0.00	-0.00	0.00^{*}	0.02^{**}
	(0.06)	(0.11)	(0.59)	(0.00)	(0.00)	(0.00)	(0.01)
OIL_{t-2}	0.03	0.01	-0.19	-0.00	-0.00	-0.00	0.00
	(0.03)	(0.06)	(0.33)	(0.00)	(0.00)	(0.00)	(0.00)
Factor2_{t-2}	0.00	0.01	0.13^{*}	0.00	-0.00	-0.00	0.00
	(0.01)	(0.01)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-2}	-0.74	0.53	-0.96	-0.17^{**}	-0.00	0.04	-0.05
	(0.72)	(1.40)	(7.66)	(0.06)	(0.02)	(0.02)	(0.10)
U_{t-2}	-0.89	-10.68^{*}	-9.96	-0.14	0.16^{*}	0.04	0.53
	(2.13)	(4.12)	(22.58)	(0.18)	(0.07)	(0.07)	(0.28)
FED_{t-2}	-0.36	-5.75	24.59	-0.37	0.12	-0.28^{**}	-0.17
	(3.07)	(5.94)	(32.53)	(0.25)	(0.10)	(0.09)	(0.41)
IPI_{t-2}	0.68	0.04	0.23	0.09^{**}	-0.03^{*}	0.01	0.08
	(0.42)	(0.81)	(4.41)	(0.03)	(0.01)	(0.01)	(0.05)
SP500_{t-3}	0.00	0.18	0.28	0.01	-0.00^{*}	0.00	0.04^{***}
	(0.06)	(0.11)	(0.59)	(0.00)	(0.00)	(0.00)	(0.01)
OIL_{t-3}	0.01	-0.12^{*}	0.38	0.00	0.00	-0.00	-0.00
	(0.03)	(0.06)	(0.32)	(0.00)	(0.00)	(0.00)	(0.00)
Factor2_{t-3}	-0.01	-0.01	0.01	-0.00	-0.00^{*}	0.00	0.00
	(0.01)	(0.01)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-3}	-0.05	-0.11	-5.02	-0.06	-0.02	-0.03	0.11
	(0.66)	(1.28)	(7.00)	(0.05)	(0.02)	(0.02)	(0.09)
U_{t-3}	0.46	3.72	25.96	-0.01	0.01	-0.02	-0.06
	(1.67)	(3.24)	(17.72)	(0.14)	(0.06)	(0.05)	(0.22)
FED_{t-3}	-0.27	0.87	-6.11	0.22	0.01	-0.16^{**}	-0.11
	(1.75)	(3.39)	(18.57)	(0.14)	(0.06)	(0.05)	(0.23)
IPI_{t-3}	-0.58	1.01	-0.37	0.07^{*}	-0.04^{**}	0.01	0.18^{***}
	(0.41)	(0.79)	(4.33)	(0.03)	(0.01)	(0.01)	(0.05)
R^2	0.08	0.15	0.83	0.29	0.98	0.99	0.31
Adj. R^2	0.02	0.10	0.81	0.24	0.98	0.99	0.27
Num. obs.	357	357	357	357	357	357	357

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.1.3: Linear Model Results: Product as Uncertainty variable

	SP500	OIL	Product	Infl	U	FED	IPI
(Intercept)	-0.00	0.00	-0.17	0.00	-0.00	0.00	-0.00
	(0.01)	(0.02)	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)
SP500_{t-1}	-0.01	0.12	1.56	0.01	-0.00	0.00^{*}	0.01
	(0.06)	(0.11)	(1.28)	(0.00)	(0.00)	(0.00)	(0.01)
OIL_{t-1}	0.00	0.26^{***}	1.56^{*}	0.01^{***}	0.00	0.00	0.01
	(0.03)	(0.06)	(0.68)	(0.00)	(0.00)	(0.00)	(0.00)
Product_{t-1}	0.00	0.01	0.78^{***}	0.00^{*}	0.00	0.00	-0.00^{*}
	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-1}	-0.75	-0.90	1.85	0.32^{***}	0.00	-0.04	-0.01
	(0.70)	(1.36)	(16.13)	(0.06)	(0.02)	(0.02)	(0.09)
U_{t-1}	0.37	6.88^{*}	8.94	0.15	0.80^{***}	-0.07	-0.43
	(1.67)	(3.23)	(38.39)	(0.14)	(0.05)	(0.05)	(0.22)
FED_{t-1}	0.37	3.93	-25.60	0.10	-0.15^{**}	1.40^{***}	0.33
	(1.78)	(3.44)	(40.89)	(0.15)	(0.06)	(0.05)	(0.23)
IPI_{t-1}	1.00^{*}	1.42	50.32^{***}	0.00	-0.03^{*}	0.06^{***}	0.01
	(0.41)	(0.79)	(9.39)	(0.03)	(0.01)	(0.01)	(0.05)
SP500_{t-2}	-0.04	0.04	1.24	-0.00	-0.00	0.00^{**}	0.02^{**}
	(0.06)	(0.11)	(1.29)	(0.00)	(0.00)	(0.00)	(0.01)
OIL_{t-2}	0.03	0.01	-0.58	-0.00	-0.00	-0.00	0.00
	(0.03)	(0.06)	(0.70)	(0.00)	(0.00)	(0.00)	(0.00)
Product_{t-2}	0.00	0.00	-0.04	-0.00	-0.00	-0.00	0.00^{**}
	(0.00)	(0.01)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-2}	-0.75	0.58	6.63	-0.17^{**}	0.01	0.04^{*}	-0.05
	(0.73)	(1.40)	(16.64)	(0.06)	(0.02)	(0.02)	(0.09)
U_{t-2}	-1.12	-10.75^{**}	-66.19	-0.16	0.16^{*}	0.04	0.53
	(2.13)	(4.12)	(48.86)	(0.17)	(0.07)	(0.06)	(0.28)
FED_{t-2}	0.20	-4.12	2.12	-0.31	0.16	-0.24^{*}	-0.25
	(3.10)	(5.98)	(71.01)	(0.25)	(0.10)	(0.09)	(0.40)
IPI_{t-2}	0.55	-0.33	9.40	0.07^{*}	-0.03^{*}	0.01	0.11
	(0.43)	(0.83)	(9.85)	(0.04)	(0.01)	(0.01)	(0.06)
SP500_{t-3}	-0.01	0.16	-0.06	0.01	-0.00	0.00	0.04^{***}
	(0.06)	(0.11)	(1.28)	(0.00)	(0.00)	(0.00)	(0.01)
OIL_{t-3}	0.01	-0.12^{*}	0.78	0.00	0.00	-0.00	-0.00
	(0.03)	(0.06)	(0.69)	(0.00)	(0.00)	(0.00)	(0.00)
Product_{t-3}	-0.00	-0.01	-0.02	-0.00	-0.00^{**}	-0.00^{**}	-0.00
	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-3}	-0.08	-0.11	-21.02	-0.07	-0.00	-0.01	0.11
	(0.67)	(1.30)	(15.38)	(0.05)	(0.02)	(0.02)	(0.09)
U_{t-3}	0.88	3.79	58.52	-0.00	0.05	0.03	-0.07
	(1.69)	(3.27)	(38.83)	(0.14)	(0.05)	(0.05)	(0.22)
FED_{t-3}	-0.53	0.17	22.95	0.19	0.01	-0.17^{**}	-0.06
	(1.76)	(3.40)	(40.37)	(0.14)	(0.06)	(0.05)	(0.23)
IPI_{t-3}	-0.69	0.73	-10.34	0.06	-0.03^{*}	0.01	0.17^{**}
	(0.42)	(0.81)	(9.60)	(0.03)	(0.01)	(0.01)	(0.05)
R^2	0.08	0.15	0.71	0.30	0.98	0.99	0.33
Adj. R^2	0.03	0.10	0.70	0.26	0.98	0.99	0.29
Num. obs.	357	357	357	357	357	357	357

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

A.2 Nonlinear Model

Table A.2.1: LR test

	Linearity VS Two regimes	Linearity VS Three regimes	Two regimes VS Three regimes
LR statistic	351.2817	578.1422	226.8604
p-value	0.000	0.000	0.000
Estimated threshold	0.5938924	-0.2953414 ; 0.5885597	-0.2953414 ; 0.5885597

Source: Author's own calculations.

Table A.2.2: Non linear model Results

	SP500	OIL	Factor2	Infl	U	FED	IPI
(Intercept)	0.02	-0.00	-0.30^{*}	0.00	-0.00	0.00	-0.00
	(0.01)	(0.03)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
High Uncertainty Regime							
SP500_{t-1}	0.09	0.38^{*}	0.30	0.01^{*}	-0.00	0.00	0.00
	(0.08)	(0.15)	(0.83)	(0.01)	(0.00)	(0.00)	(0.01)
OIL_{t-1}	0.03	0.18	0.73	0.01^{*}	-0.00	0.00	0.02^{**}
	(0.05)	(0.11)	(0.58)	(0.00)	(0.00)	(0.00)	(0.01)
Factor2_{t-1}	-0.00	-0.02	0.65^{***}	0.00	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-1}	-3.06^{*}	2.71	20.18	0.12	0.03	-0.09^{*}	0.09
	(1.38)	(2.76)	(14.98)	(0.12)	(0.05)	(0.04)	(0.19)
U_{t-1}	4.41	10.96	-18.87	-0.25	0.84^{***}	0.10	-1.19^{**}
	(3.19)	(6.39)	(34.63)	(0.27)	(0.10)	(0.10)	(0.43)
FED_{t-1}	3.31	10.19	29.66	0.73^{**}	0.01	1.55^{***}	-0.49
	(3.07)	(6.14)	(33.30)	(0.26)	(0.10)	(0.09)	(0.41)
IPI_{t-1}	2.14^{**}	3.57^{**}	7.42	0.02	-0.03	0.07^{***}	-0.04
	(0.65)	(1.29)	(7.01)	(0.05)	(0.02)	(0.02)	(0.09)
SP500_{t-2}	-0.04	0.08	1.21	-0.00	-0.00	0.01^{**}	0.02
	(0.08)	(0.16)	(0.89)	(0.01)	(0.00)	(0.00)	(0.01)
OIL_{t-2}	0.09	0.07	-0.28	-0.00	-0.00	0.00	-0.01

	(0.05)	(0.11)	(0.58)	(0.00)	(0.00)	(0.00)	(0.01)
Factor2_{t-2}	0.02^{*}	0.02	0.02	0.00	0.00	0.00	0.00
	(0.01)	(0.02)	(0.11)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-2}	-1.56	0.82	-10.27	0.05	-0.06	0.08	-0.34
	(1.44)	(2.89)	(15.65)	(0.12)	(0.05)	(0.04)	(0.19)
U_{t-2}	-3.83	-10.44	-65.13	0.01	0.24	-0.06	0.21
	(4.41)	(8.81)	(47.77)	(0.37)	(0.14)	(0.13)	(0.59)
FED_{t-2}	-2.07	-14.48	-57.74	-1.26^{**}	-0.00	-0.64^{***}	0.92
	(5.37)	(10.74)	(58.21)	(0.45)	(0.18)	(0.16)	(0.72)
IPI_{t-2}	1.22	1.17	1.52	0.13^{*}	-0.05^{*}	0.04	0.06
	(0.76)	(1.53)	(8.27)	(0.06)	(0.03)	(0.02)	(0.10)
SP500_{t-3}	-0.00	0.13	0.73	-0.00	-0.01^{**}	-0.00	0.06^{***}
	(0.09)	(0.18)	(0.96)	(0.01)	(0.00)	(0.00)	(0.01)
OIL_{t-3}	0.06	-0.29^{**}	0.15	-0.00	0.00	-0.00^{**}	0.00
	(0.05)	(0.10)	(0.56)	(0.00)	(0.00)	(0.00)	(0.01)
Factor2_{t-3}	-0.01	-0.01	0.08	-0.00^{*}	-0.00^{**}	-0.00	-0.00
	(0.01)	(0.02)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-3}	-0.45	-0.64	-16.21	-0.26^{**}	0.03	-0.09^{**}	-0.09
	(1.07)	(2.14)	(11.58)	(0.09)	(0.04)	(0.03)	(0.14)
U_{t-3}	-0.79	-0.36	89.19^{*}	0.23	-0.07	-0.05	1.00^{*}
	(3.38)	(6.76)	(36.64)	(0.28)	(0.11)	(0.10)	(0.45)
FED_{t-3}	-0.89	4.03	30.73	0.55^{*}	-0.00	0.07	-0.44
	(3.18)	(6.36)	(34.47)	(0.27)	(0.10)	(0.10)	(0.43)
IPI_{t-3}	-1.48^{*}	0.79	-0.87	0.04	-0.08^{**}	0.00	0.12
	(0.73)	(1.46)	(7.93)	(0.06)	(0.02)	(0.02)	(0.10)
Intermediate Uncertainty Regime							
SP500_{t-1}	-0.13	0.05	-3.28^{*}	0.01	0.00	0.00	0.00
	(0.13)	(0.27)	(1.45)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-1}	-0.04	0.18	-0.26	0.00	0.00	0.00	0.00
	(0.06)	(0.13)	(0.70)	(0.01)	(0.00)	(0.00)	(0.01)
Factor2_{t-1}	0.02	-0.02	0.88^{***}	-0.00	-0.00	0.00	-0.00
	(0.01)	(0.02)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-1}	2.26	-0.71	-3.30	0.42^{***}	-0.06	-0.03	-0.11

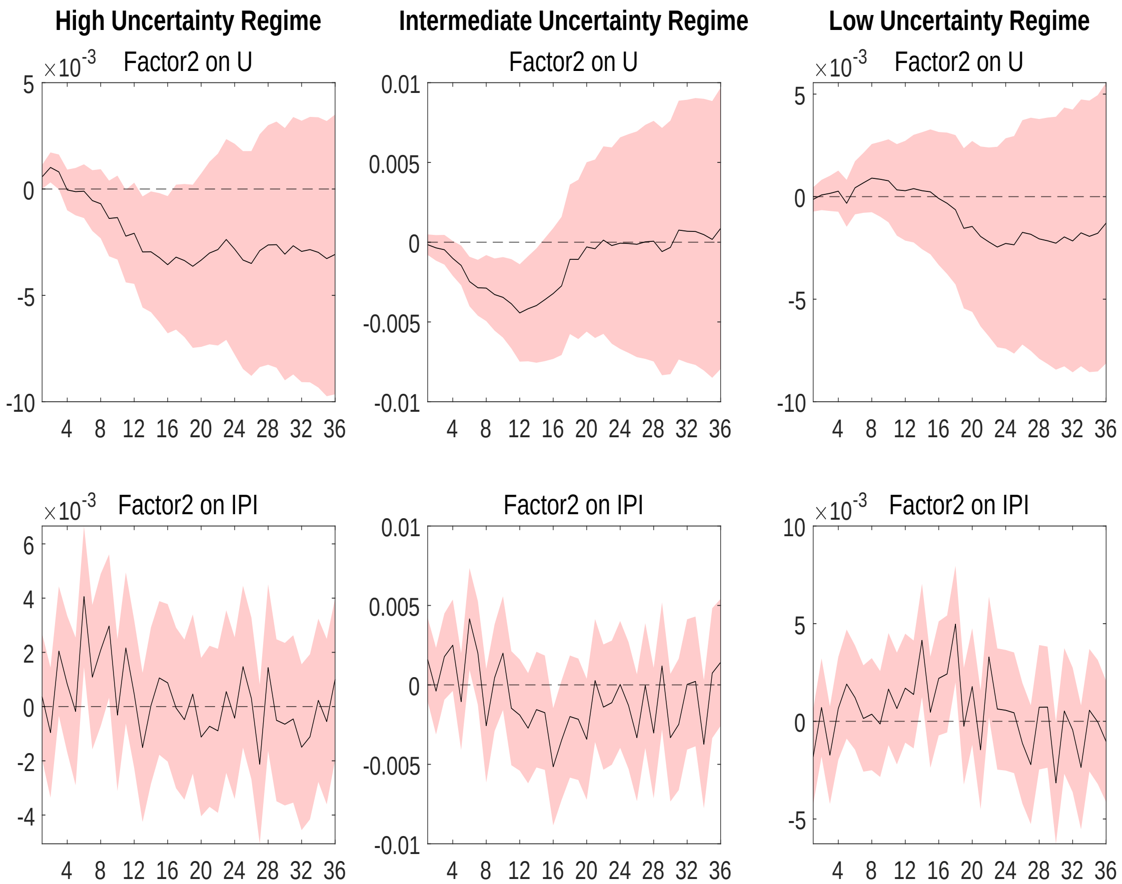
	(1.29)	(2.58)	(13.97)	(0.11)	(0.04)	(0.04)	(0.17)
U_{t-1}	-8.36^{*}	10.85	-10.80	0.77^{*}	0.88^{***}	-0.25^{*}	-0.12
	(3.59)	(7.18)	(38.91)	(0.30)	(0.12)	(0.11)	(0.48)
FED_{t-1}	-3.76	-14.34	-78.85	-0.41	-0.05	1.26^{***}	0.82
	(4.05)	(8.11)	(43.94)	(0.34)	(0.13)	(0.12)	(0.54)
IPI_{t-1}	-0.29	-0.90	7.67	-0.11	0.01	0.03	-0.09
	(0.99)	(1.97)	(10.69)	(0.08)	(0.03)	(0.03)	(0.13)
$SP500_{t-2}$	0.28^{*}	0.09	0.13	-0.00	-0.00	0.01	0.03
	(0.13)	(0.26)	(1.42)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-2}	-0.02	-0.23	-0.54	-0.00	0.00	-0.00	0.00
	(0.06)	(0.12)	(0.64)	(0.00)	(0.00)	(0.00)	(0.01)
$Factor2_{t-2}$	-0.01	-0.02	0.19	-0.00	-0.00	-0.00	0.00
	(0.01)	(0.02)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
$Infl_{t-2}$	-3.78^{**}	2.53	2.00	-0.19	0.02	0.03	0.07
	(1.40)	(2.79)	(15.12)	(0.12)	(0.05)	(0.04)	(0.19)
U_{t-2}	6.66	-19.37^{*}	-8.66	-0.60	0.16	0.23	1.15
	(4.47)	(8.93)	(48.40)	(0.37)	(0.15)	(0.13)	(0.60)
FED_{t-2}	2.00	25.66	153.67^{*}	0.75	-0.01	-0.07	-0.59
	(6.62)	(13.23)	(71.73)	(0.56)	(0.22)	(0.20)	(0.89)
IPI_{t-2}	1.86	1.20	-8.40	0.10	-0.03	-0.03	0.00
	(0.99)	(1.98)	(10.75)	(0.08)	(0.03)	(0.03)	(0.13)
$SP500_{t-3}$	0.19	-0.15	-0.30	0.00	-0.01	0.00	0.04^{*}
	(0.12)	(0.24)	(1.31)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-3}	-0.14^{*}	0.01	-0.07	0.00	0.00	0.00	-0.00
	(0.06)	(0.13)	(0.69)	(0.01)	(0.00)	(0.00)	(0.01)
$Factor2_{t-3}$	-0.01	0.03	-0.21^{*}	0.00	0.00	-0.00	0.00
	(0.01)	(0.02)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)
$Infl_{t-3}$	1.77	0.83	10.35	0.12	0.04	0.02	0.23
	(1.41)	(2.81)	(15.26)	(0.12)	(0.05)	(0.04)	(0.19)
U_{t-3}	1.35	8.40	26.39	-0.16	-0.03	0.01	-1.01^{*}
	(2.93)	(5.87)	(31.79)	(0.25)	(0.10)	(0.09)	(0.39)
FED_{t-3}	1.35	-10.83	-73.42	-0.35	0.07	-0.20	-0.18
	(3.58)	(7.15)	(38.78)	(0.30)	(0.12)	(0.11)	(0.48)

IPI_{t-3}	1.08	0.68	−13.16	0.06	−0.05	−0.01	0.29*
	(0.94)	(1.89)	(10.22)	(0.08)	(0.03)	(0.03)	(0.13)
Low Uncertainty Regime							
$SP500_{t-1}$	−0.28*	−0.12	−1.05	0.00	−0.00	0.00	0.02
	(0.11)	(0.22)	(1.22)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-1}	0.01	0.30**	1.18*	0.01**	0.00	−0.00	−0.00
	(0.05)	(0.10)	(0.52)	(0.00)	(0.00)	(0.00)	(0.01)
$Factor2_{t-1}$	0.01	0.00	0.76***	0.00	0.00*	−0.00	−0.00
	(0.01)	(0.02)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
$Infl_{t-1}$	−0.80	−1.63	−20.36	0.29**	−0.02	0.02	0.11
	(1.12)	(2.23)	(12.11)	(0.09)	(0.04)	(0.03)	(0.15)
U_{t-1}	0.34	4.07	−4.83	0.06	0.56***	−0.05	−0.14
	(2.56)	(5.12)	(27.77)	(0.22)	(0.08)	(0.08)	(0.34)
FED_{t-1}	−1.07	6.54	−32.01	0.14	−0.22*	1.25***	0.26
	(2.90)	(5.81)	(31.47)	(0.24)	(0.10)	(0.09)	(0.39)
IPI_{t-1}	0.77	0.51	−3.52	0.01	−0.04	0.04	−0.12
	(0.65)	(1.29)	(7.02)	(0.05)	(0.02)	(0.02)	(0.09)
$SP500_{t-2}$	−0.06	−0.06	−1.17	0.01	0.01	−0.00	−0.00
	(0.12)	(0.24)	(1.30)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-2}	0.02	0.12	0.39	0.00	−0.00	0.00	0.01
	(0.05)	(0.10)	(0.54)	(0.00)	(0.00)	(0.00)	(0.01)
$Factor2_{t-2}$	−0.01	0.05*	0.14	0.00	−0.00	−0.00*	−0.00
	(0.01)	(0.02)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
$Infl_{t-2}$	0.14	−1.43	0.81	−0.36***	0.06	−0.01	−0.04
	(1.13)	(2.25)	(12.22)	(0.09)	(0.04)	(0.03)	(0.15)
U_{t-2}	−1.55	−6.88	1.31	−0.03	0.18	0.04	0.48
	(2.84)	(5.69)	(30.82)	(0.24)	(0.09)	(0.09)	(0.38)
FED_{t-2}	3.21	−7.04	36.86	−0.23	0.28	0.05	−0.70
	(4.68)	(9.37)	(50.76)	(0.39)	(0.15)	(0.14)	(0.63)
IPI_{t-2}	0.55	−0.54	0.53	−0.01	−0.01	0.00	0.00
	(0.64)	(1.28)	(6.92)	(0.05)	(0.02)	(0.02)	(0.09)
$SP500_{t-3}$	0.00	0.42	0.63	0.01	0.01	−0.00	0.01
	(0.11)	(0.22)	(1.22)	(0.01)	(0.00)	(0.00)	(0.02)

OIL_{t-3}	0.01	-0.02	0.61	0.01	0.00	0.00	0.00
	(0.05)	(0.10)	(0.53)	(0.00)	(0.00)	(0.00)	(0.01)
Factor2_{t-3}	-0.00	-0.04^{*}	0.07	0.00	-0.00	0.00^{*}	0.00^{*}
	(0.01)	(0.02)	(0.11)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-3}	-1.14	0.60	-9.48	-0.09	-0.02	0.03	0.25
	(1.13)	(2.26)	(12.24)	(0.09)	(0.04)	(0.03)	(0.15)
U_{t-3}	0.82	2.60	9.73	-0.04	0.25^{**}	0.01	-0.31
	(2.63)	(5.25)	(28.48)	(0.22)	(0.09)	(0.08)	(0.35)
FED_{t-3}	-1.93	0.75	-5.50	0.09	-0.04	-0.30^{***}	0.50
	(2.94)	(5.89)	(31.91)	(0.25)	(0.10)	(0.09)	(0.39)
IPI_{t-3}	0.21	0.93	-1.42	0.02	-0.02	0.02	0.11
	(0.62)	(1.23)	(6.67)	(0.05)	(0.02)	(0.02)	(0.08)
R^2	0.28	0.28	0.86	0.42	0.98	0.99	0.44
Adj. R^2	0.12	0.13	0.82	0.29	0.98	0.99	0.32
Num. obs.	357	357	357	357	357	357	357

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Figure A.2.1: Impulse Response Functions with Factor2 as Identified or Exogenous shock

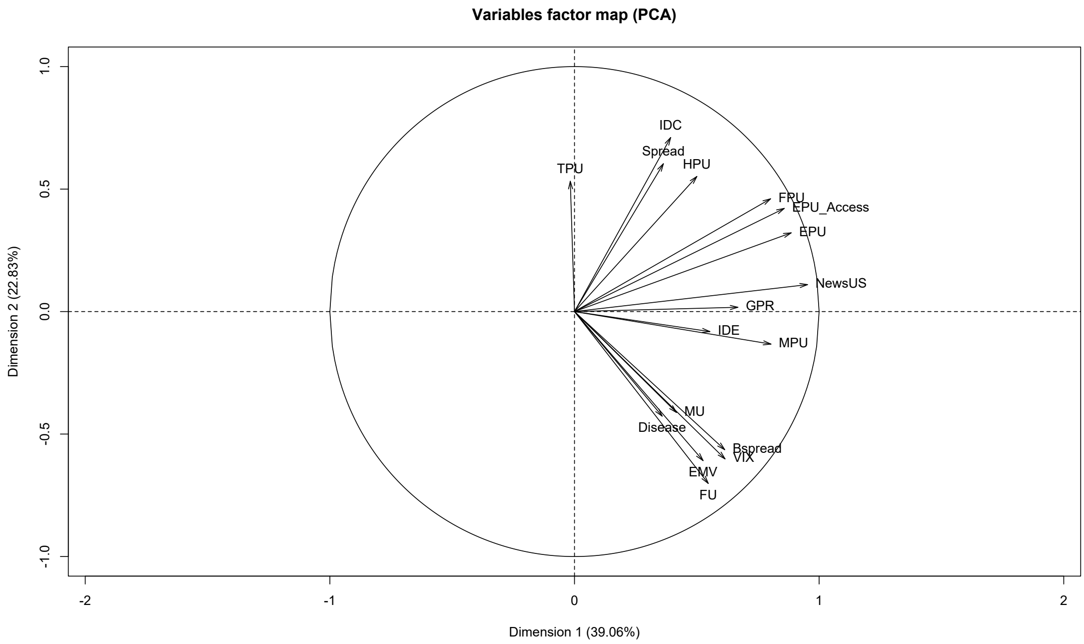


Source: Author's own calculations.
Notes: Graphs on the left panel represents impulse response functions in the high uncertainty regime. Graphs on the middle panel represents impulse response functions in the moderate uncertainty regime. Graphs on the right panel represents impulse response functions in the low uncertainty regime. The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

B Robustness Checks

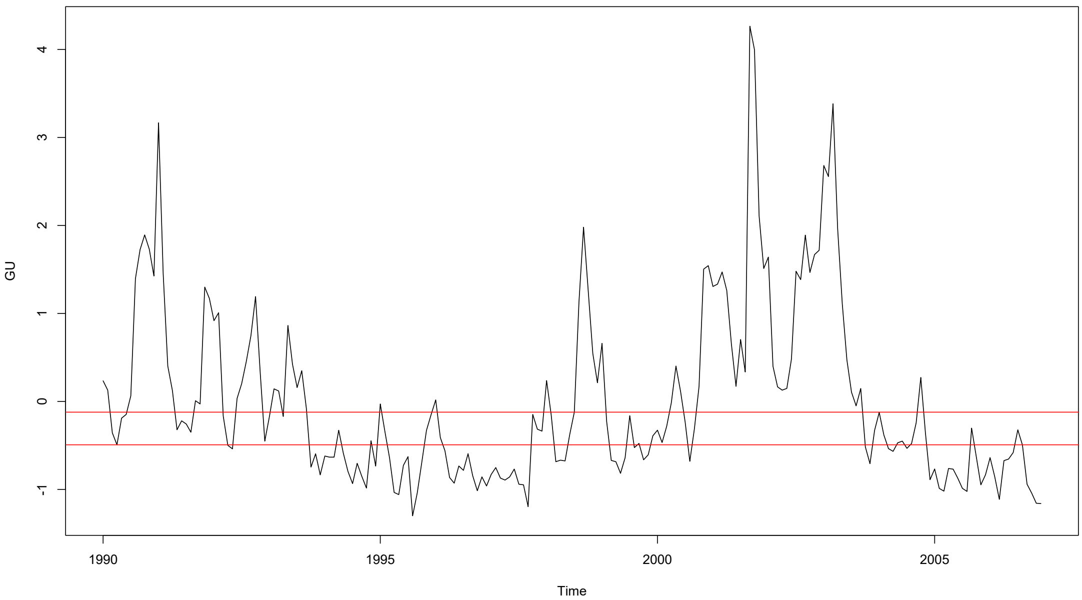
B.1 Subsample 1990-2006

Figure B.1.1: Variables Factor Map (Factor 1 and Factor 2)



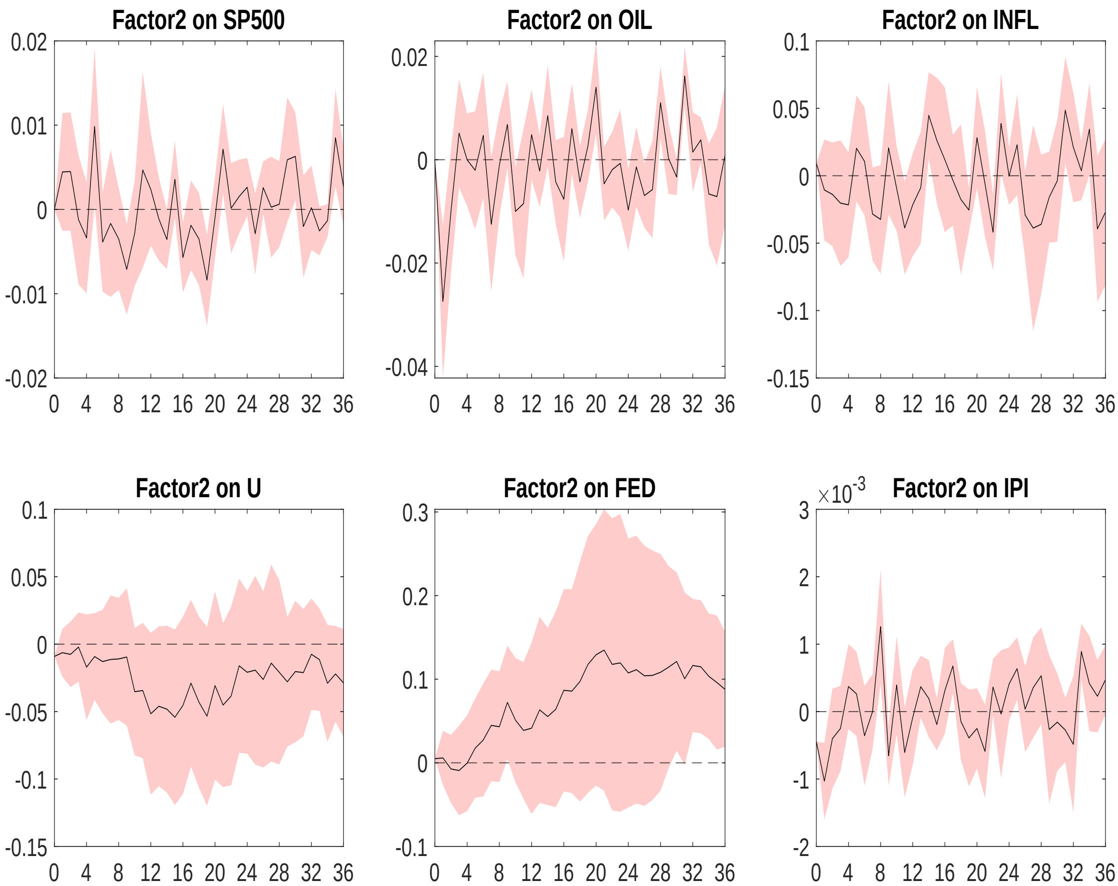
Source: Author's own calculations.

Figure B.1.2: Estimated Threshold values



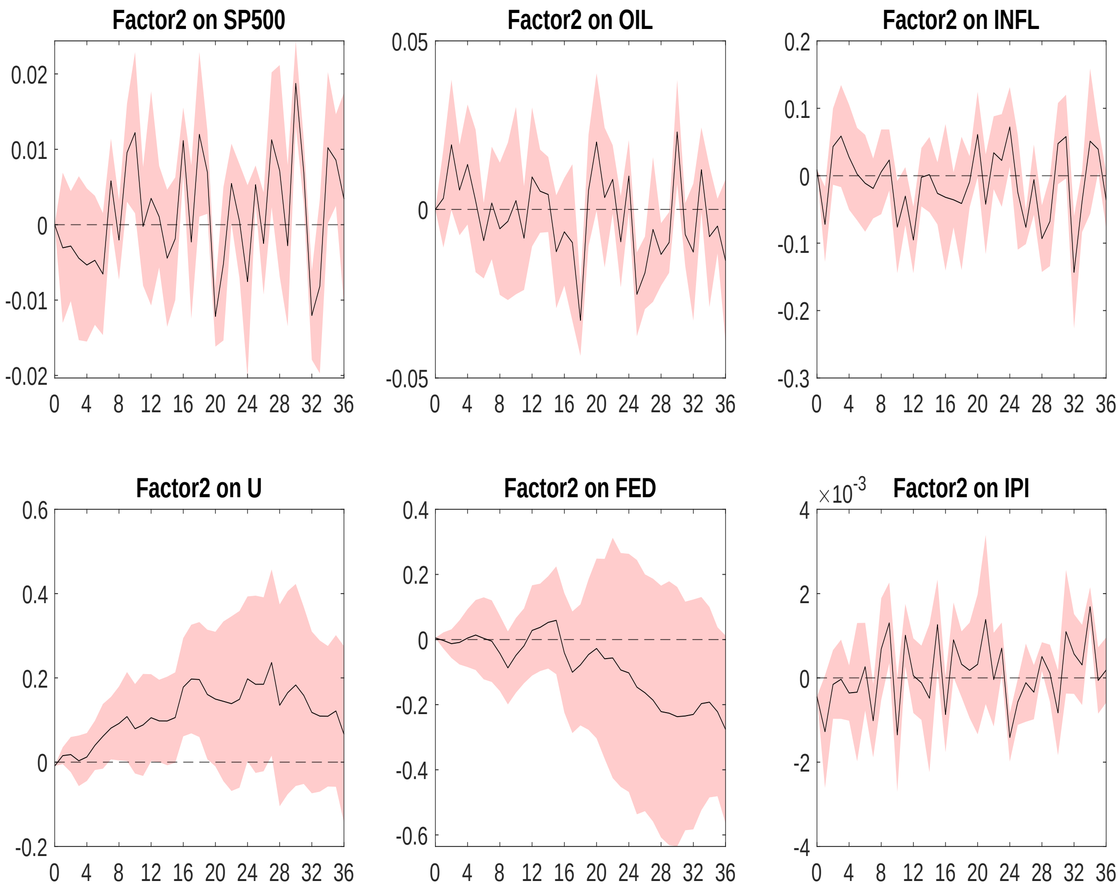
Source: Author's own calculations.
Notes: The horizontal red lines correspond to the estimated threshold values (-0.1220759 and -0.4930768)

Figure B.1.3: Impulse Response Functions in a high uncertainty regime



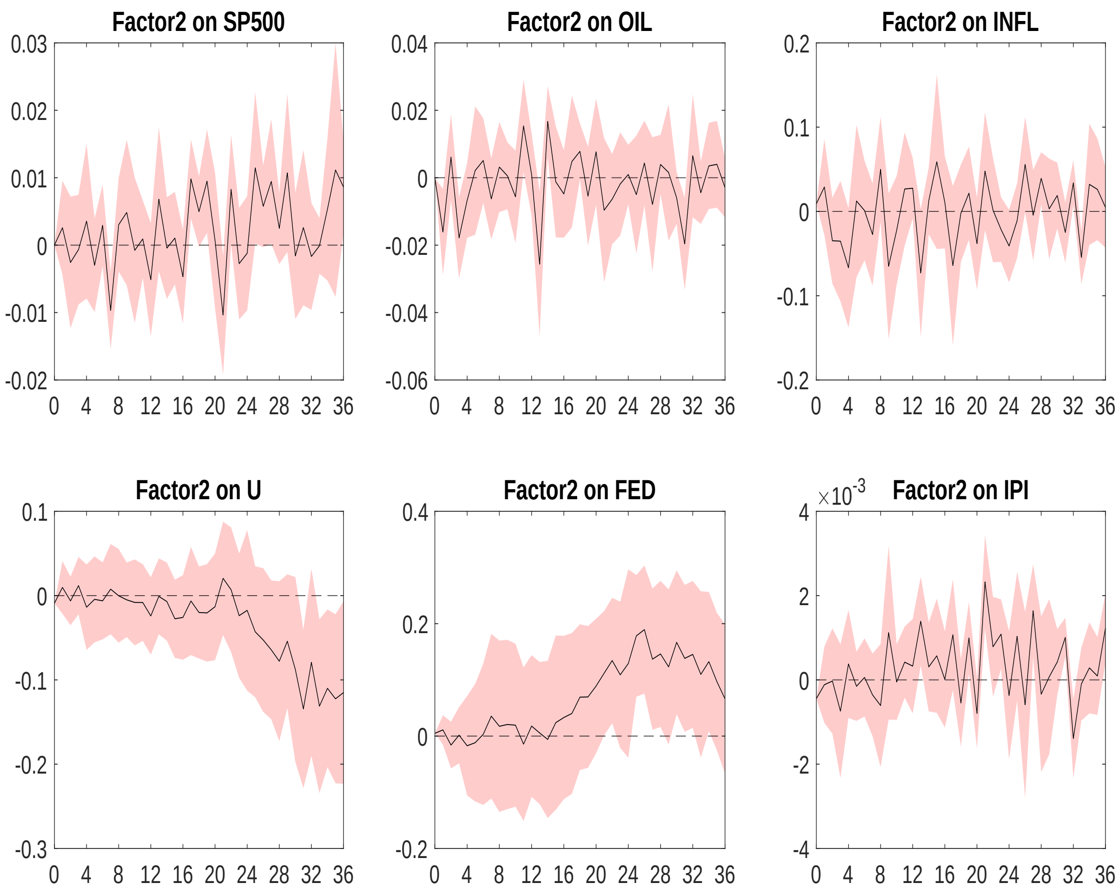
Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

Figure B.1.4: Impulse Response Functions in an intermediate uncertainty regime



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

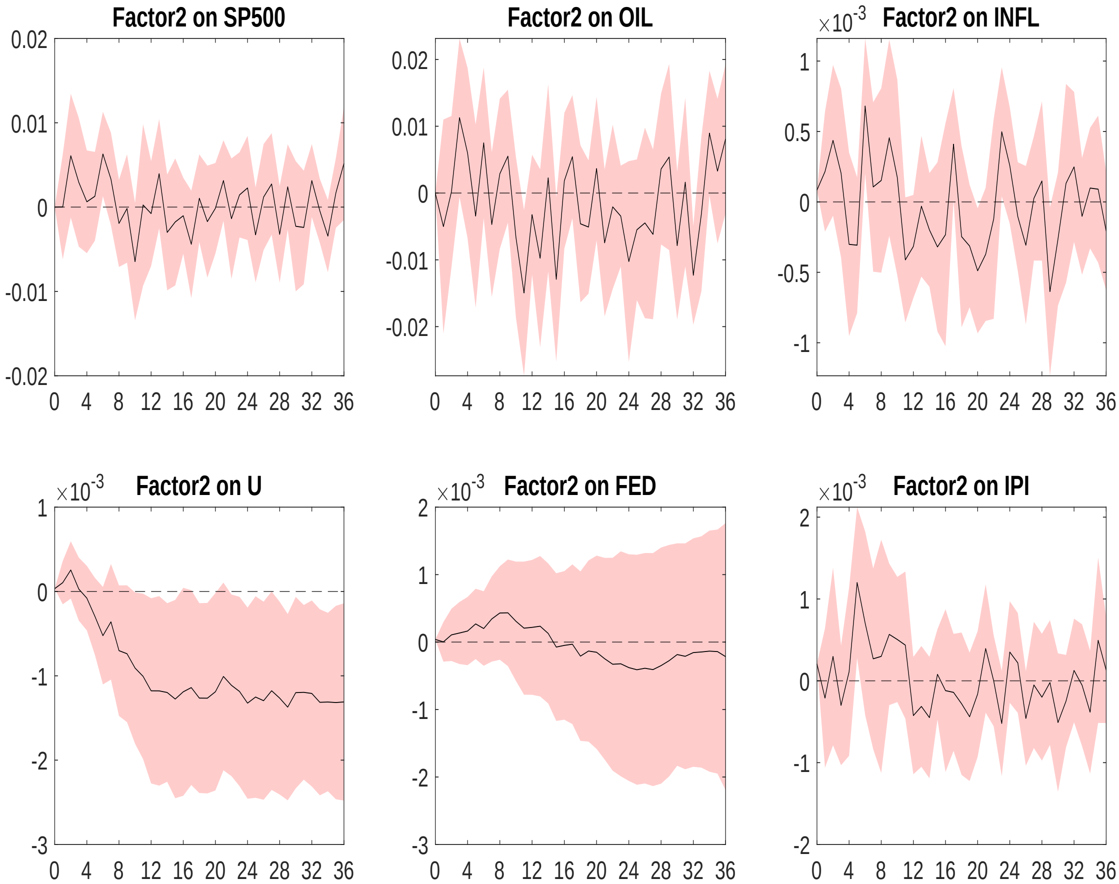
Figure B.1.5: Impulse Response Functions in a low uncertainty regime



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

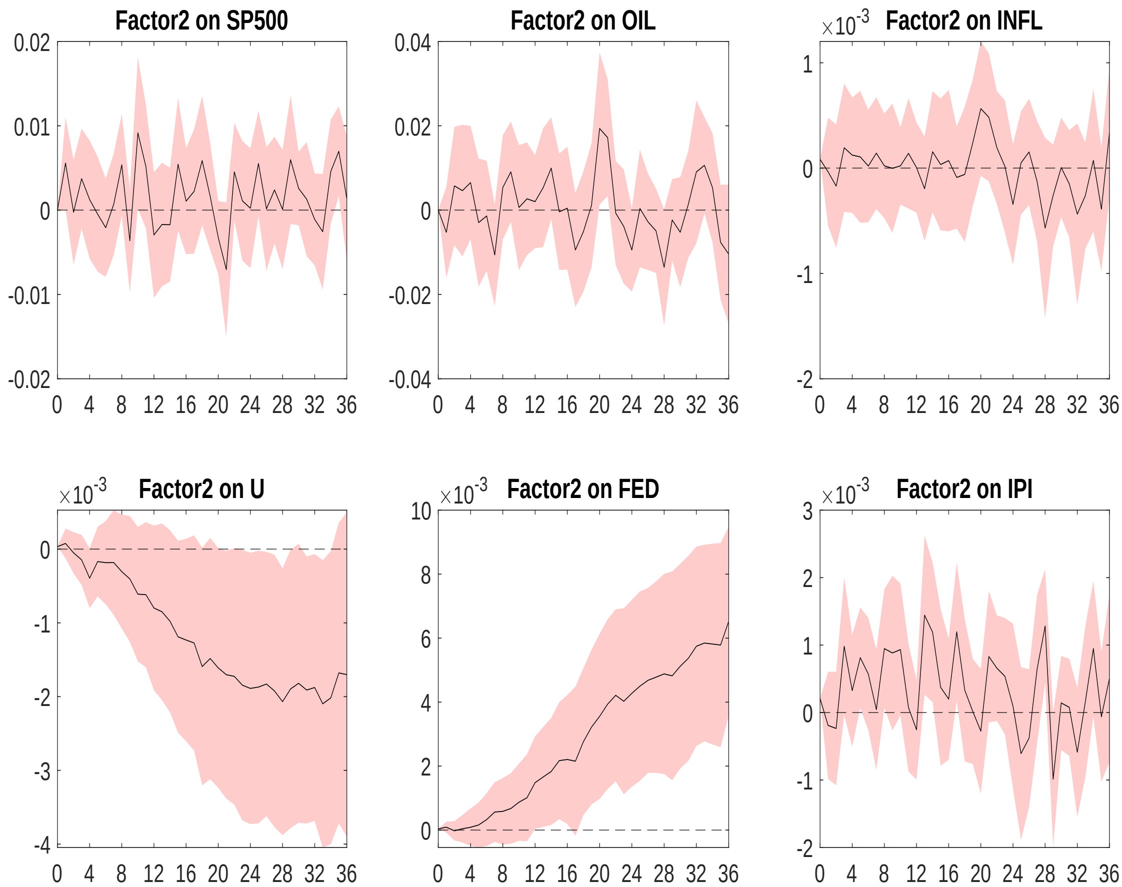
B.2 Nonlinear Framework: Two Regimes

Figure B.2.1: Impulse Response Functions in a high uncertainty regime



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

Figure B.2.2: Impulse Response Functions in a low uncertainty regime



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

B.3 Hodrick Prescott Filter

Table B.3.1: Regression Results HP: GU as Uncertainty variable

	SP500	OIL	GU	Infl	U	FED	IPI
(Intercept)	0.00	0.00	-0.00	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.03)	(0.02)	(0.01)	(0.01)	(0.00)
SP500_{t-1}	0.87^{***}	0.03	-3.26^{***}	0.60	-0.17	0.12	0.01
	(0.06)	(0.12)	(0.76)	(0.50)	(0.19)	(0.19)	(0.01)
OIL_{t-1}	0.02	1.14^{***}	-0.05	0.91^{***}	0.02	-0.01	0.01
	(0.03)	(0.06)	(0.37)	(0.24)	(0.09)	(0.09)	(0.00)
GU_{t-1}	-0.01^{*}	-0.02^{*}	0.79^{***}	-0.06	0.04^{*}	-0.04^{**}	0.00
	(0.00)	(0.01)	(0.06)	(0.04)	(0.01)	(0.01)	(0.00)
Infl_{t-1}	-0.01	0.01	0.06	1.19^{***}	-0.03	-0.01	0.00
	(0.01)	(0.01)	(0.08)	(0.05)	(0.02)	(0.02)	(0.00)
U_{t-1}	0.00	0.08^{*}	0.18	0.11	0.69^{***}	-0.05	-0.00
	(0.02)	(0.03)	(0.21)	(0.14)	(0.05)	(0.05)	(0.00)
FED_{t-1}	0.01	0.04	-0.12	0.13	-0.08	1.44^{***}	0.00^{*}
	(0.02)	(0.03)	(0.19)	(0.13)	(0.05)	(0.05)	(0.00)
IPI_{t-1}	1.27^{**}	1.79^{*}	-15.02^{**}	0.17	-3.85^{**}	5.57^{***}	0.91^{***}
	(0.39)	(0.75)	(4.98)	(3.29)	(1.27)	(1.24)	(0.05)
SP500_{t-2}	0.00	-0.02	3.47^{***}	-0.44	0.12	-0.20	0.01
	(0.06)	(0.11)	(0.76)	(0.50)	(0.19)	(0.19)	(0.01)
OIL_{t-2}	-0.01	-0.30^{***}	0.22	-0.66^{**}	0.10	-0.07	-0.01
	(0.03)	(0.06)	(0.37)	(0.25)	(0.09)	(0.09)	(0.00)
GU_{t-2}	0.01^{*}	0.02	0.01	0.04	0.01	0.02	-0.00^{*}
	(0.00)	(0.01)	(0.06)	(0.04)	(0.01)	(0.01)	(0.00)
Infl_{t-2}	-0.00	-0.00	-0.03	-0.36^{***}	0.00	0.02	-0.00
	(0.01)	(0.01)	(0.08)	(0.05)	(0.02)	(0.02)	(0.00)
U_{t-2}	0.01	-0.05	-0.05	-0.08	0.15^{**}	0.04	0.01^{***}
	(0.02)	(0.03)	(0.20)	(0.13)	(0.05)	(0.05)	(0.00)
FED_{t-2}	0.00	-0.03	0.14	-0.12	0.06	-0.46^{***}	-0.00
	(0.02)	(0.03)	(0.20)	(0.13)	(0.05)	(0.05)	(0.00)
IPI_{t-2}	-0.90^{*}	-1.16	15.55^{**}	1.94	0.88	-5.20^{***}	0.03
	(0.41)	(0.78)	(5.18)	(3.42)	(1.31)	(1.29)	(0.05)
R^2	0.88	0.87	0.77	0.89	0.97	0.99	0.96
Adj. R^2	0.88	0.86	0.76	0.88	0.97	0.99	0.96
Num. obs.	358	358	358	358	358	358	358

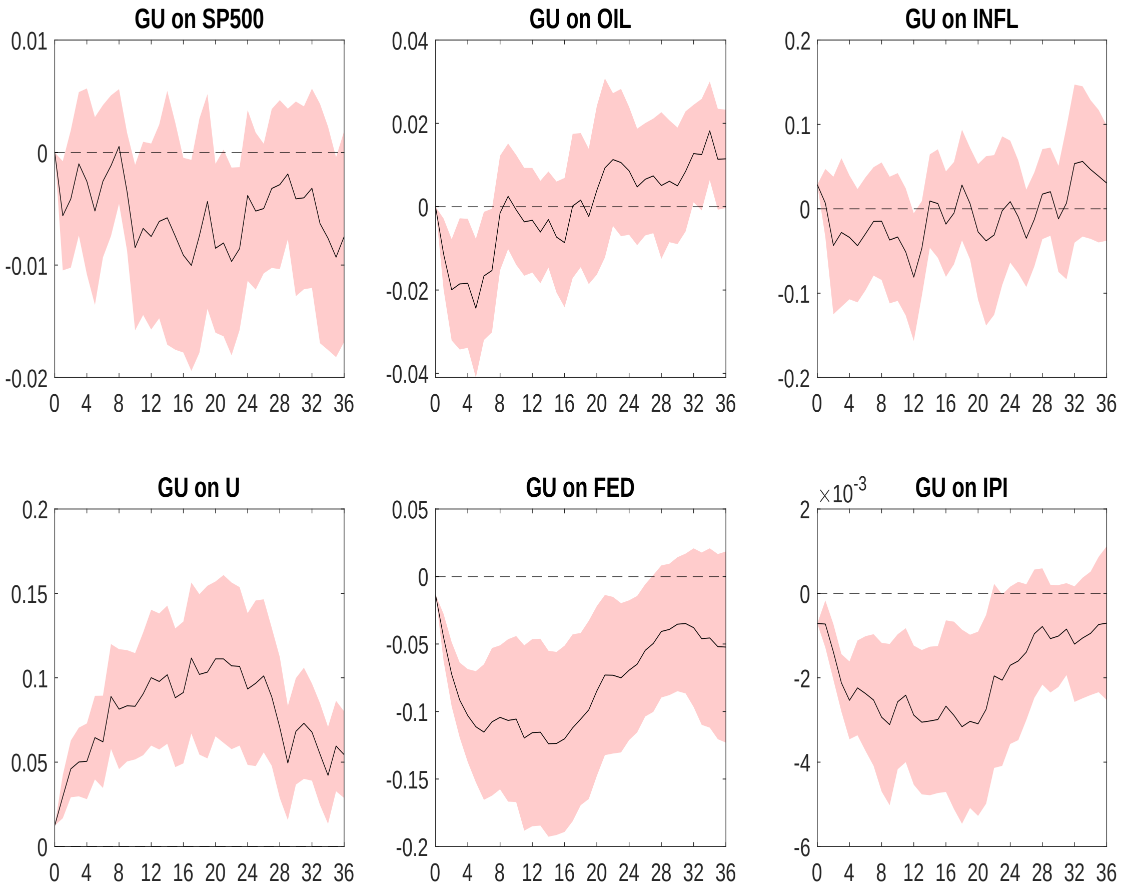
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table B.3.2: Regression Results HP: Factor2 as Uncertainty variable

	SP500	OIL	Factor2	Infl	U	FED	IPI
(Intercept)	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)
SP500_{t-1}	0.91^{***}	0.14	-1.50^{*}	0.79	-0.40^{*}	0.41^{*}	0.01
	(0.06)	(0.13)	(0.67)	(0.51)	(0.20)	(0.19)	(0.01)
OIL_{t-1}	0.02	1.15^{***}	0.69^{**}	0.91^{**}	-0.02	0.03	0.01
	(0.04)	(0.06)	(0.24)	(0.29)	(0.09)	(0.09)	(0.00)
Factor2_{t-1}	0.00	-0.01	0.72^{***}	0.03	0.01	-0.01	-0.00
	(0.00)	(0.01)	(0.06)	(0.04)	(0.02)	(0.02)	(0.00)
Infl_{t-1}	-0.01	0.00	-0.02	1.17^{***}	-0.02	-0.01	0.00
	(0.00)	(0.01)	(0.03)	(0.06)	(0.02)	(0.02)	(0.00)
U_{t-1}	0.01	0.07^{*}	-0.07	0.10	0.74^{***}	-0.08	-0.01^{*}
	(0.01)	(0.03)	(0.12)	(0.12)	(0.05)	(0.05)	(0.00)
FED_{t-1}	0.00	0.05	-0.15	0.15	-0.17^{***}	1.49^{***}	0.01^{**}
	(0.02)	(0.04)	(0.13)	(0.13)	(0.04)	(0.04)	(0.00)
IPI_{t-1}	1.17	1.83^{**}	5.33^{*}	-0.47	-4.58^{***}	6.42^{**}	0.92^{***}
	(0.63)	(0.60)	(2.68)	(3.00)	(1.22)	(2.12)	(0.05)
SP500_{t-2}	-0.03	-0.10	1.12	-0.54	0.17	-0.40	0.01
	(0.07)	(0.13)	(0.72)	(0.56)	(0.19)	(0.24)	(0.01)
OIL_{t-2}	-0.02	-0.31^{***}	-0.71^{*}	-0.68^{*}	0.11	-0.09	-0.01
	(0.04)	(0.07)	(0.28)	(0.27)	(0.10)	(0.10)	(0.00)
Factor2_{t-2}	0.00	0.01	0.18^{**}	0.02	-0.03	0.00	0.00
	(0.00)	(0.01)	(0.06)	(0.03)	(0.02)	(0.02)	(0.00)
Infl_{t-2}	0.00	-0.00	-0.01	-0.35^{***}	0.01	0.02	-0.00
	(0.00)	(0.02)	(0.03)	(0.07)	(0.02)	(0.02)	(0.00)
U_{t-2}	0.00	-0.06^{*}	0.17	-0.11	0.14^{**}	0.06	0.01^{**}
	(0.01)	(0.03)	(0.11)	(0.12)	(0.05)	(0.05)	(0.00)
FED_{t-2}	0.01	-0.04	0.20	-0.14	0.15^{***}	-0.52^{***}	-0.01^{*}
	(0.02)	(0.04)	(0.12)	(0.11)	(0.04)	(0.04)	(0.00)
IPI_{t-2}	-0.84	-1.38^{*}	-5.25	1.92	2.44^{*}	-6.39^{***}	-0.01
	(0.52)	(0.60)	(2.84)	(2.95)	(1.18)	(1.91)	(0.05)
R^2	0.88	0.87	0.83	0.89	0.97	0.99	0.96
Adj. R^2	0.88	0.86	0.82	0.88	0.96	0.98	0.96
Num. obs.	358	358	358	358	358	358	358

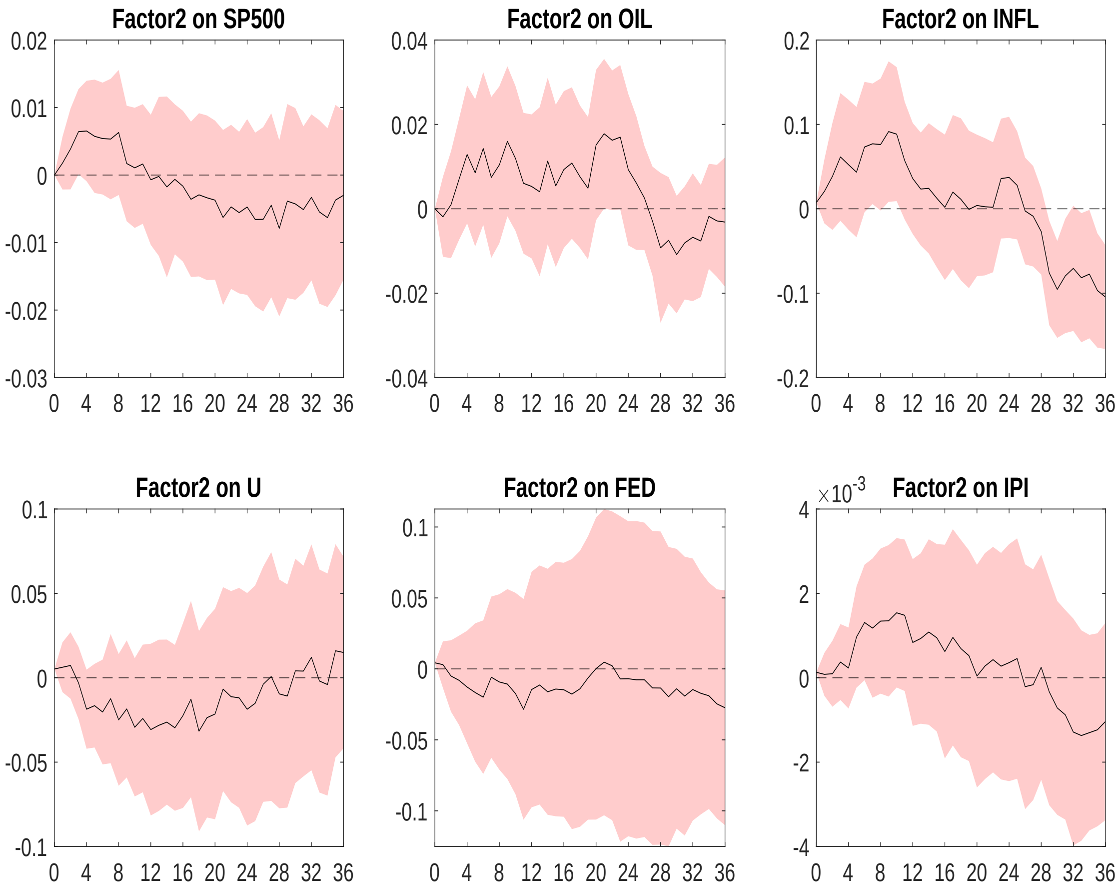
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Figure B.3.1: Impulse Response Functions (General Uncertainty)



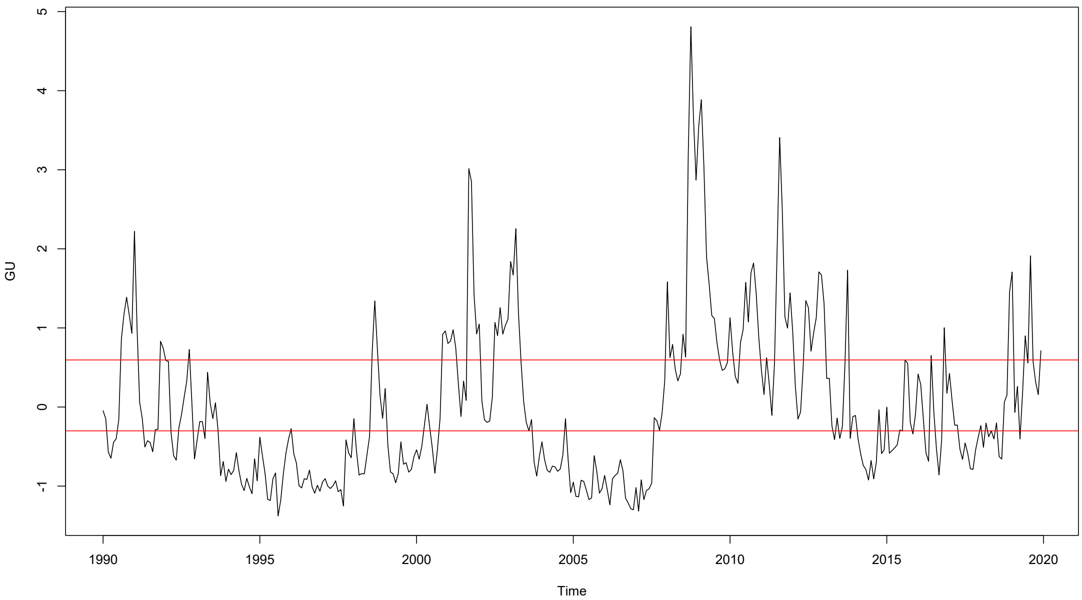
Source: Author's own calculations.
Notes: Except the uncertainty variable (GU), all variables are detrending applying the HP filter (λ = 129600) The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

Figure B.3.2: Impulse Response Functions (Factor 2)



Source: Author's own calculations.
Notes: Except the uncertainty variable ($Factor2$), all variables are detrending applying the HP filter ($\lambda = 129600$) The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

Figure B.3.3: Two thresholds of general uncertainty

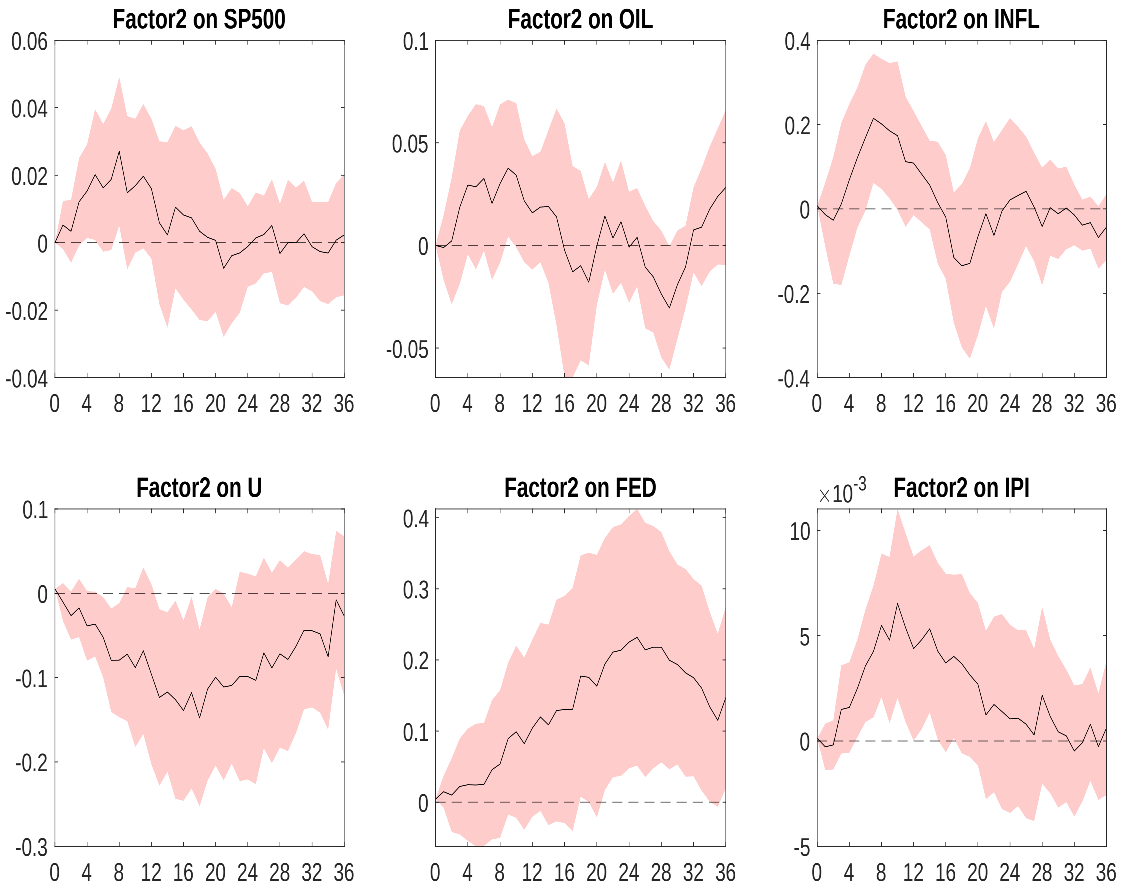


Source: Author's own calculations.
Notes: The horizontal red lines correspond to the estimated threshold values (-0.3014314 and 0.6228429)

Figure B.3.4: Impulse Response Functions in a low uncertainty regime

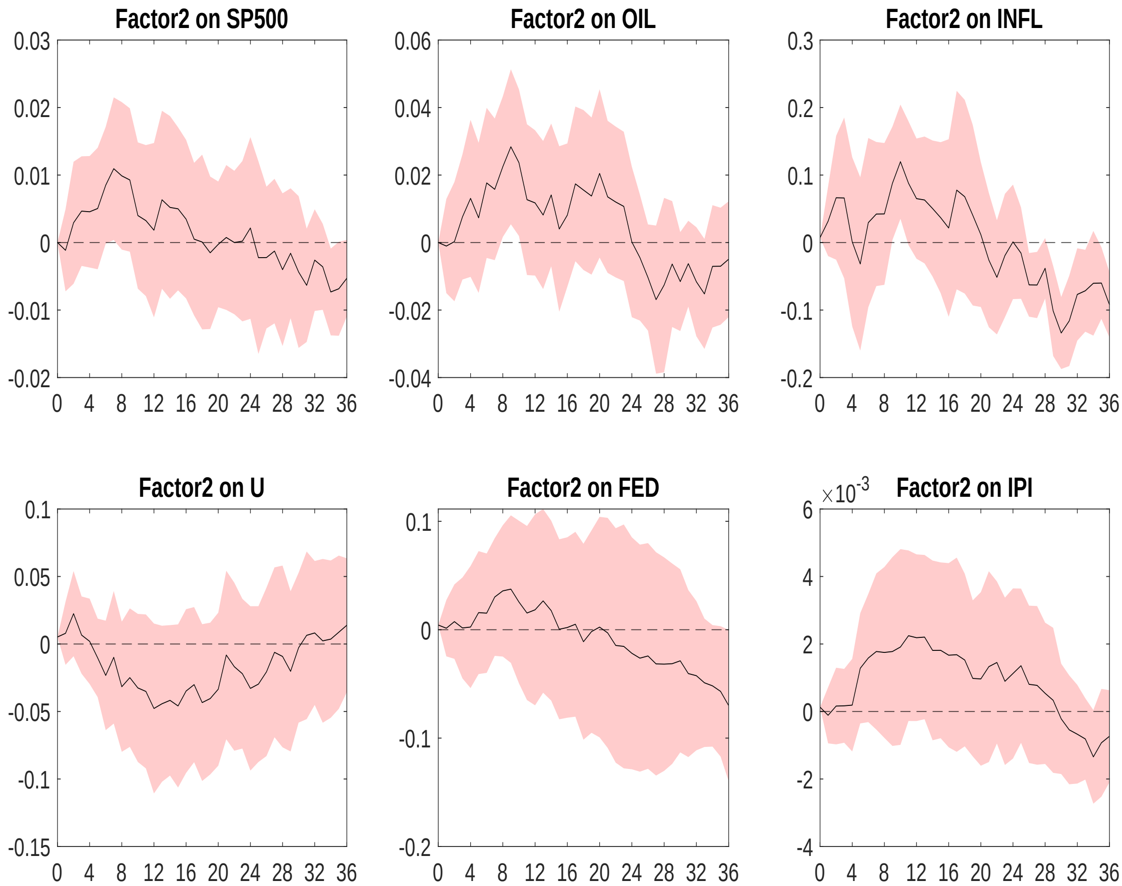
Source: Author's own calculations.
Notes: Except the uncertainty variable ($Factor2$), all variables are detrending applying the HP filter ($\lambda = 129600$) The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

Figure B.3.5: Impulse Response Functions in an intermediate uncertainty regime



Source: Author's own calculations.
Notes: Except the uncertainty variable ($Factor2$), all variables are detrending applying the HP filter ($\lambda = 129600$) The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

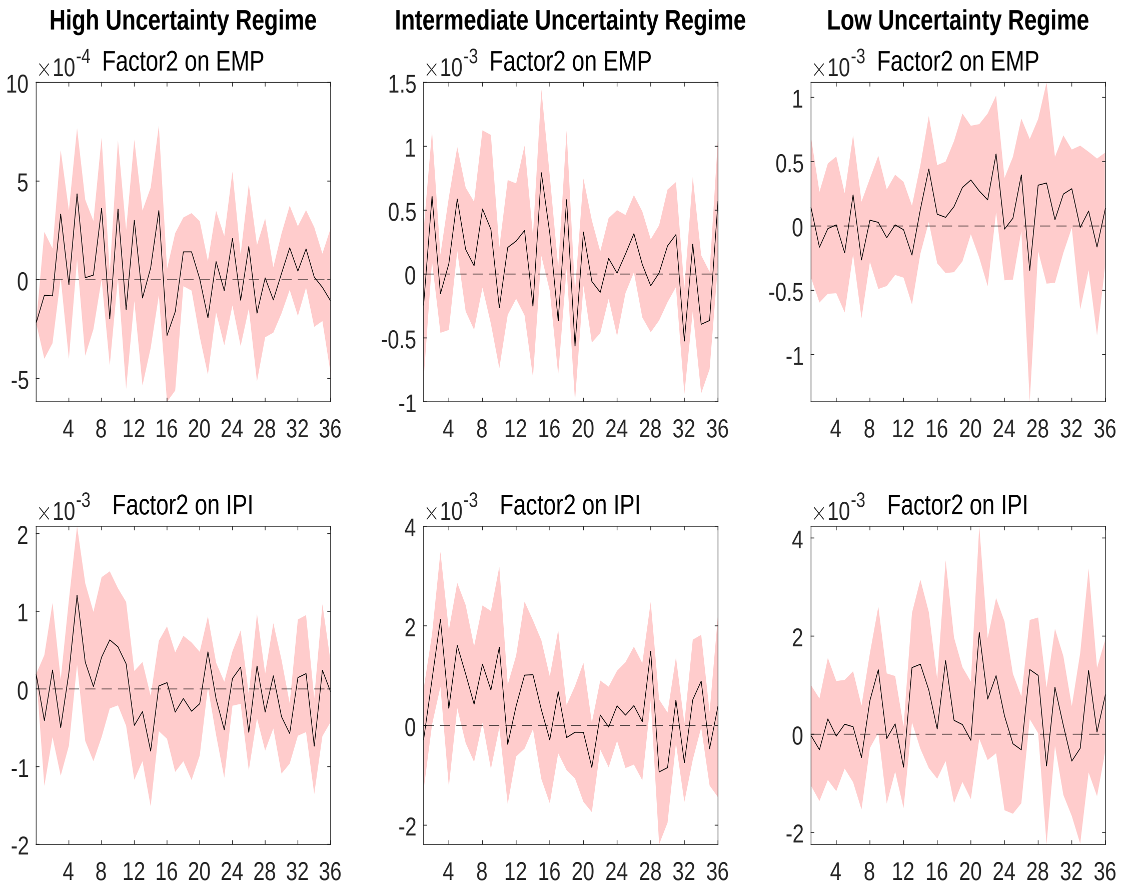
Figure B.3.6: Impulse Response Functions in a high uncertainty regime



Source: Author's own calculations.
Notes: Except the uncertainty variable ($Factor2$), all variables are detrending applying the HP filter ($\lambda = 129600$) The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

B.4 VAR 8

Figure B.4.1: Impulse Response Functions in a high uncertainty regime



Source: Author's own calculations.
Notes: Graphs on the left panel represents impulse response functions in the high uncertainty regime. Graphs on the middle panel represents impulse response functions in the moderate uncertainty regime. Graphs on the right panel represents impulse response functions in the low uncertainty regime. The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

Conclusion Générale

Cette thèse s'est interessée à la question des effets de l'incertitude sur l'activité écononomique et plus spécifiquement, à la question de l'existence d'un effet positif de l'incertitude. Un consensus semblait avoir été atteint quant à l'existence d'un effet négatif à la suite de la crise de 2007-2008 où le fort niveau d'incertitude, qui subsistait à ce moment-là, fut l'un des principaux facteurs expliquant la faible reprise économique. De nombreux travaux ont effectivement mis en avant le fait que l'incertitude pouvait avoir des effets récessifs et contribuant a alimenté la vision d'un effet négatif de l'incertitude. Cependant, des travaux théoriques mais également de récents travaux empiriques tels que ceux de Ludvigson et al. (2021) et Larsen (2021) ont montré que certaines formes d'incertitude pouvaient avoir un effet positif, brisant le consensus quant à cet effet négatif. Cette thèse s'inscrit dans ce courant de la littérature empirique.

Les deux premiers chapitres identifient des faiblesses dans la littérature. Le chapitre 1 a passé en revue la littérature sur la question de la mesure de l'incertitude. Depuis l'article fondateur de Bloom (2009), une littérature empirique fleurissante a émergé sur cette question en développant diverses méthodologies: volatilité des marchés financiers, dispersion des prévisions, variance des erreurs de prévisions, analyse textuelle de la presse. A partir d'une analyse en composantes principales, ce premier chapitre a développé un indice général d'incertitude pour les Etats-Unis. Ce chapitre mène également une analyse approfondie sur l'interprétation des différents facteurs permettant d'expliquer les composantes de l'incertitude. D'une façon intéressante, le second facteur a particulièrement attiré notre attention avec sa distinction entre les chocs d'incertitude qui sont liés à la finance (Lehman Brothers, Bulle internet, crise russe et LTCM) et les chocs qui ne sont pas liés pas à la finance (élections américaines, Guerre du Golfe, Guerre d'Irak, 11/09, Fiscal Cliff, Shutdown). Cette distinction fait le lien avec le travail de décomposition de Ludvigson et al. (2021) entre incertitude macroéconomique et incertitude financière. Cependant, ce second facteur souligne également la limite de la décomposition de ces auteurs. Leur mesure d'incertitude macroéconomique s'avère être plus "inféodée" à la finance qu'elle ne devrait l'être. L'originalité du chapitre 2 a été de mener une analyse approfondie du modèle SVAR de Ludvigson et al. (2021) où ces auteurs estiment un effet positif de l'incertitude macroéconomique sur la production industrielle à partir d'une nouvelle méthode d'identification des chocs d'incertitude dans le modèle. Les chocs d'incertitude sont contraints à être d'une amplitude suffisamment grande à des dates spécifiques comme la chute de Lehman Brothers par exemple. Les résultats de ce chapitre ont pu montrer que l'effet positif de ces auteurs n'est pas robuste et dépend de la présence d'une contrainte particulière. Il s'agit de la contrainte liée à un choc d'incertitude macroeconomique qui doit être suffisamment grand à la date de décembre 1970. De plus, nous pouvons constaté que certains chocs avaient été omis alors qu'ils sont clairement mis en évidence dans les indices d'incertitude de ces auteurs comme les attentats du 11 septembre ou encore la crise financière russe en 1998. En rajoutant des contraintes liées à ces chocs omis, les chocs d'incertitude macroéconomique ont désormais des effets récessifs. Une analyse désagrégée de leur mesure d'incertitude macroéconomique a permis d'expliquer le problème de dépendance vis-à-vis de la contrainte de décembre 1970. Le mois de décembre 1970 correspond à un point de retournement du cycle économique suivant la période de récession observée entre 1969 et novembre 1970. En associant un pic d'incertitude très élevé à ce mois spécifique de croissance, ces auteurs ont pu générer leur effet positif d'une façon artificielle.

De nombreux travaux ont souligné le fait que les chocs d'incertitude pouvaient avoir des effets différents selon l'état de l'économie, traduisant un effet non-linéaire. L'originalité des chapitres 3 et 4 a été d'estimer les effets des chocs d'incertitude selon leur nature à partir de méthodes économétriques non-linéaires. Le chapitre 3 utilise la méthode de la regression quantile qui est devenue de plus en plus populaire en macroéconomie. Cette méthode permet d'étudier l'effet de l'incertitude sur les différents percentiles de la croissance future. A l'instar des précédentes études empiriques, les résultats du chapitre 3 montrent bien qu'un choc d'incertitude général à de plus grands effets récessifs sur les quantiles inférieurs de la croissance future, c'est-à-dire, dans une période de recession. Ce chapitre a proposé une nouvelle manière de décomposer les chocs d'incertitude en revisitant la méthode developpée par Kang et al. (2021). Le chapitre 4 est dans la même lignée du chapitre 3 en appliquant une autre méthodologie empirique. A partir de la méthode des projections locales de Jordá (2005), ce chapitre étudie les effets asymétriques des chocs d'incertitude selon différents régimes d'incertitude (incertitude générale faible, modérée et forte) en endogénéïsant les seuils d'incertitude. Les résultats de ce chapitre confirment les résultats du chapitre précédent où l'incertitude non-financière a un effet positif dans des périodes où l'incertitude générale est modérée, forte. Ces périodes de forte incertitude générale peuvent être associées à des périodes de récessions par l'hypothèse contracyclique de Bloom (2009). L'argument théorique de la *growth options* liée aux innovations technologiques pourrait être une explication de cet positif. Cependant, l'explication ne laisse pas penser qu'il y aurait un effet non-linéaire. L'explication théorique s'inspirant des travaux de Gabaix (2020) serait plus appropriée. Plus les agents sont myopes, moins les agents peuvent examiner toutes les informations disponibles, moins ils peuvent anticiper avec perfection le futur et par conséquent, plus le futur est incertain pour ces derniers permettant un choc de dépenses publiques d'autant plus efficace.

Ces chapitres ont contribué à trouver un effet positif de l'incertitude qui soit plus robuste. Ces résultats contribuent à la littérature en montrant que l'incertitude peut avoir des effets positifs mais certaines conditions doivent être réunies: il faut i) que le choc d'incertitude soit d'une nature non-financière et ii) que ce choc impacte l'économie dans une période de forte incertitude générale ou de forte récession.

Cette thèse s'est focalisée sur des applications empiriques uniquement. Une extension de cette thèse serait de développer un modèle théorique de type DSGE traitant de cette question de l'effet positif de l'incertitude à partir d'une version allégée du modèle très complexe de Gabaix (2020). L'explication théorique de l'effet positif à partir de la *growth option* liée aux innovations high-tech est intéressante mais ne peut pas être vérifiée empiriquement avec les données disponibles actuellement. Cet argument théorique mis en avant par Ludvigson et al. (2021) pour expliquer leur effet positif de l'incertitude macroéconomique ne semble pas en adéquation avec la méthodologie utilisée pour construire leur mesure d'incertitude macroéconomique, basée sur les erreurs de prévisions de 132 séries macroéconomiques et financières. Aucune des séries utilisées par ces auteurs n'est explicitement liée à la technologie et aux innovations high-tech. De ce point de vue, une mesure d'incertitude liée aux innovations technologiques semble nécéssaire pour vérifier empiriquement cette théorie. Afin de vérifier empiriquement cette hypothèse d'incertitude technologique, une piste intéressante serait de développer un indice d'incertitude qui soit spécifiquement lié aux innovations technologiques à partir des techniques d'analyse textuelle et de machine learning. L'idée serait de reprendre la méthodologie utilisée par Baker et al. (2016) qui recherchent la fréquence de mots-clés liés à l'incertitude, à l'économie et à la politique économique dans la presse américaine afin de développer une mesure d'incertitude liée aux politiques économiques. Leur méthodologie a pour grand avantage de pouvoir développer de nombreuses mesures en changeant les critères de recherche des mots-clés. Pour notre future mesure d'incertitude technologique, nous selectionnerions des mots-clés qui seraient spécifiquement liés à la technologie et aux innovations high-tech. Par la suite, nous examinerions les effets du choc d'incertitude technologique en utilisant un modèle SVAR.

Cette thèse a également remis en question la décomposition de Ludvigson et al. (2021) entre incertitude macroéconomique et incertitude financière mais ne propose pas de nouvelles mesures de ce type. Une autre extension de cette thèse sera de developper de nouvelles mesures d'incertitude macroéconomique et financière mais qui soient plus indépendantes entre elles. Une piste intéréssante à suivre serait d'insérer la mesure d'incertitude générale et le second facteur de l'ACP du chapitre 1, qui sont orthogonaux entre eux par définition, dans un même modèle VAR *à la* Antolín-Díaz and Rubio-Ramírez (2018) où l'identificaton des chocs repose sur un mix de restrictions de signes et de contraintes narratives. Ainsi, il serait possible d'identifier un choc d'incertitude financier comme étant celui qui monterait le niveau général d'incertitude, qui baisserait le niveau du facteur 2 (se rapprochant du côté finance) et qui serait grand durant certaines crises financières comme Lehman Brothers. Le choc d'incertitude macroéconomique pourrait être identifié comme celui qui monterait le niveau général d'incertitude mais qui augmenterait également le niveau du facteur 2 (se rapprochant du côté non-finance) et qui serait d'une taille assez importante durant certains épisodes comme les périodes de tensions politiques (élections, Shutdown,. . .) ou encore pendant la pandémie de 2020. Puis, une fois ces chocs identifiés, la méthode de décompostion historique dans des modèles VAR permettrait de reconstruire une mesure d'incertitude macroéconomique en examinant quelle serait la contribution de ce type de choc à l'indice d'incertitude générale en tout point du temps de la période d'observation. La même procédure serait appliquée pour reconstruire une mesure d'incertitude financière en examinant quelle serait la contribution de ce type de choc à l'indice d'incertitude générale. Une fois les chocs d'incertitude bien identifiés, la méthode de la décomposition constitue un outil intéressant pour reconstruire de telles mesures mais pourrait également servir à construire des mesures de d'autres types, comme une incertitude liée aux prix des matières premières ou aux prix de l'énergie qui sont, aujourd'hui, au coeur des préoccupations.

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Résumé

Cette thèse tente d'apporter un nouvel éclairage à une littérature déjà ample quant aux effets de l'incertitude sur l'activité économique. Depuis la crise de 2007-2008, l'incertitude est vue comme néfaste pour l'économie. Or, dans la littérature théorique et empirique avec de récents travaux tels que ceux de Ludvigson et al. (2021), soulignant un effet positif de l'incertitude macroéconomique, certaines formes d'incertitude peuvent avoir un effet positif. Le chapitre 1 passe en revue les méthodes proposées dans la littérature afin de mesurer l'incertitude et construit un indice d'incertitude générale pour les Etats-Unis à partir d'une ACP. Cette ACP souligne la limite de la décomposition entre incertitude macroéconomique et financière de Ludvigson et al. (2021). Le chapitre 2 examine le modèle SVAR de ces auteurs et montre que leur effet positif mis en avant repose sur une contrainte liée à Bretton Woods qui est discutable. Les résultats montrent aussi que ces résultats ne sont pas robustes à l'ajout de d'autres contraintes (Ex : 11/09). Les chapitres 3 et 4 trouveront un effet positif plus robuste à partir de méthodes non-linéaires. Le chapitre 3 examine l'effet de la nature de chocs d'incertitude avec les méthodes de régression quantile tandis que le chapitre 4 étudie l'effet asymétrique de la nature des chocs selon différents régimes d'incertitude aves la méthode des projections locales de Jordá (2005). Les résultats de ces chapitres établissent un cadre dans lequel un effet positif peut se produire : l'incertitude doit être d'une nature non-financière et doit intervenir dans une période d'incertitude générale forte, modérée ou dans une période de récession.

Mots-clés: Incertitude, Activité Economique, Modèle SVAR, Effets Non-Linéaires

Abstract

This thesis attempts to shed new light on an already extensive literature on the effects of uncertainty on economic activity. Since the 2007-2008 crisis, uncertainty has been seen as harmful to the economy. However, in the theoretical and empirical literature with recent works such as Ludvigson et al. (2021), highlighting a positive effect of macroeconomic uncertainty, some forms of uncertainty can have a positive effect. Chapter 1 reviews the methodologies to measure uncertainty and develops a general uncertainty index for the United States from a PCA. This PCA highlights the limit of the decomposition between macroeconomic and financial uncertainty of Ludvigson et al. (2021). Chapter 2 examines the model of these authors and shows that their positive effect is based on a constraint linked to Bretton Woods which can be discussed. The results also show that these results are not robust if we add new constraints (Ex: 09/11). Chapters 3 and 4 will find a positive effect more robust than these authors applying nonlinear methodologies. Chapter 3 examines the effect of the nature of uncertainty shocks with quantile regression techniques while chapter 4 studies the asymmetric effect of the nature of shocks under different uncertainty regimes with local projection methods of Jordá (2005). The results of these chapters establish a framework in which a positive effect can occur: uncertainty must be non-financial nature during in a period of high, moderate general uncertainty or in a period of recession.

Keywords: Uncertainty, Economic Activity, SVAR models, Non-Linear Effects