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Financial Development and Climate Change Challenges with Focus on Resource-Rich Countries

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Introduction Générale

Le système financier revêt une importance cruciale dans le développement économique des nations. Dès le 19ème siècle, les travaux de Bagehot (1873) ont mis en évidence que la présence d'un marché des capitaux bien structuré en Angleterre favorisait l'allocation des ressources vers des investissements plus productifs. Par la suite, d'autres chercheurs, tels que Schumpeter (1911), Hicks (1969) et Goldsmith (1969), ont renforcé cette idée en soulignant les bénéfices d'un système financier développé. Schumpeter (1911) affirmait que la solidité du système bancaire était un moteur de croissance économique, facilitant la mobilisation de l'épargne et la réalisation d'investissements productifs. Hicks (1969) a également souligné le rôle du système financier dans la révolution industrielle, notant que son développement facilitait l'adoption de nouvelles technologies et innovations. Goldsmith (1969) a établi un lien positif entre le développement financier et la croissance économique, à travers une étude comparative de 35 pays sur la période 1860-1963. Au fil des années, de nombreuses études, notamment celles de McKinnon (1973), Shaw (1973), Kapur (1976), et d'autres, ont continué à soutenir l'idée que le développement financier est un facteur clé du développement économique. Des recherches plus récentes, telles que celles de Demetriades et Law (2006), ont confirmé l'impact positif du développement financier sur la croissance économique dans les pays en développement. Huang et Lin (2009) ont également observé que cet effet est plus marqué dans les pays en développement que dans les pays développés. Zhang et Hou (2014) ont mis en avant que le développement financier améliore la capacité des entreprises à réaliser des investissements propices à la croissance économique. En examinant les pays émergents, Lin et al. (2016) ont souligné que le développement du système financier et les réformes qui l'accompagnent sont essentiels pour assurer une croissance soutenue en Chine. De même, Kandil et al. (2017) ont identifié un effet positif du développement financier sur la croissance en Inde. Durusu-Ciftci et al. (2017) ont corroboré ces résultats en utilisant un panel de quarante pays, montrant que le développement financier stimule la croissance économique.

L'importance du développement financier ne se limite pas à la croissance économique traditionnelle. Dans le contexte actuel de changement climatique, le développement financier revêt une importance cruciale pour faire face aux défis environnementaux. Par exemple, la Banque mondiale a souligné que « le financement climatique est essentiel pour aider les pays à s'adapter aux impacts du changement climatique et à atténuer ses effets » (Banque mondiale, 2021). Cela signifie que les systèmes financiers doivent évoluer pour canaliser les investissements vers des projets durables, tels que les énergies renouvelables et l'infrastructure résiliente au climat. L'Accord de Paris, adopté en 2015, souligne également l'importance du financement dans la lutte contre le changement climatique. L'article 2 de cet accord stipule que les pays doivent "renforcer la capacité de financement pour faire face aux impacts du changement climatique" (UNFCCC, 2015). Cela implique non seulement des investissements publics, mais aussi des contributions privées, qui peuvent être catalysées par des politiques financières appropriées. Un rapport du Programme des Nations Unies pour le développement (PNUD) indique que "les pays qui investissent dans des systèmes financiers durables et inclusifs sont mieux préparés pour faire face aux défis posés par le changement climatique" (PNUD, 2020). Par exemple, le développement de marchés de capitaux verts peut faciliter l'accès à des financements pour des projets d'énergie renouvelable, de gestion des ressources en eau et d'agriculture durable. De plus, les institutions financières jouent un rôle clé dans la transition vers une économie verte. Comme le souligne le rapport de la Commission de haut niveau sur l'économie et le climat, "la transition vers une économie à faibles émissions de carbone nécessite des investissements massifs dans les infrastructures vertes, qui ne peuvent être réalisés sans un système financier adéquat" (Commission de haut niveau sur l'économie et le climat, 2018). Cela nécessite non seulement des financements directs, mais aussi des mécanismes d'incitation pour encourager les investissements privés dans des initiatives durables.

Les pays ont ainsi beaucoup à gagner dans l'amélioration de leur système financier. Cependant, plusieurs pays peinent encore à développer leur système financier, notamment ceux riches en ressources naturelles, qui rencontrent des difficultés économiques et souffrent de pauvreté, d'endettement excessif et d'un manque d'investissements privés (Gylfason et Zoega, 2002 ; Papyrakis et Gerlagh, 2004 ; Hausman et Rigobond, 2002 ; Manzano et Rigobond, 2001). Pour ces pays, le développement financier pourrait jouer un rôle clé non seulement dans la stimulation de la croissance économique, mais aussi dans la transition vers une économie plus verte et durable, capable de faire face aux défis du changement climatique.

Ressources naturelles et Développement financier

Bien qu'ayant des ressources naturelles pouvant leur permettre d'assurer leur développement économique, plusieurs pays riches en ressouces naturelles sont confrontés à un ralentissement de leurs performances économiques et connaîssent des systèmes financiers peu dynamiques et faiblement développés. Depuis les travaux pionniers de Sachs et Warner en 1995, les ressources naturelles ont été qualifiées de "malédiction" ou de "paradoxe" pour les pays qui en disposent en grande quantité. Ce constat soutient que, loin d'être un atout, les ressources naturelles, en particulier le pétrole, l'or et d'autres minéraux, peuvent avoir un impact négatif sur les performances économiques de ces pays. L'effet désigné par le terme "Voracity effect", introduit par Lane et Tornell en 1995, illustre comment les ressources naturelles peuvent engendrer un comportement de recherche de rentes de la part des gouvernements, ce qui entrave les performances économiques à long terme. En d'autres termes, au lieu de favoriser le développement économique, la richesse en ressources peut conduire à une concurrence malsaine pour le contrôle de ces ressources, sapant ainsi les fondements d'une croissance durable. Dans le même esprit, les recherches menées par Leite et Weidmann en 1999, ainsi que celles de Collier et Hoffler en 2002, mettent en lumière le lien entre les ressources naturelles et l'émergence de conflits civils et de corruption. Par exemple, leurs travaux révèlent qu'un pays sans ressources naturelles a une probabilité de seulement 0,5 % de connaître des conflits civils, tandis qu'un pays dont les ressources naturelles représentent 26 % de son PIB fait face à une probabilité alarmante de 23 % de tels conflits. Cette corrélation souligne les dangers inhérents à la dépendance excessive aux ressources naturelles. Prenons le cas spécifique du Nigéria, comme l'ont illustré Sala-i-Martin et Subramania en 2003. Malgré ses abondantes ressources naturelles, le Nigéria a connu une expérience de développement désastreuse depuis son indépendance, avec un niveau de vie stagnant pendant trois décennies. En effet, le PIB par habitant est passé de 1 113 dollars US à 1 084 dollars US entre 1970 et 2000, tandis que le taux de pauvreté a explosé, passant de 36 % à 70 % sur la même période. Ce constat met en lumière les défis auxquels ces pays sont confrontés, malgré leurs richesses apparentes.

Une littérature plus récente a également examiné le développement du système financier dans les pays riches en ressources naturelles, et les résultats sont tout aussi préoccupants. Cette lacune en matière de développement financier est particulièrement préoccupante, car elle entrave les efforts visant à transformer la richesse des ressources en un véritable développement durable. Les pays dotés de ressources naturelles ont souvent des systèmes financiers peu développés, avec un accès limité aux services bancaires et aux financements pour les PME, ce qui compromet leur potentiel de croissance économique. Le rapport de la Banque Mondiale (2017) indique que « l'absence d'un secteur financier robuste limite la capacité des pays à investir dans des infrastructures essentielles et à diversifier leurs économies ». Beck (2012) a démontré que ces pays, en particulier ceux riches en pétrole, affichent un niveau de développement financier très faible par rapport à leurs homologues moins riches en pétrole. Hoshman et al. (2013) ont utilisé la méthode des moments généralisés (MMG) pour analyser des données de 2002 à 2010 sur les pays exportateurs de pétrole, concluant que les ressources naturelles compromettent le développement du système financier. De plus, Mlachila et Ouedraogo (2020) ont confirmé cet effet néfaste, montrant que la volatilité des prix des ressources naturelles a un impact négatif sur le développement financier d'un échantillon de 68 pays riches en ressources naturelles. Sun et al. (2020) ont également corroboré cette tendance, indiquant qu'une augmentation des revenus tirés des ressources naturelles est associée à une baisse de 0,046 % du niveau de développement financier sur un échantillon de sept pays émergents entre 1990 et 2017. De même, Khan et al. (2020) ont vérifié cet effet négatif dans le cas de la Chine sur la période 1987-2017. Bien que plusieurs explications aient été avancées pour justifier cet effet négatif des ressources naturelles sur le développement financier, notamment le phénomène de la "maladie hollandaise", l'instabilité des prix des ressources naturelles entraînant une volatilité des revenus, ainsi que des questions liées à l'affectation du capital humain et au cadre institutionnel (Mlachila et Ouedraogo, 2020 ; Beck et Poelhekke, 2017), une préoccupation majeure demeure : comment présenter des solutions et des recommandations empiriques pour aider ces pays riches en ressources naturelles à sortir de cette trappe économique. Dans cette perspective, cette thèse vise à démontrer de manière empirique comment une amélioration du cadre institutionnel peut permettre aux pays riches en ressources naturelles de surmonter la "malédiction des ressources naturelles" dans le contexte de leur système financier.

Pays riches en ressources naturelles et vulnérabilité climatique

Au-delà des défis économiques auxquels sont confrontés les pays dotés de ressources naturelles abondantes, il est essentiel de reconnaître qu'ils ne sont pas à l'abri des conséquences du changement climatique. Ce phénomène demeure un enjeu mondial majeur, suscitant des inquiétudes croissantes à l'échelle planétaire. Depuis l'adoption de l'accord de Paris lors de la COP 21, ces nations se voient encouragées à explorer des alternatives à l'exploitation et à la production de certaines ressources, telles que le pétrole, qui jouent un rôle significatif dans le réchauffement climatique en raison des émissions de carbone qu'elles engendrent. Dans ce contexte, une réduction de l'exploitation des ressources naturelles pourrait engendrer des répercussions économiques sévères pour plusieurs de ces économies, qui dépendent largement de ces ressources pour leur prospérité. En effet, une baisse des revenus due à une diminution de la production de ces ressources pourrait entraver de manière significative leur capacité à s'adapter aux effets de plus en plus menaçants du changement climatique. En outre, les pays riches en ressources naturelles ne sont pas seulement vulnérables à une perte de revenus ; ils sont également susceptibles de subir des impacts physiques et sociaux liés au changement climatique, tout comme de nombreuses autres nations qui ne possèdent pas de telles richesses. Il est donc impératif que ces pays, ainsi que tous les pays en général, puissent évaluer de manière précise leur niveau de vulnérabilité face au changement climatique. Cela leur permettra de mettre en œuvre des politiques d'adaptation appropriées et efficaces. À cette fin, divers indicateurs de vulnérabilité ont été proposés tant à l'échelle micro qu'à l'échelle macro. Cependant, il convient de noter que de nombreux indicateurs, en particulier à l'échelle macro, révèlent une hiérarchisation marquée des pays en fonction de leur niveau de développement économique (Halkos et al. 2020, Chen et al. 2015). Ainsi, les pays moins développés apparaissent souvent comme les plus vulnérables, tandis que les nations plus développées semblent moins exposées. Toutefois, cette tendance n'est pas systématique, car des pays développés tels que les États-Unis ou l'Australie subissent régulièrement des perturbations climatiques significatives qui impactent le niveau de vie de leurs populations. Il est donc crucial de trouver une mesure de vulnérabilité qui soit indépendante du niveau de développement économique des pays et qui reflète véritablement la vulnérabilité aux effets directs du changement climatique. Ces effets doivent être considérés en fonction de facteurs climatiques qui ne sont pas directement liés au contexte économique. La présente thèse s'intéresse précisément à cette problématique en proposant une évaluation de la vulnérabilité climatique à l'échelle macro qui soit déconnectée du niveau de développement économique des pays.

Vulnérabilité climatique et Finance Climatique

La vulnérabilité climatique représente un défi majeur qui nécessite la mise en œuvre de mesures d'adaptation efficaces afin de minimiser les conséquences néfastes du changement climatique sur les pays et les populations. Depuis le début des années 2000, plusieurs pays développés ont pris conscience de cette problématique et ont commencé à accorder des aides climatiques destinées aux pays en développement. Cet engagement a été renforcé lors de la conférence de Copenhague (COP 15) en 2009, où les pays développés ont promis de fournir une assistance financière significative aux nations moins avancées, avec un objectif ambitieux de 100 milliards de dollars par an jusqu'en 2020. Cet engagement a été réaffirmé lors de la conférence de Paris (COP 21), où il a été prolongé jusqu'en 2025. Les flux financiers entre les pays développés et les pays en développement ont suscité un intérêt croissant de la part des chercheurs, qui ont entrepris d'examiner les déterminants de la finance climatique. Ces études visent à éclairer les motivations qui sous-tendent l'octroi de ces aides, ainsi que les caractéristiques des pays qui en bénéficient réellement (Barett, 2014 ; Doku et al. 2021 ; Bayramoglu et al. 2023). Bien que certains déterminants de la finance climatique bilatérale aient été identifiés, tels que les liens historiques issus du colonialisme et le faible niveau de développement des pays récipiendaires, des réponses ambivalentes subsistent quant à la priorité accordée aux pays les plus vulnérables face aux effets du changement climatique. Par exemple, Barett (2014) avance que la finance climatique ne se dirige pas nécessairement vers les régions les plus vulnérables, tandis que Bayramoglu et al. (2023) soutiennent que, au contraire, elle est effectivement orientée vers ces pays. Cette thèse vise à apporter une réponse éclairée à cette question complexe en démontrant que les pays les plus vulnérables ne sont pas susceptibles de recevoir des aides climatiques ni sous forme de dons que de prêts. Ainsi, cette analyse met en lumière les défis et les opportunités associés à la distribution de l'aide climatique, tout en soulignant l'importance d'une approche ciblée pour soutenir les pays qui en ont le plus besoin.

Objectifs et Plan de la Thèse

Le chapitre 1 de cette thèse se penche sur la relation complexe entre les ressources naturelles et le développement financier. En utilisant des données en panel provenant de 100 pays sur une période s'étendant de 1996 à 2017, ce chapitre met en lumière une dynamique intéressante : l'impact négatif des ressources naturelles sur le développement financier ne se manifeste pas de manière uniforme. En effet, cet effet peut varier considérablement en fonction de la qualité des institutions en place dans chaque pays. Les résultats indiquent qu'en améliorant leur cadre institutionnel, les pays peuvent atténuer cet impact négatif de manière significative, avec des réductions potentielles de 78 %, 86 % ou même 96 %, selon le niveau initial de qualité institutionnelle du pays. Cela souligne l'importance cruciale d'un environnement institutionnel solide pour maximiser les bénéfices des ressources naturelles sur le développement financier. Le chapitre 2 aborde la thématique de la vulnérabilité climatique en relation avec le niveau de développement des pays. Il propose une nouvelle mesure de la vulnérabilité climatique, soigneusement conçue pour être indépendante du niveau de développement économique. Ce chapitre introduit un indicateur novateur, dénommé « CV03 », qui se distingue par sa faible corrélation avec le développement économique. Cela permet d'obtenir une évaluation plus précise des risques climatiques auxquels les pays sont confrontés, indépendamment de leur situation économique, et met en évidence les défis spécifiques que rencontrent les nations moins développées face aux changements climatiques. Enfin, le chapitre 3 se concentre sur la finance climatique bilatérale, en mettant l'accent sur les pays particulièrement vulnérables aux effets du changement climatique. Les résultats démontrent que ces pays ne sont pas priorisés dans l'allocation de l'aide climatique ni sous forme de dons que de prêts. Ce constat soulève des questions importantes sur l'efficacité et l'équité de l'allocation de l'aide climatique. De plus, le chapitre met en avant le rôle déterminant des intérêts politiques et économiques des pays donateurs dans cette allocation, suggérant que les décisions d'aide ne sont pas uniquement motivées par des considérations humanitaires ou environnementales, mais aussi par des stratégies géopolitiques.

Chapter 1

Institutional Quality and Financial Development in Resource-Rich Countries: A Nonlinear Panel Data Approach [1]

Introduction

Are natural resources really a curse? Over the past two decades, research has increasingly focused on resource-rich countries, highlighting their often poor economic performance (e.g., Sachs and Warner, 2001; Sala-i-Martin and Subramanian, 2003; Leite and Weidmann, 2002). Many of these countries experience high levels of poverty, a decline in private investments, insufficient productive investments, excessive government debt, significant social and economic inequality, low economic diversification, cyclical boom and bust patterns, inefficient spending following positive revenue shocks, and reduced government expenditure after negative shocks (Gylfason and Zoega, 2002; Papyrakis and Gerlagh, 2004; Hausman and Rigobond, 2002; Manzano and Rigobond, 2001). Such findings tend to reinforce a negative perception of resource wealth. Moreover, natural resources are frequently associated with adverse effects on institutions, leading to rent-seeking behavior and corruption (Tornell and Lane, 1999; Torvik, 2002; Leite and Weidmann, 2002). This dynamic diminishes the incentives for governments to implement institutional and economic reforms and may provoke conflicts over resource control (Haford and Klein, 2005). This paradox has reignited interest among various studies. Recent research has sought to understand the relationship between natural resources and financial development, often asserting a negative impact of resource wealth on financial systems. Many

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resource-rich countries are characterized by underdeveloped financial systems, where banks are hesitant to extend credit and where there is sometimes an excess of liquidity (Bhattacharyya and Holder, 2014; Beck, 2010). While financial development is essential for economic growth, enhancing financial systems can help resource-rich countries address critical issues such as poverty, inequality, and export concentration. This enhancement facilitates economic diversification and supports the transition to a sustainable economy in the face of climate change. Financial development is defined as the improvement in the quality of the financial system, including the production and processing of investment information, monitoring individuals and businesses, managing risks, and easing the exchange of goods and services (World Bank, 2012). Scholars like McKinnon (1973) and Shaw (1973) have argued that financial liberalization fosters economic growth by boosting savings and stimulating investments. Levine (2005) similarly posits that financial development enhances economic growth through various channels, such as facilitating trade, mobilizing savings, diversifying investments, increasing liquidity, and reducing intertemporal risks. Given the critical role of financial development in fostering economic advancement, it is vital to explore how financial systems are affected in resource-rich countries and how these nations can leverage their natural wealth. Prior studies have identified institutional quality as a potential mechanism for resource-rich countries to capitalize on their resource wealth. A robust institutional framework can help mitigate the negative impacts of natural resources, thereby addressing the so-called "natural resource curse" or "paradox of plenty" (Mehlum et al., 2006; Boschini et al., 2007; Bhattacharyya and Holder, 2014). However, several questions remain: At what level of institutional quality can resource-rich nations effectively benefit from their resources? What efforts must countries with weak institutional frameworks undertake to maximize the benefits derived from their resources?

This chapter aims to address these questions by empirically examining the threshold levels of institutional quality that differentiate the effects of natural resources on financial development, enabling the classification of countries based on these thresholds. This work significantly contributes to the literature surrounding the relationship between natural resources and financial development, expanding upon the broader discourse regarding the resource curse hypothesis. While extensive literature exists on the resource curse, there is comparatively less research on the interplay between natural resources and financial development. Additionally, this chapter introduces a threshold endogenous variable into a threshold model, utilizing a climate variable to assess institutional quality, rather than relying on traditional methods to resolve endogeneity issues. Institutional quality may face endogeneity challenges, given the simultaneous relationship between natural resources and institutional quality as explanatory variables. Furthermore, improvements in institutional quality can result from economic performance or development, which may correlate with error terms in econometric models (Brunnschweiler, 2008; Bhattacharyya and Holder, 2014; Jensen and Wantchekron, 2004). To our knowledge, no previous empirical studies have employed a climate variable as an instrument for institutional quality in the context of natural resources and financial development.

The main findings of this study indicate that while natural resources consistently exert a significant and negative impact on financial development, this effect is particularly pronounced in countries with low institutional quality. Quantitatively, our empirical analysis reveals that improvements in institutional quality can dramatically reduce this negative impact by as much as 78%, 86%, or 96%, depending on the initial level of institutional quality in the country. The structure of the chapter is as follows: Section 1 provides a review of the determinants of financial development, recent literature on the relationship between natural resources and financial development, and the role of institutional quality in this context. Section 2 details the empirical methodology and dataset utilized. Section 3 addresses the endogeneity issues associated with the institutional quality variable. Section 4 presents descriptive statistics by country regions in our sample and the empirical results. Finally, Section 5 concludes with policy implications.

1.1 Potential Determinants of Financial Development: A Review of the Literature

The discussion surrounding the determinants of financial development has garnered the attention of various scholars, including Huang (2010), who identifies key factors such as trade, financial liberalization, and institutional quality. The following subsections will outline the determinants of financial development as presented in the literature, with a particular emphasis on resource-rich countries and the role of institutional quality in the interplay between natural resources and financial development.

1.1.1 Traditional Determinants of Financial Development

Research into the determinants of financial development has identified multiple factors contributing to its advancement, including trade, institutional quality, financial liberalization, macroeconomic stability, income levels, population dynamics, and cultural influences.

Trade openness is often cited as a crucial element in fostering financial development (Baltagi et al., 2009; Kim and Lin, 2010; Svaleryd and Vlachos, 2002). By necessitating financial transactions and managing commercial risks, trade openness enhances demand for external finance, thereby stimulating the creation and improvement of financial products and instruments.

Furthermore, as the trade sector expands, it drives up the demand for credit, thus boosting banking activity. Empirical support for the significance of trade openness comes from Rajan and Zingales (2003), who find a positive correlation between trade openness and financial market development, especially in contexts where cross-border capital flows are unrestricted. Similarly, Baltagi et al. (2009) illustrate a positive relationship between trade openness and financial development in a study involving 42 developing nations from 1980 to 2003. Hattendorff (2014) reinforces these findings, indicating that export concentration can diminish private credit relative to GDP. The quality of economic and political institutions is another critical determinant of financial development. Clague et al. (1996) and Olson (1993) emphasize that democratic regimes tend to better safeguard property rights and enforce contracts compared to autocratic ones. Such democratic processes enhance civil liberties, stabilize policies, and foster an open society, all of which are vital for financial development. Huang (2011) posits that the level of institutional development directly influences the sophistication of a nation's financial system. La Porta et al. (2000) and Bhattacharyya and Holder (2014) also advocate that effective oversight and enforcement mechanisms are essential for regulating interactions between creditors and debtors. Macroeconomic stability and sound policies are also important determinants. Factors such as inflation rates can significantly impact the financial sector, though the relationship may differ in the short and long term. Boyd et al. (2001) argue for a significant negative relationship between sustained inflation and financial development. Meanwhile, Kim and Lin (2010) identify a negative long-run correlation between inflation and financial development, juxtaposed with a positive short-run relationship. Government debt, too, plays a significant role in financial sector development. Excessive government borrowing can dampen private investment, particularly in emerging economies (Caballero and Krishnamurthy, 2004), leading to reduced demand for credit. Hauner (2009) contends that countries with high budget deficits may see their financial systems become less efficient.

Other notable determinants include economic growth, income, population factors, and cultural aspects. Greenwood and Jovanovic (1990) argue that as economies grow, competition reduces the cost of financial intermediation, thus expanding the pool of available funds for investment. Levine (1997, 2005) underscores the importance of income levels for financial development, while Jaffee and Levonian (2001) note the positive effects of GDP per capita and savings rates on the banking sector's growth in 23 transition economies. Stulz and Williamson (2003) highlight the impact of cultural variations (particularly religious and linguistic differences) on financial development, arguing that culture influences the protection and enforcement of investor rights, notably creditor rights.

1.1.2 Focus on Natural Resources and Financial Development

Natural resources, including oil, gas, and minerals, generate substantial income for resource-rich countries. However, despite these revenues, many such nations experience low levels of economic development and financial growth (Sachs and Warner, 1995). The literature suggests that resource-rich countries often face challenges to their financial development (e.g., Bhattacharyya and Holder, 2014; Beck, 2010). Several hypotheses explain this phenomenon, including the Dutch disease, institutional quality, and commodity price volatility.

The Dutch disease hypothesis posits that an increase in production within the natural resource sector can lead to declines in other sectors (Yuxiang and Chen, 2010). This shift in resources may reduce investment in non-resource sectors, thereby lowering credit demand from banks. Additionally, the focus on resource extraction can detract from manufacturing and other sectors, hindering trade and consequently affecting financial development, as trade openness is vital for such progress (Kim et al., 2010). Another explanation for the negative correlation between natural resources and financial development relates to the quality of institutions. Resource wealth can lead to corruption and rent-seeking behavior among elites, undermining the business environment, decreasing bank lending, and stunting the financial sector's growth. Leite and Weidmann (1999) argue that resource abundance opens avenues for rent-seeking and corruption. Furthermore, Ross (2001) and Collier and Hoeffler (2005) observe a negative relationship between resource abundance and the stability and quality of political systems. Aslaksen (2010) finds that both oil extraction and mineral income are linked to increased corruption. This relationship prompts the need to treat institutional quality as an endogenous variable in models that explore the impacts of both natural resources and institutional quality. The volatility of commodity prices is also noted as a factor affecting financial development. Fluctuating commodity prices create uncertainty about revenue and growth prospects, which may discourage banks from extending credit and lead to higher risk premiums. Kurronen (2012) indicates that macroeconomic instability caused by commodity price fluctuations can undermine financial development.

Several empirical studies have examined the relationship between natural resources and financial development. For instance, Beck (2010) finds that banks in resource-rich countries tend to be more liquid yet offer fewer loans to firms. Gylfason and Zoega (2002) demonstrate that natural resources can hinder financial development by inducing lower levels of financial intermediation, based on a sample of 85 countries from 1965 to 1998. Similarly, Yuxiang and Chen (2010) show through a provincial panel data analysis in China (1996–2006) that natural resources impact financial development. Kurronen (2012) identifies a trend toward smaller banking sectors in resource-dependent countries. Beck and Poelhekke (2017) illustrate a decline in private sector lending following unexpected natural resource windfalls, while Mlachila and Ouedraogo (2017) find that commodity price shocks negatively affect financial development in resource-rich nations.

1.1.3 Institutions, Natural Resources and Financial Development

The past three decades have witnessed a burgeoning literature on the significance of institutions in economic development. Since the 1990s, scholars have examined institutional quality as a key factor explaining variations in development across countries. North Douglas (1990) argues that the institutional framework shapes the incentive structure and opportunities within an economy, while Acemoglu et al. (2005) attribute differences in economic and political institutions as a fundamental cause of varying economic growth rates. Institutions not only influence resource distribution but also economic outcomes. Moreover, existing literature supports the notion that high institutional quality is essential for fostering financial development (Huang, 2011). Strong political and economic institutions can promote financial development, enhance the business climate, and increase banking credit activities. Effective institutions encourage contract enforcement, thereby incentivizing banks to lend more.

As discussed in the previous subsection, natural resources can negatively affect financial development through mechanisms like corruption, rent-seeking, political instability, and a weak rule of law. Therefore, a robust institutional framework can mitigate these adverse effects by curbing corruption, promoting contract enforcement, and reducing rent-seeking behaviors. Previous research indicates that strong institutions can alleviate the negative impacts of natural resources (Boschini et al., 2007; Bhattacharyya and Holder, 2014). However, key questions remain: At what level of institutional quality can countries effectively leverage their resource wealth? What measures must nations with weaker institutional frameworks adopt to maximize benefits from their resources? This chapter seeks to address these questions by quantitatively identifying threshold levels of institutional quality that differentiate the negative impacts of natural resources on financial development. This research significantly contributes to the existing literature on the nexus between natural resources and financial development, as well as the broader discourse surrounding the resource curse hypothesis.

1.2 Data and Methodology

This empirical analysis utilizes a dataset comprising 100 countries spanning from 1996 to 2017. The study measures financial sector development using the ratio of domestic credit to the private sector relative to GDP. For robustness checks, additional indicators of financial development, such as Broad Money (M2) and the ratio of private credit to deposits, are also examined. Key variables include institutional quality and natural resource rents.

1.2.1 Methodology

The methodology employed in this study is based on a Panel Threshold Model, which extends the Hansen Panel Threshold Model. This approach helps identify threshold effects while addressing endogeneity biases associated with the threshold variable (Seo et al., 2019). In contrast to the Panel Smooth Transition Regression (PSTR) method proposed by Gonzales et al. (2017), which also assesses nonlinear effects and has been utilized in various studies (Chien et al., 2020; Cheikh and Zaied, 2020), the extended Hansen Panel Model effectively manages endogenous issues inherent in the threshold model.

The following equation is estimated:
$FinDev_{it} = X_{it}\beta + (1, X'_{it})\delta 1\{IQ_{it} > \gamma\} + u_i + \epsilon_{it}$, $i = 1, ..., n; t = 1, ..., T$.
Where:
$FinDev_{it}$ is the dependent variable and stands for financial development indicator for country i in time t.
X_{it} encompasses independent variables, which include Natural resources variable ($Nrent_{it}$), Gross domestic product per capita ($Gdpc_{it}$), Inflation ($Inflation_{it}$) and Population (Pop_{it}).
IQ_{it} is the threshold variable representing institutional quality.
γ signifies the threshold value, u_i accounts for individual effects and ϵ_{it} represents error terms. Following the extension proposed by Seo et al. (2019), this econometric model addresses the potential endogeneity of the threshold variable. The inclusion of both natural resources and institutional quality in the model may introduce an endogeneity effect regarding the institutional quality variable. This is further complicated by the notion that institutional quality might result from economic development (Jensen and Wantchekron, 2004; Sokoloff and Engerman, 2000; Robinson et al., 2006), which can create correlations between the institutional quality variable and the model's error terms. To mitigate this endogeneity bias, a climate variable that is temperature (*Temp*) is used as an instrumental variable for institutional quality.

The parameter u_i has been removed through a first difference transformation and the parameter θ=(β',δ',γ')$'$ is estimated using the Generalized Method of Moments (GMM).

The sample moment is construted as
$\bar{g}_n(\theta) = \bar{g}_{1n} - \bar{g}_{2n}(\gamma)(\beta', \delta')' = \frac{1}{n}\sum_{i=1}^{n} g_{1i} - \frac{1}{n}\sum_{i=1}^{n} g_{2i}(\gamma)(\beta', \delta')'$,

where $g_{1i} = \begin{pmatrix} z_{ito}\Delta y_{ito} \\ \vdots \\ z_{iT}\Delta y_{iT} \end{pmatrix}$, $g_{2i}(\gamma)$=$\begin{pmatrix} z_{ito}(\Delta x'_{ito}, 1_{ito}(\gamma)'X_{ito}) \\ \vdots \\ z_{iT}(\Delta x'_{iT}, 1_{iT}(\gamma)'X_{iT}) \end{pmatrix}$, Δ the first difference operator,

X$_{iT}$=$\begin{pmatrix} (1, x'_{it}) \\ (1, x'_{i,t-1}) \end{pmatrix}$ and $\underset{2\times 1}{1_{it}}(\gamma)$=$\begin{pmatrix} 1\{q_{it} > \gamma\} \\ -1\{q_{it-1} > \gamma\} \end{pmatrix}$.

The GMM criterion function is introduced with a weight matrix W_n, $\overline{J}_n(\theta)$=$\overline{g}_n(\theta)'$ W_n $\overline{g}_n$. The minimization of $\overline{J}_n(\theta)$ produce a GMM estimate $\hat{\theta}$.
The solution of the minimization is as follows: $(\hat{\beta}\ (\gamma)'$,$\hat{\delta}\ (\gamma)')'$ = $(\overline{g}_{2n})(\gamma)'$ $W_n(\overline{g}_{2n})(\gamma))^{-1}$ $\overline{g}_{2n}W_n\overline{g}_{1n}$.
with W_n, the weight matrix. $W_n = I_l$ or

$$W_n = \begin{pmatrix} \frac{2}{n}\sum_{i=1}^{n} z_{ito}z'_{ito} & \frac{-1}{n}\sum_{i=1}^{n} z_{ito}z'_{ito+1} & 0 & \cdots \\ \frac{-1}{n}\sum_{i=1}^{n} z_{ito} + 1z'_{ito+1} & \frac{2}{n}\sum_{i=1}^{n} z_{ito} + z'_{ito+1} & \ddots & \ddots \\ 0 & \ddots & \ddots & \frac{-1}{n}\sum_{i=1}^{n} z_{iT-1}z'_{iT} \\ \vdots & \ddots & \frac{-1}{n}\sum_{i=1}^{n} z_{iT}z'_{iT-1} & \frac{2}{n}\sum_{i=1}^{n} z_{iT}z'iT \end{pmatrix}^{-1}$$

is updated to W_n = $(\frac{1}{n}\sum_{i=1}^{n}\hat{g}_i\hat{g}'_i - \frac{1}{n^2}\sum_{i=1}^{n}\hat{g}_i\sum_{i=1}^{n}\hat{g}'_i)^{-1}$, where $\hat{g}_i$=$(\hat{\Delta}\varepsilon_{ito}z'_{ito}, \ldots, \hat{\Delta}\varepsilon_{iT}z'_{iT})'$.

A bootstrap test is also used for testing linearity of the model with a null hypothesis that is H_0: δ_0 = 0, for any $\gamma \epsilon \Gamma$, Γ indicates the parameter space of γ, with the alternative hypothesis that is H_0: $\delta_0 \neq 0$.

1.2.2 Data

The data used in this analysis spans from 1996 to 2017 and is sourced from various platforms, including the World Bank's Worldwide Development Indicators, the Global Financial Development Database, the Penn World Table, the Climate Change Knowledge Portal of the World Bank Group, and the United Nations Conference on Trade and Development (UNCTAD) Data Center.

Financial Development Indicator

The financial sector encompasses institutions, instruments, markets, and the legal and regulatory frameworks that facilitate credit transactions (World Bank, 2012). Financial development is defined as enhancements in key financial functions, such as the generation and processing of information regarding investments, capital allocation, risk management, mobilization of savings, and the facilitation of transactions involving goods, services, and financial instruments

(World Bank, 2012). For this study, we measure financial sector development using the ratio of domestic credit to the private sector relative to GDP (Priv.cred), as reported by the World Bank. This metric is widely recognized as an indicator of financial development (Beck and Poelhekke, 2017; Mlachila and Ouedraogo, 2017; Bhattacharyya and Holder, 2014). To further validate our findings, we include additional financial development indicators in our robustness checks, such as Broad Money (M_2) from the World Bank and the ratio of private credit to deposits (Pdpot) from the Global Financial Development Database (Mlachila and Ouedraogo, 2017).

Natural Resources Variable

In this analysis, natural resources refer to mineral resources, oil, and natural gas. The World Bank Group (WBG) Fragile, Conflict, and Violence Group-Investment Climate Teams defines resource-rich countries as those where the average total natural resources rent (as a percentage of GDP) over the last three years is at least ten percent. To enlarge our sample size, this study includes countries with natural resources rent below ten percent of GDP. In our robustness checks, we focus solely on countries that meet the World Bank's definition. Previous studies have utilized various indicators to describe natural resource wealth, including the ratio of resource exports (such as fuel, ores, and metals) to GDP (Beck, 2010) or total natural capital and mineral resource assets (Brunnschweiler and Bulte, 2008). In this chapter, we measure natural resource wealth using the ratio of natural resources rent to GDP (Nrent) from the World Bank, a variable that is widely used and available for numerous countries (Bhattacharyya and Holder, 2014; Beck and Poelhekke, 2017).

Worldwide Governance Indicators

To evaluate institutional quality, a composite indicator has been created from the Global Governance Indicators, which assess various dimensions of governance. The Worldwide Governance Indicators include Voice and Accountability, Political Stability and Absence of Violence and Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption. Voice and Accountability (VA) measures the extent to which citizens can participate in government selection, along with freedoms of expression and association. Political Stability and Absence of Violence and Terrorism (PS) gauge perceptions regarding the likelihood of government destabilization through unconstitutional or violent means. Government Effectiveness (GE) assesses the quality of public services, civil services, and the degree of independence from political pressures, as well as the credibility of government policies. Rule of Law (RL) reflects the confidence agents have in societal rules, including contract enforcement and property rights. Control of Corruption (CC) evaluates perceptions of corruption and the extent to which public power is abused for private gain. Data for these indicators are sourced from the World Bank. A composite indicator (IQ) has been constructed from the Worldwide Governance Indicators using Principal Component Analysis (PCA), which is detailed in Section 3.

Political Regime Variable (Polity2)

The Polity project aims to code state authority characteristics for comparative or quantitative analyses. The polity score ranges from -10 to +10, categorizing regimes into three types: autocratic (-10 to -6), anocratic (-5 to +5), and democratic (+6 to +10). In this study, these scores are normalized to a scale from 0 to 1, with the corresponding regime classifications as follows: autocratic (0 to 0.2), anocratic (0.25 to 0.75), and democratic (0.8 to 1). This variable is utilized in robustness checks.

Control Variables

Several control variables are incorporated into the model, as identified in the literature as determinants of financial development (Boyd et al., 2001; Jaffee and Levonian, 2001; Levine, 2005):

◦ Gross Domestic Product per Capita (Gdpc) at 2010 constant prices, from the World Bank. This variable provides insights into the size and development level of a country's economy.

◦ Inflation, from the World Bank, representing the annual percentage variation in consumer prices.

◦ Population (Pop), sourced from the Penn World Table, which allows for assessment of country size.

1.3 The issue of endogeneity of Institutional quality indicator

1.3.1 Institutional quality indicator (IQ)

A composite indicator has been constructed from the Worldwide Governance Indicators using Principal Component Analysis (PCA). The IQ variable is an average weighted by the contributions of each Worldwide Governance Indicator to the selected axis. The values for IQ range from 0 to 1, with values closer to 1 indicating better institutional quality.

Step 1: Normalization of Values Between 0 and 1.

To facilitate the interpretation of the composite IQ indicator, values of the Worldwide Governance Indicators (which originally range from -2.5 to +2.5) are normalized to fall between 0 and 1. The normalization formula is as follows:

Normalized value = $\frac{V_{ij} - minV_j}{maxV_j - minV_j}$
Where V_{ij} is the value of indicator j for the country i and V_j represents the value of indicator j.

Step 2: Principal Axis and Contribution of Indicators to the Axis Using PCA.
The PCA methodology utilizes the normalized values of the Worldwide Governance Indicators. The selected axis accounts for 82.86% of the total information provided by the governance indicators. A graphical representation of the PCA results can be found in Appendix B, Fig. B1.

Step 3: Calculation of the Composite Indicator of Institutional Quality (IQ).
The IQ indicator is calculated as the sum of the various governance indicators, weighted by their contributions to the principal axis. The formula for the composite institutional quality indicator for country j is as follows:
$IQ_j = \sum \lambda_i v_{ij}$ with λ_i, the contribution of the indicator i to the principal axis and v_{ij} the value of the indicator i for the country j.
More specifically, IQ = 0.135 VA+ 0.1328 PS + 0.1835 GE + 0.1793 RQ + 0.1892 RL + 0.1802 CC. The values of the composite indicator IQ range from 0 to 1.

1.3.2 The Issue of Endogeneity

Institutions are often critiqued for being endogenous to political and economic systems. Specifically, they may reflect the choices made by political actors in response to changing politico-economic conditions (Aghion et al., 2004). Additionally, modifications to the institutional framework can stem from improvements in economic performance, living standards, or levels of prosperity, which aim to enhance individual freedoms and protections. This suggests that institutional quality may be correlated with error terms in econometric models. Furthermore, our model raises concerns about the exogeneity of the natural resources rent variable in relation to institutional quality, as resource wealth could influence institutional integrity through mechanisms such as corruption or rent-seeking (Collier and Hoeffler, 2005; Aslaksen, 2010; Tsui, 2011). In numerous resource-rich countries, there is often a connection between resource wealth and lower levels of democracy, deteriorating institutions, or conflict. High revenues from natural resources can foster corruption, and the control and exploitation of these resources, along with the distribution of their revenues, can become sources of political conflict, leading to a decline in governance quality. To address potential endogeneity bias and isolate the endogeneity of institutional quality in the model, we employ a climate variable (Temperature) as an instrument for the institutional quality variable. Previous studies have utilized latitude or lagged explanatory variables as instruments for institutional quality (Brunnschweiler and Bulte, 2008; Bhattacharyya and Holder, 2014). However, latitude does not account for the temporal dimension and may not be suitable for panel data, while lagged explanatory variables could be correlated with error terms.

A suitable instrument must meet certain criteria, including instrument relevance, which means it should be related to variations in the endogenous variable (corr (Z_i, X_i) $\neq 0$, with Z_i the instrumental variable and X_i the endogenous variable) and instrument exogeneity, indicating that the variation in the endogenous variable captured by the instrumental variable should be exogenous (corr (Z_i, u_i) = 0, with Z_i the instrumental variable and u_i the error terms) (see Stock and Watson, 2003). In this chapter, our instrumental variable fulfills these criteria. Regarding exogeneity, temperature is used as an instrument based on the assumption that it is exogenous to natural resource wealth and does not directly impact a country's financial development. Variations in temperature, whether during hot or cold periods, do not directly influence banks' lending decisions, which are more affected by factors such as regulatory policies, business environments, investment opportunities, or project profitability. An econometric verification can be found in Appendix, Tables B.1 and B.2. Moreover, the discovery or presence of natural resources (oil, natural gas, or minerals) is largely determined by the underlying geology, with temperature variations not being directly linked to resource presence. Countries rich in resources can be found in both warm and cold regions (e.g., Sub-Saharan Africa and colder regions like Norway or Russia). Concerning the instrument relevance criterion and the connection between the instrumental variable and the endogenous variable, the hypothesis regarding temperature as an instrument for institutional quality is that it can be associated with the level of institutional framework. It is commonly observed that tropical countries tend to have weaker institutions compared to those in cooler climates. Furthermore, studies have indicated an association between temperature and violence, suggesting increased aggression and violent behavior during warmer periods (Anderson, 2001). Under hot conditions, discomfort may lead to heightened irritability and a greater likelihood of violence. In a series of laboratory experiments, Anderson (1989, 2001) documented more hostile and aggressive interactions among participants in hotter environments. Additionally, political instability tends to be more prevalent in regions with higher temperatures. Empirical research by Carlsmith and Anderson (1979) highlighted a link between political instability and temperature, suggesting that riots and protests are more likely to occur in warmer weather. Similarly, Dell et al. (2012) empirically demonstrated that over the last 50 years, annual variations in temperature and precipitation correlate with political instability in several countries. Moreover, it is noteworthy that many equatorial countries, which often experience high temperatures, are frequently associated with elevated levels of corruption. For instance, the Corruption Perception Index 2020 published by Transparency International indicates that several equatorial nations have relatively high corruption levels. Countries like Nicaragua (22), Cambodia (22), Myanmar (28), and Nigeria (25) exhibit low scores, indicating substantial corruption, especially compared to countries like Norway (84), Sweden (85), Finland (85), Japan (74), or Uruguay (71), which are situated further from the equator. This observation is illustrated in Figure B2 in Appendix B, and additional scores from the Transparency International Corruption Index can be found in Figure B4 in Appendix B.

1.4 Descriptive Statistics and Empirical Results

1.4.1 Descriptive Statistics by Region

This section provides an overview of general descriptive statistics, comparing the regions of Asia, Latin America, sub-Saharan Africa, and the OECD (Organization for Economic Cooperation and Development) (refer to Table 1.1 and Fig. 1.1). The averages of the variables span the period from 1996 to 2017. For a detailed list of countries and their respective means for the selected variables, please see Appendix A, Table A1.

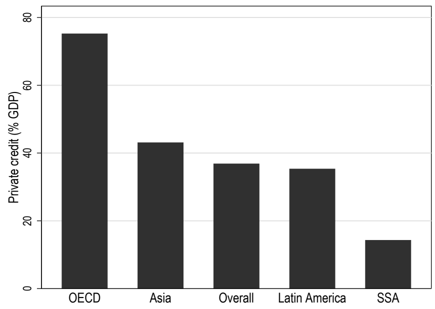
In the sample, Asian countries have an average credit level approaching 50% of GDP. However, certain nations, such as Azerbaijan (14.29% of GDP), the Kyrgyz Republic (10.62% of GDP), and Yemen (5.80% of GDP), exhibit credit levels below 20% of GDP, classifying them as having low credit levels. In contrast, Latin American countries average a lower credit level of approximately 36% of GDP compared to their Asian counterparts. Notably, countries like Argentina (15.36% of GDP), Venezuela (19.12% of GDP), and Mexico (17.98% of GDP) also report credit levels below 20% of GDP. Sub-Saharan African countries show an even lower average credit level, corresponding to about 15% of GDP. Nations such as Angola (11.18% of GDP), Gabon (10.63% of GDP), the Republic of Congo (8.36% of GDP), and Nigeria (11.73% of GDP) have credit levels that fall below this average. On the other hand, OECD countries, including Chile (67.02% of GDP), Norway (95.65% of GDP), and Australia (109.57% of GDP), which also possess significant natural resources, tend to have comparatively higher average credit levels.

Regarding institutional quality, Asian countries exhibit an average score close to 0.5, indicating a relatively good level. However, certain nations, including Azerbaijan (0.33), Kazakhstan (0.37), Yemen (0.26), and the Kyrgyz Republic (0.35), which possess significant natural resources, demonstrate lower institutional quality, falling below the overall average of 0.42. Latin American countries also average around 0.5 in institutional quality. Nevertheless, countries such as Nicaragua (0.39), Venezuela (0.28), and Paraguay (0.35) show relatively low levels of institutional quality compared to the average of 0.45, despite their considerable natural resource wealth. In contrast, Sub-Saharan African nations generally have lower institutional quality scores, with an average of 0.36. Some countries, such as Angola (0.25), the Republic of Congo (0.27), Burundi (0.25), and Nigeria (0.28), have institutional quality levels below this average. OECD countries, on the other hand, typically achieve higher institutional quality scores than those found in Asia, Africa, and Latin America. Notable examples include Australia (0.83), Chile (0.74), New Zealand (0.86), and Norway (0.85).

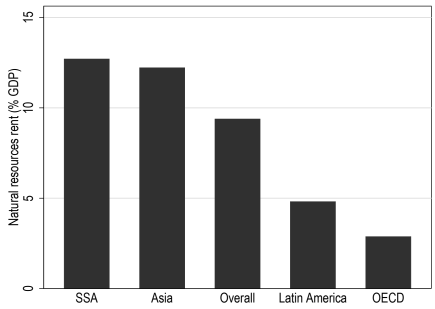
The descriptive statistics reveal that many nations endowed with abundant natural resources tend to have lower average credit levels and institutional quality. However, countries like Chile, Australia, Malaysia, and Norway, which possess both significant natural resources and strong institutional quality, maintain relatively high credit levels.

	Obs	Mean	Std.Dev	Min	Max
Asia	638	43.89212	33.57937	1.16606	166.5041
Latin America	374	35.29296	18.64048	8.39793	94.72727
SSA	660	14.25015	9.96469	0.44918	84.05232
OECD	286	75.17223	46.04798	11.61185	201.2585
Private credit					
Asia	638	12.09997	13.96238	0.01126	62.04703
Latin America	374	4.81222	5.19272	0.05694	25.42054
SSA	660	12.70365	11.75873	0.12389	61.18981
OECD	286	2.87654	4.09938	0.01126	21.39196
Natural resources rent (Nrent)					
Asia	638	0.42637	0.11448	0.13013	0.67238
Latin America	374	0.44849	0.10740	0.17797	0.76106
SSA	660	0.36529	0.10903	0.08376	0.67505
OECD	286	0.71894	0.13473	0.42104	0.88936
Institutional quality (IQ)					

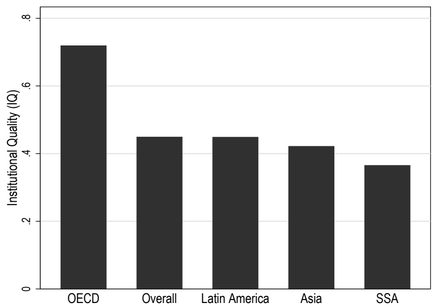
Table 1.1: Summary statistics of Private credit (% GDP), Natural resources rent (% GDP) and Institutional quality by region



(a) Mean Private credit



(b) Mean Natural resources rent



(c) Mean Institutional quality (IQ)

Figure 1.1: Means Private credit, Natural resources rent and Institutional quality by region

1.4.2 Empirical Results

This section outlines our baseline findings regarding the impact of natural resources on financial development, considering institutional quality. Detailed results are available in Table 1.2. Initially, we assessed a threshold across the entire sample and subsequently analyzed another threshold within the previously established range. The following subsections detail our baseline results along with various robustness checks.

Baseline Results

Table 1.2 illustrates the relationship between natural resources and financial development in relation to institutional quality levels. The identified threshold values for institutional quality are γ_1 = 0.3379 and γ_2 = 0.4949. These thresholds are statistically significant at the one percent level, indicating that the impact of natural resources on financial development varies according to the quality of institutions. The coefficients for natural resources rent (Nrent) are negative and significant at the one percent level both below and above the two thresholds, indicating that an increase in natural resources rent corresponds with a decrease in financial development. This finding aligns with previous research suggesting a detrimental effect of natural resources on financial development (Beck, 2010; Bhattacharyya and Holder, 2014). However, the effect varies according to the two thresholds: the impact of natural resources on financial development is more pronounced below the threshold $\gamma_1 = 0.3379$ and diminishes above both thresholds. This indicates that institutional quality plays a mitigating role in the relationship between natural resources and financial development. Therefore, financial development is more limited in countries with very low institutional quality (e.g., Azerbaijan with IQ = 0.326, Venezuela with IQ = 0.283, or the Republic of Congo with IQ = 0.272) compared to those with higher institutional quality (e.g., Australia with IQ = 0.82, Norway with IQ = 0.85, or Malaysia with IQ = 0.57). Additionally, the coefficient for the institutional quality variable (IQ) is positive and significant, underscoring its importance for financial development in both groups relative to the thresholds. Regarding other variables, the effect of Gross Domestic Product per capita (Gdpc) on financial development is positive both below and above the two thresholds, consistent with empirical studies linking economic growth and financial development (Jaffee and Levonian, 2001). Inflation negatively impacts financial development above the threshold $\gamma_2 = 0.4949$ and below the threshold $\gamma_1 = 0.3379$, as supported by existing literature on inflation's effects on the economy (Boyd et al., 2001). The size of the population significantly influences the financial sector's development in countries above the first threshold and below the second threshold.

Classification of Countries

The thresholds $\gamma_1 = 0.3379$ and $\gamma_2 = 0.4949$ segment our sample into three distinct groups: one with relatively low institutional quality (countries under the threshold $\gamma_1 = 0.3379$), another with acceptable institutional quality (countries between the two thresholds), and a final group with relatively high institutional quality (countries above the threshold $\gamma_2 = 0.4949$). The classification of countries based on these institutional quality thresholds is presented in Appendix A, Table A.2, and Figure A.1. In the first group, those above the threshold $\gamma_2 = 0.4949$ include nations with substantial natural resources and relatively good institutional quality, such as Norway, Australia, and Malaysia. This group consists of European countries (e.g., Norway, Romania), Asian countries (e.g., Malaysia, Brunei), American countries (e.g., Chile, Trinidad and Tobago), African nations (e.g., Namibia, South Africa, Botswana), as well as Persian Gulf states (e.g., Kuwait, Qatar, United Arab Emirates). The inclusion of Persian Gulf countries in this group is justified by their relatively high political stability scores, which enhance their overall institutional quality. In the group below the threshold $\gamma_1 = 0.3379$, we find countries that generate significant revenues from natural resources but have low institutional quality, such as Iran, Angola, Yemen, and Venezuela. In this cohort, the adverse impact of natural resources on financial development is notably pronounced.

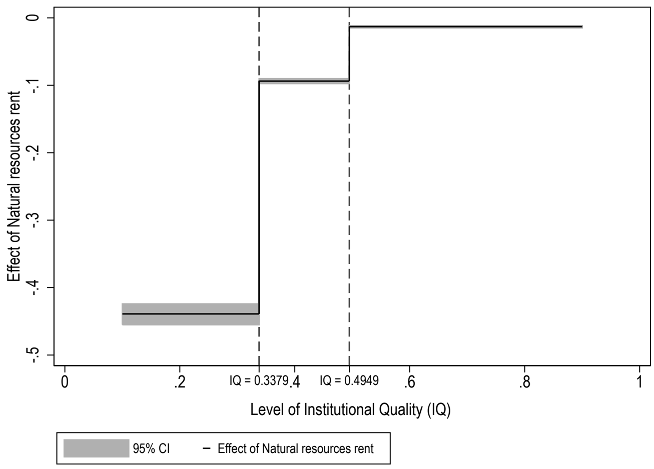
Variables	Priv.cred		
	IQ $< \gamma_1$	$\gamma_1 <$ IQ $< \gamma_2$	IQ $> \gamma_2$
Nrent	-0.43964***	-0.09388***	-0.01334***
	(0.00785)	(0.00185)	(0.00078)
Gdpc	0.00891***	0.00954**	0.00217**
	(0.00042)	(0.00603)	(0.00106)
Inflation	-0.00076***	-0.00432	-1.85794***
	(0.00012)	(0.01335)	(0.04049)
Pop	0.16364***	0.06883	0.07193***
	(0.04486)	(0.06256)	(0.04401)
IQ	1.06612***	0.67781***	0.1801***
	(0.03449)	(0.01489)	(0.01709)
γ_1	0.33793***		
	(0.00343)		
γ_2	0.49497***		
	(0.00012)		
Observations	2200		
Number of countries	100		
Number of moment conditions	336		

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 1.2: Threshold effect of natural resources on financial development according to institutional quality

Highlighting the Role of Institutional Quality in the Mitigation of the Effect of Natural Resource Rent

Figure 1.2 illustrates how enhancing institutional quality can alleviate the negative impact of natural resources on financial development. The influence of natural resources in relation to institutional quality can be described as a "stair effect". Improvements in institutional quality act as steps that gradually reduce the adverse effects of natural resources. Specifically, enhancing institutional quality from below the first threshold (γ_1 = 0.3379) to a level between the two thresholds results in an approximately 78% reduction in the negative impact of natural resources, while increasing institutional quality above the second threshold (γ_2 = 0.4949) leads to about a 96% reduction. For countries situated between the two thresholds, improving institutional quality to exceed the threshold (γ_2 = 0.4949) diminishes the negative effect of natural resources by roughly 86%. However, countries significantly below the thresholds (e.g., Myanmar, Angola, or Tajikistan within the under-threshold group) must exert more effort to enhance their institutional quality to achieve substantial results compared to countries closer to the thresholds.



Note: The Y-axis represents the effects of natural resources across various thresholds, with these negative impacts diminishing toward zero. These effects correspond to the coefficients of the natural resources rent variable (Nrent) found in Table 1.2. The X-axis displays different levels of institutional quality, including the identified threshold levels.

Figure 1.2: Effect of natural resources rent according to the two threshold levels of Institutional quality

1.4.3 Robustness Checks

In this section, we subject our baseline results to a series of robustness tests. First, we control for political regime as an alternative measure of the institutional framework. Second, we utilize another climate variable, Rainfall, as an instrumental variable. Third, we employ Principal Component Analysis (PCA) to create an alternative measure of the institutional framework using governance variables and political regime indicators. Fourth, we assess financial development through alternative indicators: Broad Money (M2) and Private Credit to Deposits. Fifth, we focus on OPEC+ countries. Fith, we examining those with natural resources rents exceeding 10% of GDP, as defined by the World Bank Group for resource-rich countries. Sixth, we focus on OPEC+ countries (Countries including in the Organization of Petrolum Exporting Countries [OPEC] with other associated countries). Finally, we compute five-year averages to mitigate potential overestimations in the coefficient estimates due to the instruments (Roodman, 2009).

Robustness: Using Alternative Measure of Institutional Framework (Political Regime)

We analyze the political regime using the Polity2 indicator as a measure of the institutional framework, with values normalized from 0 to 1. A score near 1 indicates a high level of democracy. The estimated thresholds (Polity2 = 0.9040 and Polity2 = 0.35) are significant at the one percent level, suggesting that financial development is affected differently by the political regime. Below these thresholds, the impact of natural resources on financial development is significant, while the effect above the first threshold (Polity2 = 0.9040) is not significant, potentially due to heterogeneity within that group of countries. This indicates that financial development is more constrained in less democratic nations (Polity2 scores below 0.9040 and 0.35), supporting theories that democracy can foster economic and financial development (Olson, 1993). Country classification is based on the frequency of scores below or above the thresholds from 1996 to 2017, with results detailed in Appendix C.1, Table C1, and Figure C1. In the group above the first threshold (Polity2 = 0.9040), we find countries like Australia, Norway, and Chile, which possess substantial natural resources and high institutional quality. Conversely, the group below this threshold includes countries with weak institutional frameworks and low average private credit levels, such as Kazakhstan (Private credit = 28% of GDP), Venezuela (19.12%), and Nigeria (11.72%). The presence of countries like Albania, India, Moldova, and Mongolia in the democratic category (Polity2 $>$ 0.9040) may be attributed to certain governance variables where they score lower. For example, Albania scores poorly in Rule of Law and Control of Corruption, and similar patterns are observed in India, Mongolia, and Moldova. Most countries below the second threshold (Polity2 = 0.35), characterized as "very less democratic", apart from Gambia, Kazakhstan, and Rwanda, also fall below the first threshold (γ_1 = 0.3379) based on our baseline institutional quality results.

Robustness: Using Alternative Instrumental Variable (Rainfall)

We reassessed the baseline results using Rainfall as an alternative climate variable. The estimated thresholds remained close to the baseline thresholds, and the effect of natural resources on financial development was consistent with our initial findings. Additionally, the classification of countries did not significantly differ from the benchmark. Results and classifications are available in Appendix C.2 and Table C2.

Using Principal Component Analysis (PCA) of Variables of Governance and Political Regime (Instfram)

We evaluated the baseline results using an institutional framework indicator derived from governance and political regime variables via PCA. The estimated thresholds closely mirrored the baseline values, and the effect of natural resources on financial development remained similar to the benchmark results. The classification of countries also showed minimal variation from the benchmark. Results and classifications are detailed in Appendix C.3 and Table C3.

Robustness: Using of Alternative Financial Development Measures, Money and Quasi-money (M_2) and Private Credit to Deposits (Pdpot)

We explored alternative financial development measures, including Money and Quasi-money (M_2) and Private Credit to Deposits (Pdpot). The estimated thresholds were similar to those in the baseline, and the effect of natural resources on financial development aligned with the benchmark findings. Additionally, there were no significant changes in country classifications compared to the benchmark. The results and classifications are presented in Appendix C.4 and C.5, Tables C4 and C5.

Robustness: Regression for Countries with Natural Resources Rent Exceeding 10% of GDP

We analyzed the effect of natural resources on financial development specifically for countries with natural resources rents surpassing 10% of GDP, as per the World Bank Group's criteria for resource-rich nations. The estimated threshold (γ = 0.5098) was significant and closely aligned with the baseline threshold (γ_2 = 0.4949). The impact of natural resources on financial development remained consistent under and above this threshold, and country classifications were similar to those in the baseline results. The results and classifications are presented in Appendix C.6 and Table C6.

Robustness: Regression for OPEP+ Countries and Use of Oil Rent as Measure of Natural Resources Wealth

To assess the impact of natural resources on financial development in oil-exporting countries, we conducted a regression for OPEC+ nations, which includes OPEC members and associated countries. For this estimation, we utilized an oil-related natural resource variable (Oil rent). The results remained consistent with the baseline findings, with the identified threshold (γ = 0.3674) being close to the baseline threshold (γ_1 = 0.3379). Financial development was also shown to be influenced differently across thresholds. Below this threshold, we found countries with low institutional quality, such as Angola, Iran, and Venezuela, which also appeared in the baseline results. The results and classifications are included in Appendix C.7 and Table C7.

Robustness: Regression with Five-Year Averages

To address potential overestimation issues related to instruments, we examined the baseline results using five-year averages. Instruments may overfit the instrumented variable, leading to biased coefficient estimates (Roodman, 2009a). We conducted estimates using five-year averages without overlap. The estimated thresholds for private credit, Money and Quasi-money (M_2), and Private Credit to Deposits (Pdpot) were close to the baseline results, with country classifications showing similarities. The first threshold of institutional quality varied slightly from γ_1 = 0.34 to γ_1 = 0.35, while the second threshold ranged from γ_2 = 0.48 to γ_2 = 0.52, both remaining in line with the baseline thresholds (γ_1 = 0.3379 and γ_1 = 0.4949). The effect of natural resources rent was comparable to the baseline, demonstrating that the negative impact of natural resources on financial development was less pronounced in countries with high institutional quality and more significant in those with low institutional quality. The results and classifications are found in Appendix C.8, Tables C8, C9, and C10.

1.5 Conclusion and Policy implications

This chapter examined financial development levels in resource-rich countries, emphasizing institutional quality. Utilizing a sample of 100 countries from 1996 to 2017 and employing a Panel threshold model with instrumental variables, our empirical findings indicate that natural resources influence financial development differently based on institutional quality thresholds. Beyond these thresholds, the impact of natural resources on financial development tends to diminish. Additionally, financial development appears more restricted in less democratic countries, highlighting the significance of robust institutions and governance for financial progress in resource-rich contexts. Our results are consistent across various robustness checks, including alternative institutional measures, financial development indicators, and sub-sample estimations, all demonstrating a threshold effect related to institutional quality, even when focusing solely on oil-exporting nations.

Resource-rich countries face the critical challenge of leveraging their natural wealth to foster development. The notion of a "resource curse" is neither universal nor unavoidable; the benefits of natural resources for economic advancement often hinge on institutional quality. Many resource-rich nations confront economic challenges such as volatility in natural resource prices, high poverty rates, inequality, and limited access to international financing. While developing the financial system can aid in addressing these issues, resource-rich countries must enhance their financial systems by improving the business environment, combating corruption, and strategically managing natural resource revenues to promote productive investments in infrastructure and research and development. Furthermore, strengthening fiscal frameworks and ensuring transparency in the management of natural resource revenues are essential for maximizing the benefits of these resources.

Appendix

A Mean of main variables for each country and classification of the baseline result

Table A1: Countries included in sample with the mean over 1996 to 2017 of level of Private credit to GDP, level of natural resources rent to GDP, level of institutional quality and Political regime

Countries	Priv.cred[1](% of GDP)	Nrent[2] (% of GDP)	Inst.Quality[3](QI)	Polity2
Albania	21.97431	1.660842	0.4281029	0.8704545
Algeria	12.74407	17.57583	0.3259202	0.5090909
Angola	11.18491	39.69035	0.2513568	0.3886364
Argentina	15.36358	3.271051	0.4592159	0.9
Armenia	21.17652	1.960566	0.4367453	0.7
Australia	109.5566	5.660488	0.8257618	1
Azerbaijan	14.27807	26.75862	0.3259927	0.1545455
Bahrain	55.94916	6.094538	0.5347618	0.863636
Bangladesh	32.43856	0.9356724	0.3295951	0.6863636
Bolivia	46.85971	8.316453	0.4048257	0.8954545
Botswana	22.76093	3.221399	0.6400324	0.8977273
Brasil	44.60785	3.634561	0.4992064	0.89
Brunei	43.19307	24.84664	0.6183122	0.5
Bulgaria	42.95342	1.765806	0.5297192	0.9386364
Burkina Faso	16.93651	12.15207	0 .4254011	0.4954545
Burundi	16.45524	23.71202	0.2475125	0.6227273
Cambodia	27.04586	3.152403	0.3338966	0.5636364
Cameroon	10.24398	7.932315	0.310613	0.3
Central Africa Rep.	7.734913	11.31092	0.2365977	0.5840909
Chile	67.01899	12.308	0.7356899	0.9681818
China	120.781	3.701427	0.4055948	0.15
Colombia	32.62123	5.527412	0.4200505	0.85
Congo Dem. Rep.	2.928507	29.16959	0.1643202	0.6181818
Congo Rep.	8.357259	43.88071	0.2722378	0.3
Costa Rica	38.64921	1.314027	0.623113	1
Cote d'ivoire	17.24355	5.581296	0.3174953	0.5386364
Croatia	52.59269	0.9054268	0.5536045	0.825

Continued on next page

Table A1 – *Continued from previous page*

Countries	Priv.cred[1](% of GDP)	Nrent[2] (% of GDP)	Inst.Quality[3](QI)	Polity2
Czech Republic	44.26042	0.638727	0.6720551	0.9727273
Denmark	142.9004	1.135195	0.8688659	1
Dominican Rep.	23.78316	1.184308	0.4303828	0.8954545
Ecuador	23.6116	11.22237	0.3676138	0.8022727
El Savador	46.87209	0.6741883	0.4537591	0.8704545
Eswatini	17.06022	3.16583	0.386499	0.05
Fiji	50.70606	1.603247	0.4653005	0.5681818
Gabon	10.63838	30.01801	0.4012123	0.4431818
Gambia	10.06702	4.669286	0.4054053	0.2681818
Ghana	12.85673	12.30657	0.4924083	0.8181818
Guatemala	25.73044	1.863613	0.3789365	0.9
Honduras	42.95783	1.962539	0.3786168	0.8386364
Hungary	40.58741	0.4768645	0.6609793	1
India	40.36329	3.203901	0.4556751	0.95
Indonesia	30.16471	7.390823	0.3864872	0.7886364
Iran	40.27767	24.19632	0.318297	0.322723
Jamaica	24.60627	1.63648	0.5088265	0.95
Jordan	75.20231	1.015963	0.5029664	0.375
Kazakhstan	28.58456	20.31087	0.3748526	0.2272727
Kenya	27.10485	3.590536	0.3629234	0.7613636
Korea, Rep.	115.1363	0.0291824	0.643807	0.890909
Kuwait	63.22749	46.05127	0.5296967	0.15
Kyrgyz Republic	10.62442	5.189247	0.3468347	0.5931818
Lesotho	13.27348	4.517438	0.4673059	0.8545455
Libya	17.76345	44.27612	0.2501867	0.2613636
Madagascar	10.84052	7.323228	0.4027155	0.7886364
Malawi	7.926478	8.58466	0.4247514	0.7886364
Malaysia	120.4506	10.3114	0.5777114	0.7090909
Mali	17.15351	8.884127	0.4055227	0.8
Mexico	17.97842	4.329631	0.4744507	0.4744507
Moldova	22.98916	0.2575239	0.4227421	0.9181818
Mongolia	30.98882	22.02646	0.4847718	1
Morroco	53.15513	1.706878	0.4560149	0

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Table A1 – *Continued from previous page*

Countries	Priv.cred[1](% of GDP)	Nrent[2] (% of GDP)	Inst.Quality[3](QI)	Polity2
Myanmar	9.523341	9.518814	0.2002052	0.2727273
Namibia	46.55132	2.155399	0.5605335	0.8
Nepal	43.23766	1.1437	0.357429	0.6840909
New zealand	125.1545	1.591771	0.862332	1
Nicaragua	24.51418	2.36113	0.3922555	0.9113636
Niger	9.065287	11.25872	0.3687918	0.675
Nigeria	11.72463	14.6698	0.2789515	0.6636364
Norway	95.65064	8.346615	0.8516135	1
Panama	76.32882	0.1782304	0.5251574	0.95
Paraguay	24.81861	1.695663	0.3507883	0.8931818
Peru	29.14093	6.287373	0.4474528	0.8681818
Philippines	36.85671	1.78282	0.4350794	0.9
Poland	36.06548	1.134613	0.6433326	0.9863636
Qatar	41.97543	32.78033	0.5913471	0
Romania	23.33452	2.008969	0.508029	0.09318182
Russia	33.31562	14.46364	0.3570906	0.727273
Rwadan	13.29069	7.56778	0.3815634	0.3090909
Saudi Arabia	35.94287	38.46899	0.4433578	0.0227273
Senegal	18.46666	3.136851	0.4647881	0.7931818
Sierra Leone	4.237527	16.47777	0.3132	0.7454545
South Africa	67.54594	5.516906	0.5666061	0.95
Sri Lanka	33.05047	0.1736733	0.4487825	0.7454545
Sudan	7.671038	9.437152	0.1989226	0.2545455
Sweden	97.21115	0.5153506	0.8565837	1
Tajikistan	15.63432	1.37063	0.2563448	0.3613636
Tanzania	8.644349	6.553055	0.410008	0.4772727
Thailand	108.7055	2.101658	0.4913067	0.4913067
Togo	22.70171	14.26477	0.3269623	0.3772727
Trinidad and Tobago	34.28259	13.31138	0.550652	0.9977273
Tunisia	53.81865	4.259737	0.4764511	0.475
Turkey	34.08243	0.3599438	0.475879	0.7977273
Uganda	10.36084	14.28365	0.379731	0.3886364
Ukraine	36.44396	5.345716	0.3686626	0.8

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Table A1 – *Continued from previous page*

Countries	Priv.cred[1](% of GDP)	Nrent[2] (% of GDP)	Inst.Quality[3](QI)	Polity2
United Arab Emirates	53.30253	20.68863	0.6141449	0.1
United States	51.63616	0.8689496	0.7749295	0.9909091
Venezuela	19.1236	15.6773	0.2829811	0.6909091
Vietnam	72.00848	7.505833	0.4008017	0.15
Yemen	5.804289	23.67655	0.264922	0.4409091
Zambia	9.108412	13.67554	0.4182645	0.7454545
Zimbabwe	24.91508	7.91854	0.2426732	0.4272727

1: Private credit (% of GDP)

2: Natural ressources rent (% of GDP)

3: Institutional quality (IQ)

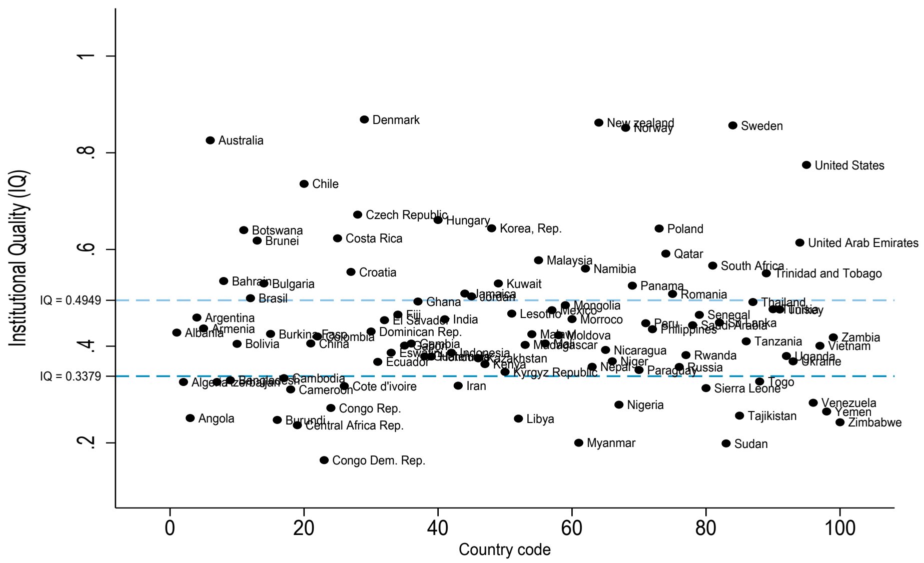
Table A2: Classification of countries by the Institutional quality (IQ) threshold

IQ < 0.3379	$0.3379 <$ IQ < 0.4949		IQ > 0.4949
Algeria	Albania	Sri Lanka	Australia
Angola	Argentina	Tanzania	Bahrain
Azerbaijan	Armenia	Thailand	Botswana
Bangladesh	Bolivia	Tunisia	Brasil
Burundi	Burkina Faso	Uganda	Brunei
Cambodia	China	Ukraine	Bulgaria
Cameroon	Colombia	Vietnam	Chile
Central Africa Republic	Dominican Republic	Zambia	Costa Rica
Congo Dem. Rep.	Ecuador		Czech Republic
Brasil	El savaldor		Denmark
Brunei	Eswatini		Croatia
Burkina Faso	Fiji		Hungary
Burundi	Gabon		Jamaica
Cambodia	Gambia		Jordan
Cameroon	Ghana		Korea, Rep.
Central Africa Rep.	Guatemala		Kuwait
Chile	Honduras		Malaysia
China	India		Namibia
Colombia	Indonesia		New Zealand
Congo Dem. Rep.	Kazakhstan		Norway
Congo Rep.	Kenya		Panama
Cote d’ivoire	Kyrgyz Republic		Poland
Iran	Lesotho		Qatar
Libya	Madagascar		Romania
Myanmar	Malawi		South Africa
Nigeria	Mali		Sweden
Sierra Leone	Mexico		Trinidad and Tobago
Sudan	Moldova		United Arab Emirates
Tajikistan	Mongolia		United States
Togo	Morroco		
Venezuela	Nepal		

Continued on next page

Table A2 – *Continued from previous page*

IQ < 0.3379	0.3379 < IQ < 0.4949	IQ > 0.4949
Yemen	Nicaragua	
Zimbabwe	Niger	
	Paraguay	
	Peru	
	Philippinnes	
	Russia	
	Rwanda	
	Saudi Arabia	
	Senegal	



Note: Y axis refers to the levels of institutional quality of each country of the sample including the threshold levels. X axis corresponds to a country code, a number from 0 to 100 and attributed to the countries of the sample.

Figure A1: Classification of countries according to the two threshold levels of Institutional quality

B Issue of endogeneity: Econometric estimations for checking assumptions

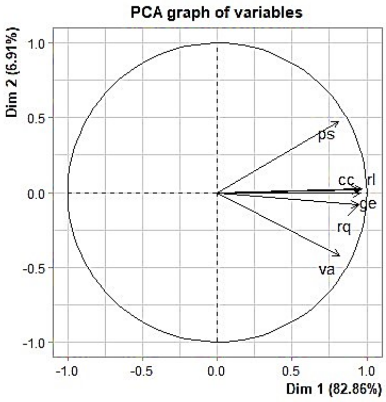


Figure B1: Principal component analysis graph of indicators of governance

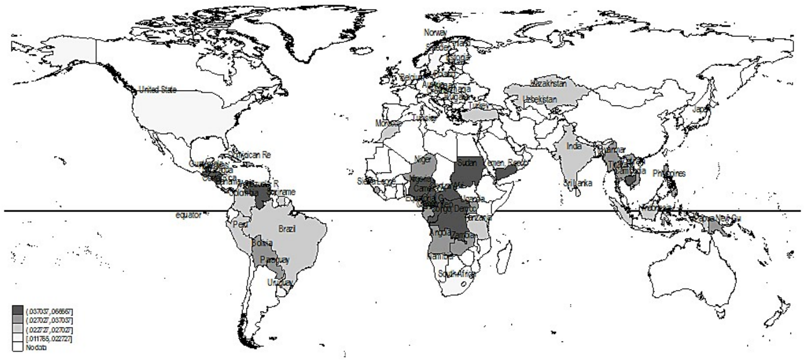


Figure B2: Corruption perception index 2020 for some countries.

Note: The inverse of transparency international's score has been used for the graph. A high value indicated by a more accentuated gray colour stands for high level of corruption.

	IQ
Temp	-0.06474***
	(0.00385)
Intercept	0.57791***
	(0.00825)
R-squared	0.11262
F-statistic (testing $\alpha_1 = 0$)	
Prob>F	0.0000

Estimation: $IQ = \alpha_0 + \alpha_1 Temp + \varepsilon$

Table B1: Linear estimation of Institutional quality and temperature by OLS

	Priv.cred
Nrent	-0.24928***
	(0.05151)
Gdpc	0.00047***
	(0.00005)
Inflation	-0.00262
	(0.00547)
Pop	0.04014***
	(0.00289)
IQ	0.98008***
	(0.05478)
Intercept	-11.42026***
	(2.45521)
R-squared	0.4694
Adjusted R-squared	0.4682
F-statistic	392.12
Prob>F	0.0000

Estimation: Priv.cred = α_0 + α_1Nrent + α_2Gdpc + α_3Inflation + α_4Pop + α_5IQ + ε

Table B2: Linear estimation of the main model (with Private credit) by OLS

The F-Statistic (for the first regression in Table B1) is larger than 10, indicating that there is a possible link between temperature and Institutional quality. Temperature could be a good instrument.
From the second regression (in Table B2), the residual (u_i) of the regression has been used to check if the instrumental variable could be correlated to the model. The correlation between temperature and the residual gives: Corr (temp, residual) = -0.0142. The instrument (temperature) is very weakly correlated to the errors terms, indicating an exogeneity of the instrumental variable to the main model. Hence, Temperature could be a good instrument for the model.

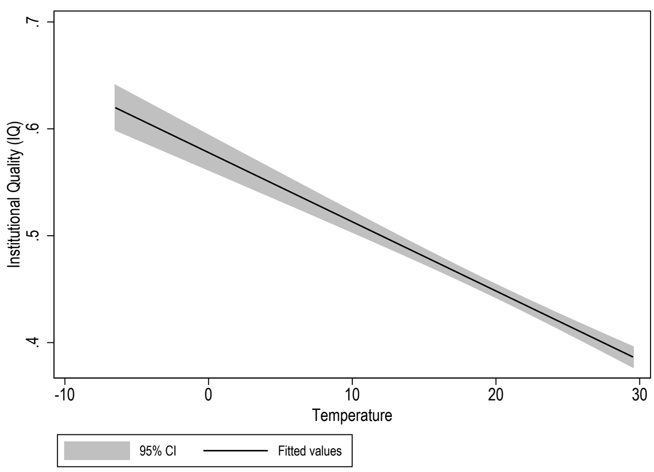


Figure B3: Linear prediction Institutional quality (IQ) and temperature

SCORE	COUNTRY/TERRITORY	RANK
88	Denmark	1
88	New Zealand	1
85	Finland	3
85	Singapore	3
85	Sweden	3
85	Switzerland	3
84	Norway	7
82	Netherlands	8
80	Germany	9
80	Luxembourg	9
77	Australia	11
77	Canada	11
77	Hong Kong	11
77	United Kingdom	11
76	Austria	15
76	Belgium	15
75	Estonia	17
75	Iceland	17
74	Japan	19
72	Ireland	20
71	United Arab Emirates	21
71	Uruguay	21
69	France	23
68	Bhutan	24
67	Chile	25
67	United States of America	25
66	Seychelles	27
65	Taiwan	28
64	Barbados	29
63	Bahamas	30
63	Qatar	30
62	Spain	32
61	Korea, South	33
61	Portugal	33
60	Botswana	35
60	Brunei Darussalam	35
60	Israel	35
60	Lithuania	35
60	Slovenia	35
59	Saint Vincent and the Grenadines	40
58	Cabo Verde	41
57	Costa Rica	42
57	Cyprus	42
57	Latvia	42
56	Georgia	45
56	Poland	45
56	Saint Lucia	45
55	Dominica	48
54	Czechia	49
54	Oman	49
54	Rwanda	49
53	Grenada	52
53	Italy	52
53	Malta	52
53	Mauritius	52
53	Saudi Arabia	52
51	Malaysia	57
51	Namibia	57
50	Greece	59
49	Armenia	60
49	Jordan	60
49	Slovakia	60
47	Belarus	63
47	Croatia	63
47	Cuba	63
47	Sao Tome and Principe	63
45	Montenegro	67
45	Senegal	67
44	Bulgaria	69
44	Hungary	69
44	Jamaica	69
44	Romania	69
44	South Africa	69
44	Tunisia	69
43	Ghana	75
43	Maldives	75
43	Vanuatu	75
42	Argentina	78
42	Bahrain	78
42	China	78
42	Kuwait	78
42	Solomon Islands	78
41	Benin	83
41	Guyana	83
41	Lesotho	83
40	Burkina Faso	86
40	India	86
40	Morocco	86
40	Timor-Leste	86
40	Trinidad and Tobago	86
40	Turkey	86
39	Colombia	92
39	Ecuador	92
38	Brazil	94
38	Ethiopia	94
38	Kazakhstan	94
38	Peru	94
38	Serbia	94
38	Sri Lanka	94
38	Suriname	94
38	Tanzania	94
37	Gambia	102
37	Indonesia	102
36	Albania	104
36	Algeria	104
36	Cote d'Ivoire	104
36	El Salvador	104
36	Kosovo	104
36	Thailand	104
36	Vietnam	104
35	Bosnia and Herzegovina	111
35	Mongolia	111
35	North Macedonia	111
35	Panama	111
34	Moldova	115
34	Philippines	115
33	Egypt	117
33	Eswatini	117
33	Nepal	117
33	Sierra Leone	117
33	Ukraine	117
33	Zambia	117
32	Niger	123
31	Bolivia	124
31	Kenya	124
31	Kyrgyzstan	124
31	Mexico	124
31	Pakistan	124
30	Azerbaijan	129
30	Gabon	129
30	Malawi	129
30	Mali	129
30	Russia	129
29	Laos	134
29	Mauritania	134
29	Togo	134
28	Dominican Republic	137
28	Guinea	137
28	Liberia	137
28	Myanmar	137
28	Paraguay	137
27	Angola	142
27	Djibouti	142
27	Papua New Guinea	142
27	Uganda	142
26	Bangladesh	146
26	Central African Republic	146
26	Uzbekistan	146
25	Cameroon	149
25	Guatemala	149
25	Iran	149
25	Lebanon	149
25	Madagascar	149
25	Mozambique	149
25	Nigeria	149
25	Tajikistan	149
24	Honduras	157
24	Zimbabwe	157
22	Nicaragua	159
21	Cambodia	160
21	Chad	160
21	Comoros	160
21	Eritrea	160
21	Iraq	160
19	Afghanistan	165
19	Burundi	165
19	Congo	165
19	Guinea Bissau	165
19	Turkmenistan	165
18	Democratic Republic of the Congo	170
18	Haiti	170
18	Korea, North	170
17	Libya	173
16	Equatorial Guinea	174
16	Sudan	174
15	Venezuela	176
15	Yemen	176
14	Syria	178
12	Somalia	179
12	South Sudan	179

Figure B4: Corruption perceptions index 2020
Source: Transparency International

C Results Robustness Checks and Classifications

C.1 Robustness: Using Alternative Measure of Institutional Framework (Political Regime)

Variables	Priv.cred		
	Polity2 $< \gamma_1$	$\gamma_1 <$ Polity2 $< \gamma_2$	Polity2 $> \gamma_2$
Nrent	-0.17639***	-0.04654***	0.04554
	(0.03162)	(0.07304)	(0.10339)
Gdpc	0.11052***	0.5133***	0.00049
	(0.01112)	(0.2166)	(0.00007)
Inflation	-0.03352***	-0.00567	-1.18415***
	(0.00877)	(0.01661)	(0.07251)
Pop	0.87973***	0.71332	0.041***
	(0.00398)	(0.08048)	(0.0108)
Polity2	0.84192***	0.34372***	2.059***
	(0.03449)	(0.01489)	(0.10602)
γ_1	0.35***		
	(0.02709)		
γ_2	0.90404***		
	(0.00054)		
Observations	2178		
Number of countries	99		
Number of moment conditions	336		

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

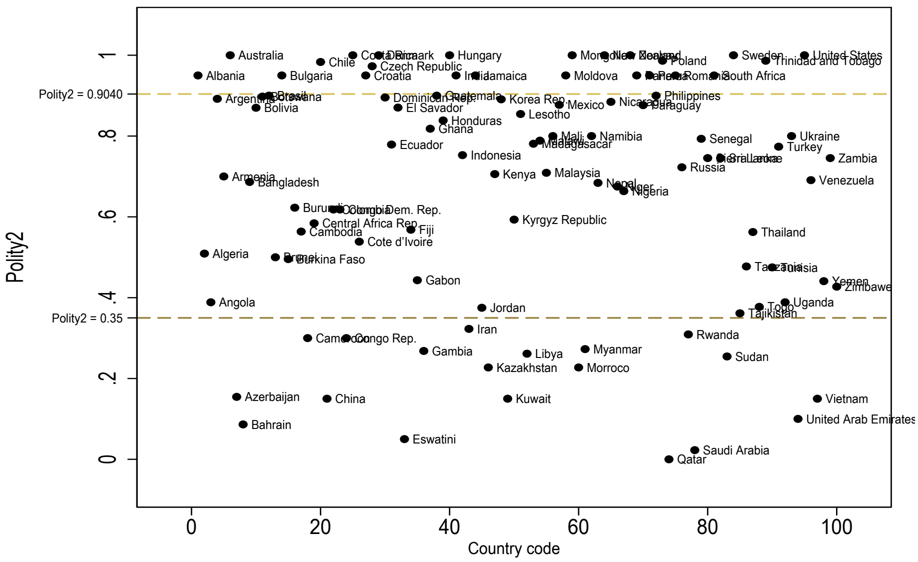
Table C1: Threshold effect of natural resources on financial development according to the political regime

Classification Robustness using alternative measure of institutional framework (Political regime):

- Polity2 $<$ 0.35: Cameroon, Congo Rep., Gambia, Iran, Kazakhstan, Libya, Myanmar, Rwanda, Sudan.
- 0.35$<$ Polity2 $<$ 0.9040: Algeria, Angola, Argentina, Armenia, Bangladesh, Bolivia, Botswana, Brasil, Burkina Faso, Burundi, Cambodia, Central Africa Republic, Colombia, Congo Dem.

Rep, Cote d'Ivoire, Dominican Republic, Ecuador, El Savador, Eswatini, Fiji, Gabon, Ghana, Guatemala, Honduras, Indonesia, Jamaica, Jordan, Kenya, Korea Republic, Kyrgyz Republic, Lesotho, Madagasacar, Malawi, Malaysia, Mali, Mexico, Namibia, Nepal, Nicaragua, Niger, Nigeria, Paraguay, Peru, Philippines, Russia, Senegal, Sri Lanka, Tajikistan, Tanzania, Thailand, Togo, Tunisia, Turkey, Uganda, Ukraine, Venezuela, Yemen, Zambia, Zimbabwe.

- Polity2 $>$ 0.9040: Albania, Australia, Bulgaria, Chile, Costa Rica, Croatia, Czech Republic, Denmark, Hungary, India, Jamaica, Moldova, Mongolia, New Zealand, Norway, Panama, Korea Rep., New Zealand, Norway, Poland, Romania, South Africa, Sweden, Trinidad and Tobago, United States.



Note: Y axis refers to the levels of Polity2 of each country of the sample including the threshold levels. The X axis corresponds to a country code, a number rising from 0 to 100 and attributed to the countries of the sample.

Figure C1: Classification of countries according to the threshold levels of political regime

C.2 Robustness: Using Alternative Instrumental Variable (Rainfall)

Variables	Priv.cred		
	IQ $< \gamma_1$	$\gamma_1 <$ IQ $< \gamma_2$	IQ $> \gamma_2$
Nrent	-0.33827*** (0.00685)	-0.07941*** (0.01042)	-0.01586*** (0.00013)
Gdpc	0.00476*** (0.00021)	0.00844*** (0.00038)	0.00263*** (0.00024)
Inflation	-0.00164*** (0.00022)	-0.07139 (0.00049)	-2.79238*** (0.07527)
Pop	0.40312*** (0.03623)	0.16405*** (0.04868)	0.77011 (0.07363)
IQ	0.56716*** (0.00449)	0.31831*** (0.01546)	1.24708*** (0.00124)
γ_1	0.33069*** (0.00213)		
γ_2	0.54309*** (0.00005)		
Observations	2200		
Number of countries	100		
Number of moment conditions	336		

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table C2: Threshold effect of natural resources on financial development according to institutional quality with instrumental variable Rainfall

Classification Robustness using alternative instrumental variable (Rainfall):

- IQ < 0.3306: Algeria, Angola, Azerbaijan, Bangladesh, Burundi, Cambodia, Cameroon, Central Africa Rep., Congo Dem. Rep., Congo Rep., Cote d'Ivoire, Iran, Libya, Myanmar, Nigeria, Sierra Leone, Sudan, Tajikistan, Togo, Venezuela, Yemen, Zimbawe.

- 0.3306 < IQ <0.5439: Albania, Argentina, Armenia, *Bahrain*, Bolivia, *Brasil*, *Bulgaria*, Burkina Faso, China, Colombia, Dominican Rep., Ecuador, El Savador, Eswatini, Fiji, Gabon,

Gambia, Ghana, Guatemala, Honduras, India, Indonesia, *Jamaica*, *Jordan*, Kazakhstan, Kenya, Kyrgyz Republic, Lesotho, Madagasacar, Malawi, Mali, Mexico, Moldova, Mongolia, Morroco, Nepal, Nicaragua, Niger, *Panama*, Paraguay, Peru, Philippines, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Sri Lanka, Tanzania, Thailand, *Trinidad and Tobago*, Tunisia, Turkey, Uganda, Ukraine, Vietnam, Yemen, Zambia.
- IQ $>$ 0.5439: Australia, Botswana, Brunei, Chile, Costa Rica, Croatia, Czech Republic, Denmark, Hungary, Korea Rep., Kuwait, Malaysia, Namibia, New Zealand, Norway, Poland, Qatar, South Africa, Sweden, United Arab Emirates, United States.

C.3 Robustness: Using Principal Component Analysis of Variables of Governance and Political Regime (Instfram)

Variables	Priv.cred		
	Instfram $< \gamma_1$	$\gamma_1 <$ Instfram $< \gamma_2$	Instfram $> \gamma_2$
Nrent	-0.27197*** (0.04383)	-0.10361*** (0.01542)	-0.01578*** (0.00328)
Gdpc	0.00466*** (0.00019)	0.00343*** (0.00033)	0.00366*** (0.00015)
Inflation	-0.00018 (0.00021)	-0.10383*** (0.00924)	-0.97905*** (0.03752)
Pop	0.40648*** (0.04591)	0.33619*** (0.01966)	0.53315 (0.03469)
Instfram	0.17937*** (0.00398)	0.15306*** (0.00104)	0.9255*** (0.00861)
γ_1	0.2989*** (0.00254)		
γ_2	0.52845*** (0.00124)		
Observations	2200		
Number of countries	100		
Number of moment conditions	336		

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table C3: Threshold effect of natural resources on financial development according to the Principal Component Analysis of governance variables and political regime

Robustness using Principal Component Analysis of variables of Governance and Political regime (Instfram):

- IQ $<$ 0.2989: Algeria, Angola, Azerbaijan, Burundi, Cameroon, Central Africa Rep., Congo Dem. Rep., Congo Rep., Cote d'Ivoire, Iran, Libya, Myanmar, Nigeria, Rwanda, Sudan, Tajikistan, Togo, Venezuela, Yemen, Zimbawe.

- 0.2989 $<$ IQ $<$ 0.5284: Albania, Argentina, Armenia, Bangladesh, Bolivia, *Brasil*, Burkina

Faso, Cambodia, China, Congo Dem. Rep., Dominican Rep., Ecuador, El Savador, Eswatini, Fiji, Gabon, Gambia, Ghana, Guatemala, Honduras, India, Indonesia, *Jamaica*, *Jordan*, Kazakhstan, Kenya, Kyrgyz Republic, Lesotho, Madagasacar, Malawi, Mali, Mexico, Moldova, Mongolia, Morroco, Nepal, Nicaragua, Niger, *Panama*, Paraguay, Peru, Philippines, Romania, Russia, Saudi Arabia, Senegal, Sierra Leone, Sri Lanka, Tanzania, Thailand, Tunisia, Turkey, Uganda, Ukraine, Vietnam, Zambia.
- IQ $>$ 0.5284: Australia, Bahrain, Botswana, Brunei, Bulgaria, Chile, Costa Rica, Croatia, Czech Republic, Denmark, Hungary, Korea Rep., Kuwait, Malaysia, Namibia, New Zealand, Norway, Poland, Qatar, South Africa, Sweden, Trinidad and Tobago, United Arab Emirates, United States.

C.4 Robustness: Using Alternative Financial development Measure: Money and Quasi-money (M_2)

Variables	M_2		
	IQ $< \gamma_1$	$\gamma_1 <$ IQ $< \gamma_2$	IQ $> \gamma 2$
Nrent	-0.36827*** (0.01408)	-0.20154*** (0.05879)	-0.00567*** (0.00029)
Gdpc	0.00269*** (0.00027)	0.01535*** (0.00069)	0.00132*** (0.00032)
Inflation	-0.00306*** (0.00007)	-0.05047*** (0.01100)	0.00148 (0.00042)
Pop	0.30921*** (0.04561)	0.15474*** (0.07796)	0.26693 (0.03206)
IQ	2.99543*** (0.06686)	1.06683*** (0.01954)	2.1350*** (0.01489)
γ	0.3396*** (0.00149)		
γ	0.51947*** (0.00045)		
Observations	2200		
Number of countries	100		
Number of moment conditions	336		

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table C4: Threshold effect of natural resources on financial development according to institutional quality with alternative measure of financial development: Money and quasi-money (M_2)

Robustness using alternative financial development measure, Money and quasi-money (M_2):
- IQ $<$ 0.3396: Algeria, Angola, Azerbaijan, Bangladesh, Burundi, Cambodia, Cameroon, Central Africa Rep., Congo Dem. Rep., Congo Rep., Cote d'Ivoire, Iran, Libya, Myanmar, Nigeria, Sierra Leone, Sudan, Tajikistan, Togo, Venezuela, Yemen, Zimbawe.
- 0.3396 $<$ IQ $<$ 0.5194: Albania, Argentina, Armenia, Bolivia, *Brasil*, China, Colombia, Dominican Rep., Ecuador, El Savador, Eswatini, Fiji, Gabon, Ghana, Gambia, Guatemala,

Honduras, India, Indonesia, *Jamaica*, *Jordan*, Kazakhstan, Kenya, Kyrgyz Republic, Lesotho, Madagasacar, Malawi, Mali, Mexico, Moldova, Mongolia, Morroco, Nepal, Nicaragua, Niger, Paraguay, Peru, Philippines, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Sri Lanka, Tanzania, Thailand, Tunisia, Turkey, Uganda, Ukraine, Vietnam, Zambia.
- IQ $>$ 0.5194: Australia, Bahrain, Botswana, Brunei, Bulgaria, Chile, Costa Rica, Croatia, Czech Republic, Denmark, Hungary, Korea Rep., Kuwait, Malaysia, Namibia, New Zealand, Norway, Panama, Poland, Qatar, South Africa, Sweden, Trinidad and Tobago, United Arab Emirates, United States.

C.5 Robustness: Using Alternative Financial Development Measure: Private Credit to Deposits (Pdpot)

Variables	Pdpot		
	IQ $< \gamma_1$	$\gamma_1 <$ IQ $< \gamma_2$	IQ $> \gamma_2$
Nrent	-1.14900***	-0.33613***	-0.01223***
	(0.15016)	(0.03374)	(0.00511)
Gdpc	0.00567***	0.00843***	0.00218***
	(0.00012)	(0.00034)	(0.00032)
Inflation	-0.00168***	-0.02289***	-3.22189
	(0.00031)	(0.01019)	(0.03409)
Pop	0.29991***	0.03114***	0.50376
	(0.01623)	(0.02628)	(0.07404)
IQ	1.3136***	0.42724***	0.87215***
	(0.08802)	(0.02105)	(0.01336)
γ_1	0.3349***		
	(0.00222)		
γ_2	0.5439***		
	(0.00045)		
Observations	2200		
Number of countries	100		
Number of moment conditions	336		

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table C5: Threshold effect of natural resources on financial development according to institutional quality with alternative measure of financial development: Private credit to deposits (Pdpot)

Classificaton of Robustness using alternative financial development measure, Private credit to deposits (Pdpot):

- IQ < 0.3349: Algeria, Angola, Azerbaijan, Bangladesh, Burundi, Cambodia, Cameroon, Central Africa Rep., Congo Dem. Rep., Congo Rep., Cote d'Ivoire, Iran, Libya, Myanmar, Nigeria, Sierra Leone, Sudan, Tajikistan, Togo, Venezuela, Yemen, Zimbawe.

- 0.3349 < IQ < 0.5439: Albania, Argentina, Armenia, *Bahrain*, Bolivia, *Brasil*, *Bulgaria*, Burkina Faso, China, Colombia, Dominican Rep., Ecuador, El Savador, Eswatini, Fiji, Gabon, Gambia, Ghana, Guatemala, Honduras, India, Indonesia, *Jamaica*, *Jordan*, Kazakhstan, Kenya, Kyrgyz Republic, Lesotho, Madagasacar, Malawi, Mali, Mexico, Moldova, Mongolia, Morroco, Myanmar, Nepal, Nicaragua, Niger, Nigeria, *Panama*, Paraguay, Peru, Philippines, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Sierra Leone, Sri Lanka, Sudan, Tanzania, Thailand, *Trinidad and Tobago*, Tunisia, Turkey, Uganda, Ukraine, Vietnam, Zambia.
- IQ > 0.5439: Australia, Botswana, Brunei, Chile, Costa Rica, Croatia, Czech Republic, Denmark, Hungary, Korea Rep., Kuwait, Malaysia, Namibia, New Zealand, Norway, Poland, Qatar, South Africa, Sweden, United Arab Emirates, United States.

C.6 Robustness: Regression for Countries with Natural Resources Rent Exceeding 10% of GDP

Variables	Priv.cred	
	IQ $< \gamma$	IQ $> \gamma$
Nrent	-0.2449***	-0.06229***
	(0.0458)	(0.00563)
Gdpc	0.00062***	0.00050***
	(0.00017)	(0.00012)
Inflation	-0.00096	-0.90738***
	(0.00015)	(0.06070)
Pop	0.1044***	0.1391***
	(0.02994)	(0.05394)
IQ	0.77092***	0.6622***
	(0.02779)	(0.04728)
γ	0.5098***	
	(0.01549)	
Observations	726	
Number of countries	33	
Number of moment conditions	336	

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table C6: Threshold effect of natural resources on financial development according to institutional quality

Classification of countries with natural resources rent exceeding 10% of GDP:

- IQ $<$ 0.5098: Algeria, Angola, Azerbaijan, Burkina Faso, Burundi, Central Africa Republic, Congo Dem. Rep., Congo Rep., Ecuador, Gabon, Ghana, Iran, Kazakhstan, Libya, Mongolia, Myanmar, Niger, Nigeria, Russia, Saudi Arabia, Sierra Leone, Togo, Uganda, Venezuela, Yemen, Zambia.
- IQ $>$ 0.5098: Brunei, Chile, Kuwait, Malaysia, Qatar, Trinidad and Tobago, United Arab Emirates.

C.7 Robustness: Regression for OPEP+ Countries and Using Oil Rent as Measure of Natural Resources Wealth

Variables	Priv.cred	
	IQ $< \gamma$	IQ $> \gamma$
Oilrent	-1.17894*** (0.25242)	-0.75654*** (0.5908)
Gdpc	0.00553*** (0.00160)	0.00074*** (0.00034)
Inflation	0.00393 (0.02219)	-0.18909 (0.22877)
Pop	0.46969*** (0.17649)	0.45646 (0.21221)
IQ	0.34269*** (0.00112)	0.84408*** (0.00389)
γ	0.3674*** (0.07926)	
Observations	462	
Number of countries	21	
Number of moment conditions	336	

Standard errors in parentheses *** p <0.01, significant at 1%, ** p <0.05, significant at 5%, * p <0.1 significant at 10%.

Table C7: Threshold effect of natural resources on financial development for OPEP+ countries

Classification for OPEP+ countries:
- IQ $<$ 0.3674: Algeria, Angola, Azerbaijan, Congo Rep., Ecuador, Iran, Libya, Nigeria, Russia, Sudan, Venezuela.
- IQ $>$ 0.3674: Bahrain, Brunei, Gabon, Kazakhstan, Kuwait, Malaysia, Mexico, Qatar, Saudi Arabia, United Arab Emirates.

C.8 Robustsness: Regression with Five-Year Averages

Variables	Priv.cred		
	IQ $< \gamma_1$	$\gamma_1 <$ IQ $< \gamma_2$	IQ $> \gamma_2$
Nrent	-0.55294***	-0.10112***	-0.01366***
	(0.00325)	(0.00698)	(0.00279)
Gdpc	0.02685***	0.01215***	0.01148***
	(0.00511)	(0.00228)	(0.00205)
Inflation	-0.01016**	-0.05843	-0.02756**
	(0.00902)	(0.05966)	(0.00998)
Pop	0.12903**	0.01242	0.08042**
	(0.09346)	(0.44135)	(0.04587)
IQ	0.53074***	0.22832***	0.09667***
	(0.01241)	(0.02031)	(0.04127)
γ_1	0.35398***		
	(0.00447)		
γ_2	0.51987***		
	(0.01251)		
Observations	400		
Number of countries	100		
Number of moment conditions	21		

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table C8: Threshold effect of natural resources on financial development according to institutional quality with five-year averages with Private credit.

Classification of countries with five-year averages, and Private credit (Priv.cred):

- IQ $<$ 0.3539: Algeria, Angola, Azerbaijan, Bangladesh, Burundi, Cambodia, Cameroon, Central Africa Rep., Congo Dem. Rep., Congo Rep., Cote d'Ivoire, Iran, *Kyrgyz Republic*, Libya, Myanmar, Nigeria, Sierra Leone, Sudan, Tajikistan, Togo, Venezuela, Yemen, Zimbawe.

- 0.3539 $<$ IQ $<$ 0.5198: Albania, Argentina, Armenia, Bolivia, *Brasil*, China, Colombia, Dominican Rep., Ecuador, El Savador, Eswatini, Fiji, Gabon, Ghana, Gambia, Guatemala, Honduras, India, Indonesia, *Jamaica*, *Jordan*, Kazakhstan, Kenya, Lesotho, Madagasacar, Malawi, Mali, Mexico, Moldova, Mongolia, Morroco, Nepal, Nicaragua, Niger, Paraguay, Peru, Philippines, *Romania*, Russia, Rwanda, Saudi Arabia, Senegal, Sri Lanka, Tanzania, Thailand, Tunisia, Turkey, Uganda, Ukraine, Vietnam, Zambia.

- IQ $>$ 0.5198: Australia, Bahrain, Botswana, Brunei, Bulgaria, Chile, Costa Rica, Croatia, Czech Republic, Denmark, Hungary, Korea Rep., Kuwait, Malaysia, Namibia, New Zealand, Norway, Panama, Poland, Qatar, South Africa, Sweden, Trinidad and Tobago, United Arab Emirates, United States.

Variables	M_2		
	IQ $< \gamma_1$	$\gamma_1 <$ IQ $< \gamma_2$	IQ $> \gamma_2$
Nrent	-0.47708***	-0.11264***	-0.01961***
	(0.00648)	(0.01392)	(0.00149)
Gdpc	0.02511***	0.01318***	0.00491***
	(0.00772)	(0.00981)	(0.00069)
Inflation	-0.0647***	-0.02972	-1.80872*
	(0.01896)	(0.26907)	(1.02898)
Pop	0.11817***	0.01495	0.04008**
	(0.04754)	(0.06772)	(0.02885)
IQ	0.19843***	0.04678***	0.01335***
	(0.01956)	(0.01303)	(0.00944)
γ_1	0.35248***		
	(0.00781)		
γ_2	0.48268***		
	(0.00513)		
Observations	400		
Number of countries	100		
Number of moment conditions	21		

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table C9: Threshold effect of natural resources on financial development according to institutional quality with five-year averages with alternative measure of financial development: M_2.

Classification of countries with five-year averages, and Money and Quasi-money (M_2):
- IQ $<$ 0.3524: Algeria, Angola, Azerbaijan, Bangladesh, Burundi, Cambodia, Cameroon, Central Africa Rep., Congo Dem. Rep., Congo Rep., Cote d'Ivoire, Iran, *Kyrgyz Republic*, Libya, Myanmar, Nigeria, Sierra Leone, Sudan, Tajikistan, Togo, Venezuela, Yemen, Zimbawe.
- 0.3524 $<$ IQ $<$ 0.4826: Albania, Argentina, Armenia, Bolivia, Brasil, China, Colombia, Dominican Rep., Ecuador, El Savador, Eswatini, Fiji, Gabon, Ghana, Gambia, Guatemala, Honduras, India, Indonesia, Jamaica, Jordan, Kazakhstan, Kenya, Lesotho, Madagasacar, Malawi, Mali, Mexico, Moldova, Morroco, Nepal, Nicaragua, Niger, Paraguay, Peru, Philippines, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Sri Lanka, Tanzania, Tunisia, Turkey, Uganda, Ukraine, Vietnam, Zambia.
- IQ $>$ 0.4826: Australia, Bahrain, Botswana, Brunei, Bulgaria, Chile, Costa Rica, Croatia, Czech Republic, Denmark, Hungary, *Jamaica*, *Jordan*, Korea Rep., Kuwait, Malaysia, *Mongolia*, Namibia, New Zealand, Norway, Panama, Poland, Qatar, South Africa, Sweden, *Thailand*, Trinidad and Tobago, United Arab Emirates, United States.

Classification of countries with five year averages, and Private credit to deposits (Pdpot):
- IQ $<$ 0.3479: Algeria, Angola, Azerbaijan, Bangladesh, Burundi, Cambodia, Cameroon, Central Africa Rep., Congo Dem. Rep., Congo Rep., Cote d'Ivoire, Iran,*Kyrgyz Republic*, Libya, Myanmar, Nigeria, Sierra Leone, Sudan, Tajikistan, Togo, Venezuela, Yemen, Zimbawe.
- 0.3479 $<$ IQ $<$ 0.5220: Albania, Argentina, Armenia, Bolivia, *Brasil*, China, Colombia, Dominican Rep., Ecuador, El Savador, Eswatini, Fiji, Gabon, Ghana, Gambia, Guatemala, Honduras, India, Indonesia, *Jamaica*, *Jordan*, Kazakhstan, Kenya, Lesotho, Madagasacar, Malawi, Mali, Mexico, Moldova, Mongolia, Morroco, Nepal, Nicaragua, Niger, Paraguay, Peru, Philippines, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Sri Lanka, Tanzania, Thailand, Tunisia, Turkey, Uganda, Ukraine, Vietnam, Zambia.
- IQ $>$ 0.5220: Australia, Bahrain, Botswana, Brunei, Bulgaria, Chile, Costa Rica, Croatia, Czech Republic, Denmark, Hungary, Korea Rep., Kuwait, Malaysia, Namibia, New Zealand, Norway, Panama, Poland, Qatar, South Africa, Sweden, Trinidad and Tobago, United Arab Emirates, United States.

Variables	Pdpot		
	IQ $< \gamma_1$	$\gamma_1 <$ IQ $< \gamma_2$	IQ $> \gamma_2$
Nrent	-0.73273***	-0.11609***	-0.01372***
	(0.03622)	(0.08093)	(0.00175)
Gdpc	0.08365***	0.01405**	0.01062**
	(0.00535)	(0.00964)	(0.00908)
Inflation	-0.04718**	-0.08624	-0.01744*
	(0.03041)	(0.57136)	(0.01651)
Pop	0.12849***	0.01267	0.01869**
	(0.04137)	(0.04145)	(0.01628)
IQ	0.41707***	0.16731***	0.05418***
	(0.01186)	(0.01671)	(0.00896)
γ_1	0.34798***		
	(0.00399)		
γ_2	0.52207***		
	(0.04928)		
Observations	400		
Number of countries	100		
Number of moment conditions	21		

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table C10: Threshold effect of natural resources on financial development according to institutional quality with five-year averages with alternative measure of financial development: Private credit to deposits (Pdpot).

Chapter 2

Which Countries are "Particularly Vulnerable" to Climate Change ? A New Climate Vulnerability Indicator

Introduction

Are least developed countries the most vulnerable to climate change? The global emission of greenhouse gases continues to rise, and average global temperatures are projected to climb steadily in the coming decades (IPCC, 2021). As the planet warms, a variety of risks are likely to emerge, with potential impacts across multiple dimensions. Climate change effects appear to touch all sectors, from economic systems to social structures and natural ecosystems. The consequences are vast and varied: more frequent extreme weather events, floods, wildfires, cyclones, coastal erosion, and rising sea levels (NASA, 2020). These effects threaten to affect every country worldwide, regardless of geographic location or development status. Given its global reach, climate change represents a significant challenge for every continent. Europe, Oceania, the Americas, Africa, and Asia are all susceptible to climate-related events that could damage natural environments, human livelihoods, and economic stability. For instance, Australia has experienced devastating wildfires (BBC, 2020), the United States is frequently battered by hurricanes and storms (NOAA, 2021), Moldova has faced severe floods (World Bank, 2018), Yemen has suffered from both floods and droughts (UNDP, 2021), Niger has endured persistent droughts (FAO, 2020a), and India has been hit by intense heatwaves (Singh et al., 2021). These examples underscore the universal nature of climate change, illustrating that no country is immune to its impacts.

While numerous climate vulnerability indicators have been proposed at both micro and macro scales, many are highly correlated with the economic development levels of countries. This can create a biased perspective on which nations are truly the most vulnerable. For example, Halkos et al. (2020) argue that developing countries appear more vulnerable than emerging and developed countries. However, this vulnerability may stem from the specific indicators used, which tend to emphasize economic development rather than inherent climate risks. When considering exogenous climatic factors such as the heterogeneity of weather patterns, this assumption may not always hold. Couharde et al. (2019) demonstrate that the climate event ENSO (El Niño Southern Oscillation) affects countries differently depending on their climatic conditions. Their study shows that both tropical and temperate countries, whether developed or developing[1], are impacted by such events, indicating that intrinsic climate characteristics play a significant role in determining vulnerability. Additionally, relying on indicators closely tied to a country's economic condition can introduce endogeneity bias into econometric estimations, potentially skewing results and policy recommendations. For accurate forecasts and meaningful empirical studies on climate change vulnerability, it is essential to use indicators that accurately reflect the true level of exposure to climate risks (Dell et al., 2014). This chapter seeks to address these challenges by proposing a new vulnerability indicator that captures "true" exogenous vulnerability resulting from climatic shocks. To achieve this, we present a set of climate vulnerability indicators that correct existing measures to reduce their correlation with economic development, thereby minimizing bias in empirical analyses.

The contribution of this chapter to the literature on climate vulnerability is significant. It provides a comprehensive review of existing vulnerability indicators and introduces a new metric that is less influenced by a country's level of economic development. This chapter is structured as follows: the next section outlines the potential impacts of climate change that contribute to a country's vulnerability. The second section examines how climate vulnerability is assessed, while the third section introduces a macro-vulnerability indicator and analyzes its correlation with economic development, leading to the revised set of indicators discussed in the fourth section. The fifth section focuses on econometric estimations to explore the causal relationship between climate vulnerability (as measured by both the original and new indicators) and economic development. The sixth section provides a detailed description of the distribution of countries based on the selected climate vulnerability indicator. The seventh section addresses the particular case of resource-rich countries, and the final section concludes the chapter.

[1]Most developing countries are located in tropical climates, such as Burundi, Burkina Faso, and Cambodia. In their study, Couharde et al. 2019 use a sample that includes several developed countries situated in temperate climates, such as Australia and Greece.

2.1 Overview of Climate Change Impacts

Climate change effects are being observed across all continents and numerous islands. These impacts are diverse, ranging from the shrinking of glaciers to land erosion. Climate change affects natural, human, social, and economic systems simultaneously, often leading to severe consequences. Several phenomena linked to climate variability have been identified as potential effects of climate change. Examples of such events include sea level rise, flooding, storms, extreme precipitation, heatwaves, cyclones, droughts, wildfires, rising ocean temperatures, ocean acidification, and land erosion. These events can impact natural, economic, social, and human systems in different ways. The following subsections will explore the potential impacts of climate change on these systems in more detail.

2.1.1 Impacts on Natural and Biological Systems

Climate variability is expected to have significant effects on ecosystem services, primary productivity, forestry, and water availability.

Ecosystem Services: Natural habitats such as coral and oyster reefs, mangroves, and wetlands provide essential services like sediment filtration, pollutant removal, carbon storage, and coastal flood protection. These ecosystems, however, are highly sensitive to climate changes, especially temperature increases (Hoegh-Guldberg et al., 2007; Duarte et al., 2020). A decline in biodiversity can severely reduce these ecosystem services, impacting vital functions such as coral reefs' role in flood prevention. Research indicates that coral reef degradation will accelerate with rising ocean temperatures and acidification, leading to significant coastal damage (Gattuso et al., 2021).

Food Systems: Climate change is expected to put immense pressure on food and forestry systems, exacerbating food insecurity. Climate-related events such as droughts, floods, marine heatwaves, and wildfires can sharply reduce agricultural productivity and food availability. Marine heatwaves, for example, have been shown to cause fishery collapses and damage aquaculture (Smale et al., 2019). Furthermore, crop flowering and maturation often correlate with temperature (Craufurd and Wheeler, 2009). Increasing temperatures can lead to reproductive failure in many crops, significantly reducing yields. More recent studies show that yields of major staple crops could decline by up to 10% for every degree Celsius of warming (Zhao et al., 2017). Additionally, climate variability and extreme weather events affect crop quality, such as protein content in wheat, which has been linked to temperature and rainfall variability (Porter and Semenov, 2005; Asseng et al., 2019). Rainfall variability is also associated with significant yield reductions (Hlavinka et al., 2009; Rowhani et al., 2011). African countries are projected to be among the most affected by these reductions (Thornton et al., 2011; Tschakert et al., 2021).

Forestry Systems: Tropical forests are critical for regulating global carbon, water, and chemical cycles, helping to maintain a stable climate. However, excessive rainfall and humidity can lead to flash floods and disrupt the fruiting cycles of various plant species. Furthermore, forests are vulnerable to wildfires and storms. Extreme temperatures are leading to increased wildfire frequency in many regions (IPCC, 2021). For example, studies predict that wildfire frequency could increase by 30% globally by the end of this century, with South America and Australia being particularly vulnerable (Xu et al., 2020).

Water Systems: Water is essential for life, supporting agriculture, energy production, manufacturing, and human health. However, climate change is expected to exacerbate water scarcity and reduce freshwater availability. Recent studies indicate that glacial melt and decreasing snowpacks, alongside rising global temperatures, are already threatening freshwater resources, especially in regions dependent on seasonal snowmelt (Pritchard, 2019; Milner et al., 2021). Moreover, glacier runoff loss is expected to severely impact water supplies in major river basins, particularly in Asia and South America (Huss and Hock, 2018).

2.1.2 Impacts on economic systems

Climate change variability poses significant threats to economic growth and development across various countries, with projected economic losses affecting multiple sectors.

Climate change disrupts economic activities through various mechanisms, including interruptions to transportation systems, damage to infrastructure, and supply chain disruptions for industries. These factors can lead to decreased production and diminished economic growth (Dell et al., 2012; Brown et al., 2012). Additionally, the demand for energy tends to increase during extreme weather events, necessitating more resources to manage both cooler and warmer periods (Ebinger and Vegara, 2011). Furthermore, climate change can negatively impact exports (Jones and Olken, 2010). Certain sectors, particularly tourism, are highly vulnerable to climate change impacts. Shifts in tourist destinations, reductions in ski seasons, and the loss of ski areas are among the expected consequences. Studies indicate that island economies, ski resorts, and coastal cities are likely to face significant challenges due to climate change (Neuvonen et al., 2015; Yang and Wan, 2010; Scott and McBoyle, 2007). Recent assessments suggest that even slight increases in temperatures can drastically alter visitor patterns and revenue in these regions (Becken et al., 2019). The economic repercussions of climate-related events will likely lead to an increased demand for insurance against climate risks, as businesses aim to protect their production systems, supply chains, and market opportunities. The loss of sea ice and glacier runoff is anticipated to disrupt transportation across frozen lakes and rivers (Jiang et al., 2005; Baraer et al., 2012; Voigt et al., 2011). Additionally, erosion, landslides (Korrupt et al., 2012; Uhlmann et al., 2013; Schneider et al., 2012), and rising sea levels (Woodworth et al., 2011; Haigh et al., 2010) are expected to impact coastal infrastructure.

Moreover, climate-related events can lead to substantial economic costs due to infrastructure damage and supply chain disruptions. The costs of maintaining and repairing transportation networks are likely to increase (Hayhoe et al., 2010). For instance, Hurricane Sandy in October 2012 severely disrupted mobility and economic activities in the United States, flooding several under-river subway tunnels and resulting in widespread economic impacts (Blake et al., 2012). Cities with extensive port facilities may face increased flooding risks (Hallegatte et al., 2013). Recent projections indicate that significant economic damages will affect major port cities exposed to rising sea levels by the 2070s, specifically highlighting cities like Bangkok, Mumbai, Shanghai, and Miami (Hanson et al., 2011; Fattal et al., 2021).

2.1.3 Impacts on social and human systems

Climate change significantly impacts human and social systems, exacerbating food insecurity, increasing competition for arable land, prompting rural outmigration, heightening urban insecurity, and worsening poverty and inequality. These dynamics can lead to increased migration pressures (Feng et al., 2012; Machiory et al., 2012) and a rise in health issues, including allergic diseases, tropical illnesses, and vector-borne diseases.

The growing frequency of extremely hot days contributes to heat-related health problems, a situation worsened by droughts and high humidity (Hajat et al., 2010). Moreover, the deterioration of healthcare infrastructure can hinder the provision of health services, leading to systemic failures in healthcare delivery. Extreme temperature events can reduce individuals' capacity to work, thereby lowering labor productivity, particularly in rural areas. Displacement caused by climate-related events, such as floods and droughts, is projected to increase. Access to food and overall food security are also threatened by climate change (Ericksen, 2008). Declines in agricultural yields can drive up child malnutrition rates, especially in developing regions like Sub-Saharan Africa, which already rely heavily on food aid. For instance, the floods in Pakistan in November 2022 led to a significant rise in health issues due to the proliferation of vector-borne diseases (Khan and Ahmad, 2023).

These potential impacts illustrate that both developed and developing nations are susceptible to be affected by climate change. This global challenge underscores the urgency of addressing climate phenomena beyond just economic factors.

2.2 Climate Change Vulnerability Assessment

As highlighted in the previous section, climate change poses a global threat that can impact all countries. Consequently, over the past two decades, research has increasingly concentrated on measuring countries' vulnerability to climate change. This section defines climate change vulnerability, outlines various approaches used in vulnerability assessment, and presents existing climate vulnerability indicators at both macro and micro scales. However, our study will specifically focus on macro-scale vulnerability indicators.

2.2.1 Traditional Definition of Climate Change Vulnerability

Since the Intergovernmental Panel on Climate Change (IPCC) assessment of climate change impacts in 2001, a formal and traditional definition of climate vulnerability has been established. Climate change vulnerability is generally defined as the susceptibility of a system to be negatively affected by climate change impacts, or the extent to which the structure, composition, and functioning of a system may be harmed by these effects (IPCC, 2014). According to the IPCC's framework, traditional assessments of climate change vulnerability center around three key components: exposure, sensitivity, and adaptive capacity (IPCC, 2002, 2014; Fussel and Klein, 2006). Exposure refers to the degree to which a system is subject to climate change events (Fussel and Klein, 2006). Sensitivity indicates how much a system can be affected by climate change impacts (Fussel and Klein, 2006). Adaptive capacity denotes the ability of a system to adjust or modify its characteristics to reduce potential damages or effectively cope with climate change effects (Fussel and Klein, 2006). The emphasis on adaptive capacity is particularly significant, as it seems to contribute to the strong correlation observed between climate vulnerability indicators and the level of economic development in countries.

2.2.2 Assessment Approaches

The costs and damages associated with climate change vary significantly among countries, largely depending on their level of vulnerability. Consequently, assessing climate vulnerability is increasingly crucial for nations aiming to manage climate change impacts effectively and to develop and implement adaptation strategies and policies. Vulnerability assessments are often conducted through impact assessments, employing various methodologies. This subsection provides a brief overview of the different frameworks available in the literature for evaluating climate change vulnerability. Notably, our focus will be on macro-scale indicators, and we will utilize an initial indicator derived from the "Indicator-based approach," as this method is commonly used for macro-level analyses.

Indicator-Based Approach: This method employs a specific set of proxy indicators to measure vulnerability by calculating indices, averages, or weighted averages of the selected indicators. It is one of the most widely utilized methods for assessing climate vulnerability, adaptable to both micro and macro levels. Previous studies have successfully applied this approach (O'Brien et al., 2004; Brooks et al., 2005; Sullivan and Meigh, 2005; Luers et al., 2003; Malakar and Mishra, 2016). For instance, Malakar and Mishra (2016) used this approach to evaluate climate change vulnerability in various Indian cities, combining indicators related to socio-economic conditions, such as the percentage of the population with access to drinking water, electricity, and banking services.

Vulnerability-Resilience Indicator Prototype (VRIP): This framework focuses on national-level proxies for sensitivity and adaptive capacity to assess overall vulnerability and resilience to climate change (Moss et al., 2002; Brenken and Malone, 2005; Jung et al., 2014; Induja and Viswanathan, 2018). It primarily examines sensitivity and adaptive capacity indicators, enabling a comprehensive assessment of countries' vulnerabilities and resilience against climate change effects.

Livelihood Vulnerability Index (LVI): This index utilizes several indicators to evaluate the impacts of climate variability on households (Hahn et al., 2009; Joshua et al., 2018). It employs geometric means to assess various aspects of household living conditions, incorporating variables such as the percentage of households reliant on agriculture and fishing for subsistence, those without crop savings, and those lacking access to information about impending natural disasters. However, this approach is primarily focused on micro-level data.

Dynamic International Vulnerability Assessment (DIVA): DIVA is a model designed to analyze coastal systems, focusing on the biophysical and socio-economic consequences of sea-level rise and socio-economic development (Hinkel et al., 2009; Torresan et al., 2008; Jochen et al., 2010). It evaluates total costs, including coastal flooding, wetland loss, economic impacts, and social costs related to temperature changes and rising sea levels.

Multicriteria Decision Analysis (MCDA): This approach employs adaptive capacity and sensitivity indices through analytic hierarchy processes (AHP) and incorporates livelihoods frameworks to evaluate household vulnerability. Like other approaches, it is often applied at the micro scale.

Welfare or Econometric Approach: This methodology uses household-level socio-economic survey data, including poverty indicators and expected utility loss, to analyze vulnerability levels across different social groups. It assesses welfare loss associated with climate events (Hoddinott and Quisumbing, 2003; Deressa et al., 2008). This approach is often linked to three models: Vulnerability as expected poverty, Vulnerability as low expected utility (which estimates the probability that a climate shock will reduce household consumption below a minimum threshold), and Vulnerability as uninsured exposure to risk. However, these methods tend to focus primarily on micro-level impacts, particularly among farmers or rural populations directly affected by climate events such as droughts, floods, or extreme temperatures.

2.2.3 An Overview of Existing Vulnerability Indicators

Numerous indicators have been developed in the literature to assess vulnerability to climate change. Tables 2.1 and 2.2 categorize these indicators, distinguishing between those suited for micro-level analysis and those oriented toward macro-level evaluations. This chapter specifically focuses on macro-scale indicators. Notably, many of these indicators (regardless of whether they operate at the micro or macro levels) incorporate components of adaptive capacity, often comprising sub-indicators that correlate strongly with a country's economic development. Regarding macro-scale vulnerability indicators, several widely applied examples include:

ND-GAIN Vulnerability Indicator: Developed in alignment with the IPCC assessment framework, this indicator encompasses three critical components: exposure, sensitivity, and adaptive capacity (Chen et al., 2015). It is calculated using the arithmetic mean of 36 sub-indicators, addressing various aspects of life, including ecosystems, food security, water resources, health, habitat, and infrastructure. The ND-GAIN indicator is available for 185 countries over an extensive timeframe (1995-2021).

WorldRiskIndex (WRI): This index provides a global assessment of vulnerability for 171 countries but does not follow the IPCC assessment framework. The authors define vulnerability based solely on sensitivity and adaptive capacity components, treating climate risk as a function of exposure and vulnerability. The WRI is calculated using 28 indicators, which include 5 variables assessing exposure, 7 evaluating sensitivity (susceptibility), 5 measuring coping capacity, and 11 concerning adaptive capacity (Birkmann and Welle, 2016; Birkmann et al., 2022). Key variables in the index include Gross Domestic Product (GDP) per capita, extreme poverty levels, insurance coverage, public health expenditure, and the proportion of the population lacking access to improved sanitation (factors that are often closely tied to economic development). The exposure component is derived from a weighted mean of its sub-indicators, relating to the number of people at risk from earthquakes, storms, floods, droughts, and sea-level rise. Meanwhile, the vulnerability component is calculated as a weighted mean of three sub-components: susceptibility (5 sub-indicators), coping capacity (7 sub-indicators), and adaptive capacity (11 sub-indicators). Further details regarding the WRI are discussed in subsection 2.5.6.

The INFORM Index Indicator: This indicator evaluates countries based on their potential vulnerability to natural disasters, focusing specifically on responses to humanitarian crises. It defines climate vulnerability primarily through the sensitivity component, considering climate risk as a function of exposure, vulnerability, and coping capacity. The INFORM Index is constructed from 22 sub-indicators assessing exposure, 18 indicators evaluating sensitivity, and 14 measuring the lack of coping capacity. The index is calculated using a combination of arithmetic and geometric means of the selected sub-indicators. Similar to the World Risk Index, this indicator incorporates several variables closely linked to economic development, such as the Human Development Index, official development aid received, the multidimensional poverty index, access to electricity, internet users, and access to health systems (Birkmann et al., 2022). The INFORM Index covers 192 countries and utilizes data from a relatively short period (2012-2022) compared to other vulnerability indicators.

Physical Vulnerability to Climate Change Index (PVCCI): This index exclusively focuses on the physical characteristics associated with climate change. It employs indicators that evaluate the likelihood of climate-related events, including risks of flooding, aridification, rainfall shocks, temperature shocks, and increased storm intensity. The PVCCI is computed using the quadratic mean of selected sub-indicators (Feinduno et al., 2020). However, this indicator is limited in its focus on the exposure component and does not incorporate projected data on carbon emission scenarios, unlike the ND-GAIN Vulnerability Indicator. Additionally, the PVCCI is time-invariant, making it unsuitable for application in panel data studies.

Global Climate Risk Index (CRI) from Germanwatch: This indicator assesses climate vulnerability in terms of fatalities and is computed as a weighted average of the number of people affected, with coefficients assigned based on the severity of impacts, and the total economic losses expressed in US dollars and as a proportion of GDP (Eckstein et al., 2020). The CRI is highly correlated with GDP as it factors in economic losses. Scores are published in reports, making them less practical for empirical studies.

Micro-level indicators concentrate on specific climate shocks, such as sea level rise, flood risks, or water scarcity, often targeting particular groups like farmers or specific regions. For instance, Preston et al. (2008) employ a specialized indicator to assess the vulnerability of natural systems in Australia, which frequently experiences wildfires and extreme heat events. Poo et al. (2021) develop a climate change risk indicator for evaluating seaports in the United Kingdom, utilizing a framework that considers coastal regions vulnerable to landslides, flooding, or hurricanes. Their findings indicate that seaports receive high-risk scores that vary seasonally and depend on geographical location. For example, the Liverpool and Grangemouth areas have high-risk values in January but lower values in July, whereas Southampton and Felixstowe exhibit the opposite trend. Uddin et al. (2019) analyze the vulnerability of coastal regions in Bangladesh by employing socioeconomic and biophysical indicators through Principal Component Analysis (PCA). Their research concludes that these coastal areas are highly susceptible to natural disasters such as cyclones, sea level rise, and storm surges. Jurgilevich et al. (2021) assess the vulnerability of Helsinki, Finland, demonstrating that economic conditions significantly influence the labor market and workplace distribution, thereby affecting population growth, density, and green spaces, which ultimately impact the city's future vulnerability. Thakur et al. (2020) create a Forest Vulnerability Index to evaluate the climate change vulnerability of the Indian Himalaya region. They argue that factors such as the prevalence of invasive species, low tree species richness, grazing, soil erosion, and fire exacerbate the region's vulnerability, driven by a complex interaction of biological, physical, and social factors. Tun Oo et al. (2018) investigate the vulnerability of farm households to sea level rise using the Livelihood Vulnerability Index (LVI) approach and socioeconomic vulnerability indices. Their results facilitate the classification of vulnerable townships, identifying Bogale as the most sensitive to climate impacts and the highest in exposure to natural hazards.

In this chapter, our focus is on macroeconomic indicators, and we prefer the ND-GAIN Vulnerability Indicator. This index considers multiple aspects of life, including ecosystems, food security, water availability, health, habitat, and infrastructure, and provides data for a broad range of countries over an extended period (1995 to 2021).

Indicator	Description	Number of countries	Time Period	Components	Assessment Approach	Reference
ND-GAIN Vulnerability Index	Climate Vulnerability Including several Sectors	185 countries	1995-2021	Exposure Sensitivity Adaptive Capacity	Indicator Based Approach	Chen et al. 2015 Dogru et al. 2019
World Risk Index	Assessing vulnerability to climate change	171 countries	2000-2023	Exposure Sensitivity Adaptative Capacity	Additive and Multiplicative function of selected indicators	Birkmann and Welle, 2016 Birkmann et al. 2022
Inform Index	Evaluation of potential climate impacts	192 countries	2012-2022	Exposure Sensitivy Adaptation Capacity	Arithmetic and geometric mean of selected indicators	Birkmann et al. 2022
PVCCI	Physical evaluation of climate events	191 countries	Time invariant	Exposure	Quadratic mean of selected indicators	Feinduno et al. 2020
Global Climate Risk Index	Evaluation in term of fatalities and loses	191 countries	2007-2021	Sensitivy Adaptive capacity	Weighted average of selected indicators	Eckstein et al. 2020

Table 2.1: Macro-Indicators

Indicator	Description	Regions	Components	Assessment Approach	Reference
Vulnerability For Ecosystem and Natural resources	Assessing Vulnerability of Natural system	Australia	Exposure Sensitivity Adaptative Capacity	Indicator Based Approach	Preston et al. 2008
Farmers Vulnerability index	Climate Vulnerability for Smallholder farmers	Afghanistan	Exposure Sensitivity Adaptative Capacity	Indicator Based Approach	Omerkhil et al. 2020
Vulnerability of coastal Region	Assessment of Coastal Region	Bangladesh	Exposure Sensitivity Adaptative Capacity	Indicator Based Approach	Uddin et al. 2019
Vulnerability for Farm Households	Assessing Vulnerability for farm Households to sea level rise	Myanmar	Exposure Sensitivity Adaptative Capacity	Livelihood Vulnerability Index Approach (LVI)	Tun Oo et al. 2018
Climate Change Risks Indicator (CCRI)	Assessment for Seaports	United Kingdom	Exposure	Evidential Reasoning Approach (ER)	Poo et al. 2021
Urban Vulnerability to Climate change	Assessment of Urban Vulnerability to Climate change	Finland	Exposure Sensitivity Adaptative Capacity	Quantitative, Qualitative and Participatory approach	Jurgilevich et al. 2021
Indicator of Forest Vulnerability	Assessment of Climate Vulnerability of Forest	Indian West Himalaya	Exposure	Integrated approach (Entropy methods)	Thakur et al. 2020
Heat Vulnerability Indicator	Heat Vulnerability Assessment	Toronto (Canada)	Exposure Sensitivity Adaptative Capacity	Cluster Analysis Methods	Rinner et al. 2010
Indicator For Flood Vulnerability	Flood Risks Assessment	Germany	Exposure Sensitivity	Multicriteria Assessment	Meyer et al. 2009
Coastal Assessment of Climate Vulnerability	Assessment climate Vulnerability of Island coast	Graham Island Coast (Canada)	Exposure Sensitivity Adaptative capacity	Qualitative Statement	Dolan and Walker, 2006
Social Vulnerability index For water availability	Social Vulnerability induced by Changes in water availability	Africa	Sensitivity Adaptative Capacity	Indicator Based Approach	Adger and Vincent, 2005
Vulnerability of Farming Sector	Assessing Vulnerability of farmers to climate change	South Africa	Exposure Sensitivity Adaptative capacity	Indicator Based Approach	Gbetibouo et al. 2010

Table 2.2: Micro-Indicators

2.3 The ND-GAIN Vulnerability Indicator

In this chapter, we utilize the ND-GAIN vulnerability indicator (Chen et al., 2015) as our primary metric for assessing countries' vulnerability to climate change. This indicator falls under the indicator-based approach and evaluates various systems within countries, including natural, human, social, and economic systems, using a quantitative scale from 0 to 1 (with values closer to 1 indicating higher vulnerability). We prefer this indicator among macroeconomic metrics because it encompasses multiple dimensions of life such as ecosystems, food security, water resources, health, habitat, and infrastructure and it provides data for a wide range of countries.

2.3.1 Components of the ND-GAIN Vulnerability Indicator

The ND-GAIN vulnerability indicator evaluates climate change vulnerability by examining the physical, human well-being, and socioeconomic impacts of climate change. It focuses on three key components: exposure, sensitivity, and adaptive capacity. Exposure pertains to the physical impacts and anticipated damages associated with climate-related events, reflecting the likelihood of countries experiencing such events. Sensitivity refers to the extent to which human, economic, social, and natural systems are affected by climate-related events. Adaptive Capacity measures the ability of countries to manage the effects of climate change and mitigate significant damages or reduce their severity. The indicator consists of 36 variables spanning six sectors: ecosystems, food supply, water supply, habitat, health, and infrastructure. A vulnerability score for each sector is calculated by averaging the six constituent indicators for that sector. The overall vulnerability score is then derived from the mean of these sector scores. The scores range from 0 to 1, with higher values indicating greater vulnerability. Below, we detail the sub-indicators associated with each sector, highlighting their respective exposure, sensitivity, and adaptive capacity components.

Food Sector

Exposure Indicators: Projected Changes in Cereal Yields and Population Growth.
Climate change is expected to impact food supply for key crops, including rice, wheat, and maize (Rosenzweig et al., 2013). The ND-GAIN vulnerability indicator utilizes the average effects on these three crops, which account for two-thirds of global food consumption, to assess climate change's impact on the agricultural sector (Chen et al., 2015). The projected change in cereal yields is determined by calculating the percentage change in annual average yields from a baseline to a future projection under various emission scenarios (IPCC, 2014). Data is sourced from the Earth System Grid Federation. Population dynamics and consumption patterns

are crucial factors in determining food demand (Godfray et al., 2012). A growing population increases food demand, making countries with higher population growth more susceptible to fluctuations in food supply. The projected change in population is calculated by measuring the percentage change from a baseline population to an average predicted size for each country, using data from The World Bank Health Nutrition and Population Statistics (HNPStats).

Sensitivity Indicators: Food Import Dependency and Rural Population.
Food import dependency measures the proportion of a country's cereal consumption sourced from imports. This includes various cereals such as wheat, rice, barley, and maize, as defined by the FAO ("crops harvested for dry grain only"). Countries highly dependent on food imports are more vulnerable to international price shocks. Climate change can exacerbate price volatility in food markets (Nelson et al., 2010). Data for this indicator is obtained from FAOSTAT's cereal import dependency ratio (The rural population comprises individuals living in rural areas, where agriculture is often the primary source of income (World Bank, 2014). A high percentage of rural population can signify a country's reliance on agricultural subsistence. Subsistence farmers are particularly vulnerable to climate-related events like droughts and floods (Thorlakson et al., 2012). Data is collected from the Worldwide Development Indicators regarding rural population (% of total population).

Adaptive Capacity Indicators: Agricultural Capacity and Child Malnutrition Agricultural capacity is evaluated using four indicators of agricultural technology: irrigation capacity, total fertilizer use on arable land, total pesticide use, and the number of tractors in agriculture. The agricultural capacity indicator is computed as the average of the two highest scores from these four indicators, accounting for situations where data may be missing or where rainfall and soil quality reduce the need for irrigation or fertilizers. These indicators reflect a country's resources for adapting to climate change. Data is sourced from FAOSTAT and the Worldwide Development Indicators (WDI). Child malnutrition is assessed by the percentage of children under five with a low weight-for-height ratio. This indicator reflects a country's capacity to meet the nutritional needs of its most vulnerable population group. Data for this indicator is also obtained from the Worldwide Development Indicators.

Water Sector

Exposure Indicators: Projected Changes in Annual Runoff and Groundwater Recharge.
The projected change in annual runoff indicates how climate change will impact surface water resources in a country through alterations in temperature and precipitation. This indicator reflects the difference between precipitation and evapotranspiration, as well as changes in soil moisture storage (Chen et al., 2015). It serves as a proxy for measuring the effects of climate change on surface water resources, calculated as the percentage change in annual runoff

from a baseline to a future projection based on emission scenarios. Data is sourced from the Aqueduct project by the World Resources Institute. Projected changes in annual groundwater recharge indicate how climate change may influence groundwater resources. Both groundwater and surface water are crucial sources of freshwater for drinking and other uses. This indicator complements the surface runoff indicator by measuring the percentage decrease in annual groundwater recharge from a baseline to a future projection, also based on emission scenarios. Data is obtained from Portmann et al. (2013).

Sensitivity Indicators: Freshwater Withdrawal Rate and Water Dependency Ratio.
The freshwater withdrawal rate represents the proportion of total actual renewable water resources withdrawn in a given year. This indicator serves as a proxy for assessing water stress within a country. Countries already experiencing water stress are likely to be more vulnerable to water scarcity exacerbated by climate change. Data for this indicator is from AQUASTAT, reflecting freshwater withdrawal as a percentage of total actual renewable water resources. The water dependency ratio measures the proportion of a country's total renewable water resources that originate from outside its borders. This includes both surface and groundwater that enters the country or is obtained through treaties. This indicator highlights the extent of a country's renewable water resources that it does not fully control (Chen et al., 2015). High dependency on foreign water resources can make a country more susceptible to water insecurity due to climate change, particularly during droughts or other adverse climate events. Data is sourced from AQUASTAT.

Adaptive Capacity Indicators: Dam Capacity and Access to Reliable Drinking Water.
Dam capacity indicates a country's ability to manage changes in the distribution of freshwater resources. This metric relates to a country's water storage capacity, including the construction of dams and reservoirs, which can help mitigate the effects of climate change on freshwater distribution. The indicator is measured by the per capita capacity of all dams within a country. Data is obtained from AQUASTAT, reflecting dam capacity per capita. Access to reliable drinking water reflects a country's ability to ensure improved drinking water access and to manage general water shortages. Data is sourced from the Worldwide Development Indicators (WDI), showing the percentage of the population with access to improved water sources.

Health Sector

Exposure Indicators: Projected Changes in Deaths from Climate-Induced Diseases and Length of Transmission Season for Vector-Borne Diseases.
The projected change in deaths from climate change-induced diseases reflects the impacts of climate change on various health conditions. This indicator measures the percentage increase in Disability-Adjusted Life Years (DALY) from a historical baseline to a future projection based

on emission scenarios. Data is sourced from Ebi (2008). The projected change in the length of the transmission season for vector-borne diseases indicates how climate change affects the duration of these diseases. This indicator is quantified by the absolute increase in the malaria transmission season length from a baseline to a future projection using emission scenarios. Data is obtained from Caminade et al. (2014) and the World Health Organization (WHO).

Sensitivity Indicators: Dependency on External Resources for Health Services and Slum Population.
Dependency on external resources for health services signifies a country's vulnerability and internal capacity weaknesses regarding climate change impacts on health. Countries with a high reliance on external aid may be more susceptible to climate-related health crises. Data for this indicator comes from the World Development Indicators (WDI), reflecting external resources for health as a percentage of total health expenditure. The slum population indicates the vulnerability of certain groups to climate-related health impacts. This metric encompasses individuals living in slum conditions characterized by inadequate living space, poor housing durability, and limited access to improved water and sanitation. Slum residents are particularly at risk for waterborne diseases that may increase due to climate change. Data is sourced from the Millennium Development Goal (MDG) indicators, showing the slum population as a percentage of the urban population.

Adaptive Capacity Indicators: Medical Staff and Access to Improved Sanitation Facilities.
The medical staff indicator assesses a country's capacity to respond to climate-related health crises. It is measured by the total number of physicians, nurses, and midwives per 1,000 people in a country. Data for this indicator is derived from the Worldwide Development Indicators (WDI). Access to improved sanitation facilities indicates a country's ability to manage infectious diseases. This access is crucial for mitigating climate-related health impacts and preventing the spread of infectious diseases. The indicator measures the proportion of the population with access to sanitation facilities that minimize contact between humans, animals, and waste. Data is sourced from the Worldwide Development Indicators (WDI), showing the percentage of the population with access to improved sanitation facilities.

Ecosystem Services Sector

Exposure Indicators: Projected Changes in Biome Distribution and Marine Biodiversity.
The projected change in biome distribution indicates how climate change may alter terrestrial biodiversity within a country. This indicator is measured by the proportion of land area expected to be impacted by different potential biome types under specific emission scenarios. Data is sourced from Gonzalez et al. (2010). The projected change in marine biodiversity reflects how climate change events can affect the diversity of marine species in a country. This indicator is

quantified by the anticipated species turnover from a baseline projection to a future projection. Data is obtained from Cheung et al. (2009).

Sensitivity Indicators: Dependency on Natural Capital and Ecological Footprint.

Natural capital dependency measures a country's reliance on ecosystem services. Climate change can disrupt these services, rendering nations highly dependent on natural capital more vulnerable to its impacts. This indicator is calculated as the ratio of natural capital to the total wealth of a country, with data sourced from the World Bank. The ecological footprint indicates a country's ability to regenerate and sustain its ecosystem services. This metric relates to the number of hectares of land and water required to support the population's lifestyle in terms of ecosystem service demand. Data is obtained from National Footprint Accounts.

Adaptive Capacity Indicators: Protected Biomes and Engagement in International Environmental Conventions.

Protected biomes reflect a country's capacity to safeguard and manage its ecosystem services in the face of climate change. Data for this indicator comes from the Environmental Performance Index (EPI). Engagement in international environmental conventions indicates a country's commitment to participating in global negotiations and planning appropriate climate actions. This indicator is measured by the ratio of a country's current status of convention engagement to the maximum level of engagement among all countries, as reported by Chen et al. (2015). Data is sourced from Environmental Treaties and Resource Indicators.

Human Habitat Sector

Exposure Indicators: Projected Changes in Warm Periods and Flood Hazards.

The projected change in warm periods indicates the likelihood of extreme heat events or heatwaves that can impact living conditions. This indicator is measured by the absolute change in the Warm Spell Duration Index, which defines excessive warmth periods using a percentile-based threshold method (Alexander et al., 2006). It compares baseline projections to future projections under various emission scenarios, with data sourced from the Warm Spell Duration Index. The projected change in flood hazard reflects the potential impacts of climate change on living conditions. This indicator is measured by predicting the maximum monthly precipitation over five consecutive days, serving as a measure of extreme precipitation and a risk factor for flooding. The percent change in flood hazard is calculated from baseline to future projections using emission scenarios, with data obtained from rx5day.

Sensitivity Indicators: Urban Concentration and Age Dependency Ratio.

Urban concentration measures the sensitivity of urban populations to climate change impacts. Countries with higher urban concentrations are considered more vulnerable to these effects. This indicator is quantified by the sum of squared percentages of the population in each large city, weighted by the proportion of the urban population relative to the total country population (Chen et al., 2015; Henderson, 2000; Van Eck and Koomen, 2008). Data is sourced from Worldwide Development Indicators (WDI) and UN Urbanization Prospects, focusing on urban populations in agglomerations of 750,000 or more. The age dependency ratio reflects the sensitivity of specific age groups, particularly those under 14 and over 65, to climate change impacts. Extreme weather and flooding can disproportionately affect these vulnerable populations. Data are sourced from Worldwide Development Indicators, capturing the percentages of populations aged 65 and older and those aged 0-14.

Adaptive Capacity Indicators: Quality of Trade and Transport-Related Infrastructure and Paved Roads.

The quality of trade and transport-related infrastructure indicates a country's capacity to manage essential systems for the transport of goods and evacuation during climate-related emergencies. This indicator is based on logistics professionals' perceptions of infrastructure quality, rated on a scale from 1 (very low) to 5 (very high). Scores are averaged and normalized to a scale of 0 to 1 for the ND-GAIN Vulnerability Indicator. Data is sourced from Worldwide Development Indicators. Paved roads serve as a measure of a country's capacity to improve transportation, particularly in rural areas. This indicator complements the quality of trade and transport infrastructure, focusing on overall transport improvements. It is measured by the total length of paved roads relative to all roads, with data sourced from Worldwide Development Indicators (WDI).

Infrastructure Sector

Exposure Indicators: Projected Changes in Hydropower Generation Capacity and Projections of Sea Level Rise Impacts.

The projected change in hydropower generation capacity indicates how climate change may affect electricity production from hydroelectric sources. Climate change is anticipated to impact hydropower capacity due to alterations in hydrological cycles affecting both surface and groundwater resources (Schaeffer et al., 2012). This indicator is calculated by measuring the percent change in hydropower generation capacity from a historical baseline to future projections under various emission scenarios, with data sourced from Hamududu and Killingtveit (2012). The projection of sea level rise impacts assesses how coastal infrastructure may be influenced by climate change through rising sea levels and potential storm surges. This indicator is determined by estimating the projected sea level rise (0.63 m according to IPCC, 2013) and the average height of storm surges (3 m, based on Smith et al., 2010), evaluating the effects on land areas situated below 4 m above sea level. Data is derived from a 1 arc-minute global relief model that incorporates land topography and ocean bathymetry.

Sensitivity Indicators: Dependency on Imported Energy and Population Living Below 5 m

Above Sea Level.
Dependency on imported energy reflects a country's sensitivity to changes in foreign energy supplies, which may be exacerbated by climate change, leading to issues such as rising prices or supply crises. This indicator is quantified by the percentage of total energy consumption that is imported. Data are sourced from Worldwide Development Indicators, specifically the net energy imports as a percentage of total energy use. The proportion of the population living below 5 m above sea level serves as an indicator of vulnerability to coastal risks such as sea-level rise and storm surges. This indicator measures the percentage of the population residing in areas where elevation is at or below 5 m. Data are obtained from Worldwide Development Indicators, indicating the population living in areas with elevations below 5 meters as a percentage of the total population.

Adaptive Capacity Indicators: Access to Electricity and Disaster Preparedness.
Access to electricity is crucial for enhancing living standards and enabling populations to better cope with climate change effects by supporting healthcare, food storage, disaster relief, and educational services. This indicator reflects a country's capacity to manage climate impacts through reliable energy provision and its resilience to supply disruptions. It is measured by the proportion of the population with access to grid power, with data sourced from Worldwide Development Indicators (WDI). Disaster preparedness indicates a country's ability to respond to climate-related disasters. Resilient infrastructure can significantly reduce the damage caused by natural disasters. This indicator is assessed every two years based on five priorities from the Hyogo Framework for Action (HFA) (Chen et al., 2015). Data are collected from HFA National Progress reports.

2.3.2 Temporal Evolution of the ND-GAIN Vulnerability Indicator and Its Relationship With Economic Development

The ND-GAIN vulnerability indicator is derived from the arithmetic mean of 36 sub-indicators related to essential life sectors: food, water, health, ecosystems, habitat, and infrastructure. Although the ND-GAIN indicator has been utilized in various studies (Fuller, 2021; Halkos et al., 2020), it does exhibit some limitations. An analysis of a sample of 185 countries from 1995 to 2021 highlights specific observations regarding the ND-GAIN vulnerability indicator. One notable limitation is the temporal trend of the ND-GAIN indicator (referred to as "NDG" in this chapter). The data reveals a downward trend over time, as illustrated in Figures 2.1 and 2.2, suggesting that, on average, countries are becoming less vulnerable to climate change. This trend appears inconsistent with the global warming trajectory and the potential challenges many nations face. Examining the sub-components of NDG (Figure 2.1), the "Exposure" component remains relatively stable over time, as it comprises indicators related to static factors like sea level and biodiversity. Conversely, the "Sensitivity" component shows some variations over the years across all countries. The "Capacity" sub-component displays a downward trend that closely mirrors that of the overall NDG indicator, with a relatively high standard deviation compared to the other sub-components. This indicates that the "Capacity" component contributes significantly to the differences in vulnerability levels among countries. Another limitation is the strong negative correlation between NDG and countries' economic development, which raises concerns about potential endogeneity if analyzed alongside macroeconomic variables like Gross Domestic Product per capita (GDP per capita). On average, a pronounced negative relationship exists between vulnerability levels and GDP per capita, with a high R-squared value indicating that around 63% of the variation in the NDG indicator is associated with GDP per capita (Figure 2.4). This correlation remains robust across different country groupings (OECD vs. non-OECD) and geographical regions (Africa, America, Europe), as shown in Figure 2.5. The sub-components also correlate with GDP per capita, albeit to varying degrees (Figure 2.4). The "Exposure" sub-component shows the weakest correlation with GDP per capita, while the "Capacity" sub-component exhibits the strongest correlation, suggesting that this sub-component drives much of the relationship between NDG and economic development. It includes indicators like agricultural capacity, dam capacity, access to improved sanitation, and infrastructure quality, all of which are closely tied to economic development. However, a high income level does not necessarily equate to lower vulnerability to climate change impacts. For example, developed countries like the United States experience severe weather events such as hurricanes, while Australia faces significant wildfires, both of which profoundly affect their populations. Conversely, some developing nations may be less impacted by climate-related events due to natural protections like extensive forests, coral reefs, mangroves, or wetlands that shield against floods. In terms of country classification, nations in Oceania and Africa, as well as small island countries, are identified as the most vulnerable (Figure 2.3). Their geographical positioning makes them particularly susceptible to rising sea levels, resulting in heightened risks of flooding and extreme temperatures. Given the strong connection between the NDG indicator and GDP per capita, many less developed countries in Oceania and Africa, characterized by low adaptive capacities, are inherently more vulnerable according to NDG. In contrast, European and OECD countries rank as the least vulnerable, indicating that the NDG indicator reflects a clear hierarchy of climate vulnerability in relation to economic development. Therefore, according to the NDG indicator, less developed countries are more vulnerable to climate change impacts, while developed countries are less vulnerable.

		NDG			Exposure			Sensitivity			Capacity (Lack of capacity)		
Group		Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations
All countries	Overall	0.4422	0.0953	N = 4995	0.4364	0.0771	N = 4995	0.3398	0.0870	N = 4860	0.5495	0.1781	N = 4752
	Between		0.0949	n = 185		0.0773	n = 185		0.0855	n = 180		0.1770	n = 176
	Within		0.0109	T = 27		0	T = 27		0.0172	T=27		0.0241	T = 27
OECD	Overall	0.3283	0.0393	N = 999	0.3969	0.0636	N = 999	0.2653	0.0665	N = 999	0.3231	0.0947	N = 999
	Between		0.0392	n = 37		0.0644	n = 37		0.0669	n = 37		0.0941	n = 37
	Within		0.0069	T = 27		0	T = 27		0.0083	T = 27		0.0182	T = 27
Non-OECD	Overall	0.4707	0.0831	N = 3996	0.4462	0.0771	N = 3996	0.3591	0.0811	N = 3861	0.6097	0.1433	N = 3753
	Between		0.0825	n = 148		0.0773	n = 148		0.0791	n = 143		0.1415	n = 139
	Within		0.0117	T = 27		0	T = 27		0.0188	T = 27		0.0253	T = 27
Small Islands	Overall	0.4932	0.0785	N = 918	0.4829	0.0764	N = 918	0.3673	0.0831	N = 810	0.6047	0.1282	N = 702
	Between		0.0787	n = 34		0.0775	n = 34		0.0821	n = 30		0.1281	n = 26
	Within		0.0121	T = 27		0	T = 27		0.0194	T = 27		0.0256	T = 27
No Small Islands	Overall	0.4307	0.0949	N = 4077	0.4259	0.0733	N = 4077	0.3343	0.0867	N = 4050	0.5399	0.1837	N = 4050
	Between		0.0946	n = 151		0.0735	n = 151		0.0853	n = 150		0.1828	n = 150
	Within		0.0106	T = 27		0	T = 27		0.0167	T = 27		0.0237	T = 27
Africa	Overall	0.5215	0.0723	N = 1431	0.4652	0.0693	N = 1431	0.4011	0.0812	N=1404	0.7135	0.1098	N = 1404
	Between		0.0721	n = 53		0.0699	n = 53		0.0796	n = 52		0.1081	n = 52
	Within		0.0110	T= 27		0	T = 27		0.0193	T = 27		0.0239	T = 27
America	Overall	0.4189	0.0507	N = 918	0.4464	0.0388	N = 918	0.2912	0.0656	N=918	0.5217	0.1084	N = 810
	Between		0.0504	n = 34		0.0393	n = 34		0.0649	n = 34		0.1079	n = 30
	Within		0.0103	T = 27		0	T = 27		0.0143	T = 27		0.0220	T = 27
Asia	Overall	0.4329	0.0713	N = 1242	0.4280	0.0896	N = 1242	0.3432	0.0647	N = 1242	0.5348	0.1481	N = 1242
	Between		0.0709	n = 46		0.0906	n = 46		0.0629	n = 46		0.1407	n = 46
	Within		0.0124	T = 27		0	T = 27		0.0177	T = 27		0.0286	T = 27
Europe	Overall	0.3381	0.0437	N = 1053	0.3701	0.0453	N = 1053	0.2867	0.0599	N = 1053	0.3583	0.1112	N = 1053
	Between		0.0435	n = 39		0.0458	n = 39		0.0593	n = 39		0.1111	n = 39
	Within		0.0081	T = 27		0	T = 27		0.0126	T = 27		0.0182	T = 27
Oceania	Overall	0.5254	0.1029	N = 351	0.5211	0.0486	N = 351	0.3882	0.1247	N=243	0.5981	0.1876	N = 243
	Between		0.1061	n = 13		0.0505	n = 13		0.1291	n = 9		0.1964	n = 9
	Within		0.0135	T = 27		0	T = 27		0.0264	T = 27		0.0276	T = 27

Table 2.3: Summary statistics for NDG and its sub-components

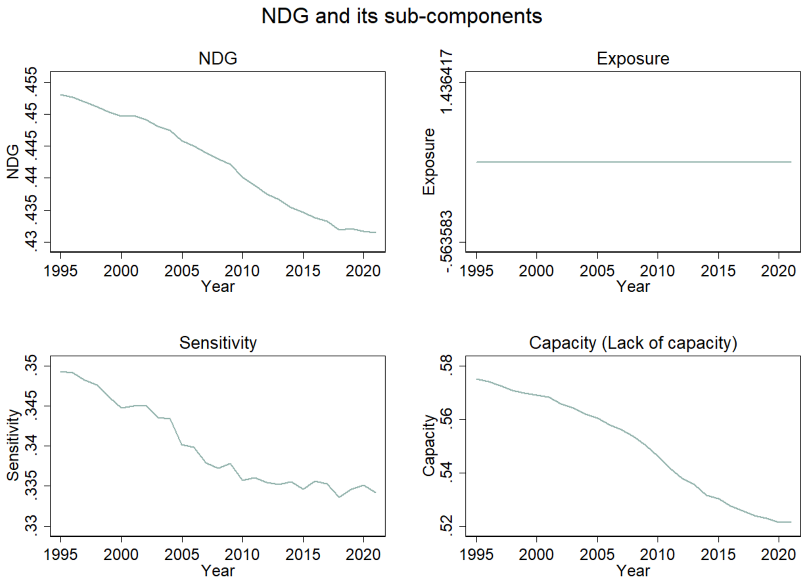


Figure 2.1: Temporal evolution of NDG and its sub-components for all countries

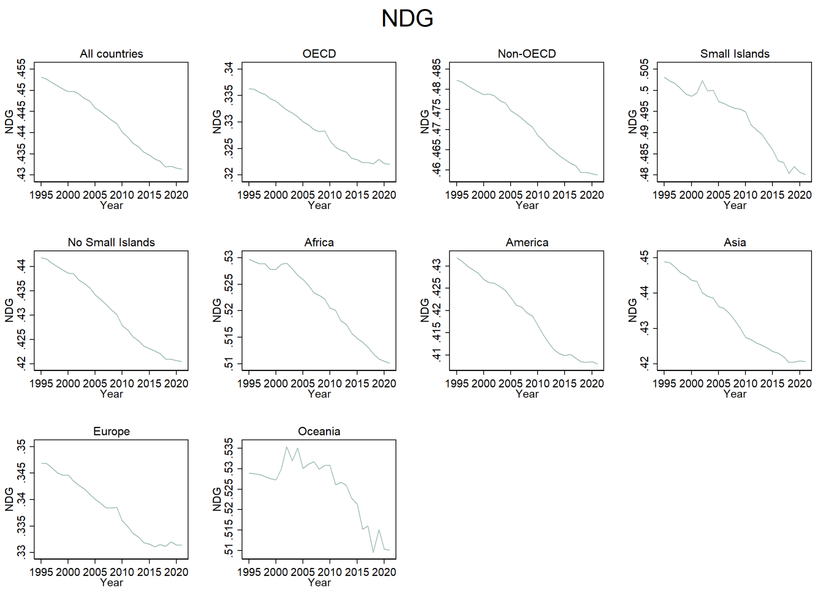


Figure 2.2: Temporal evolution of NDG by group of countries and continent

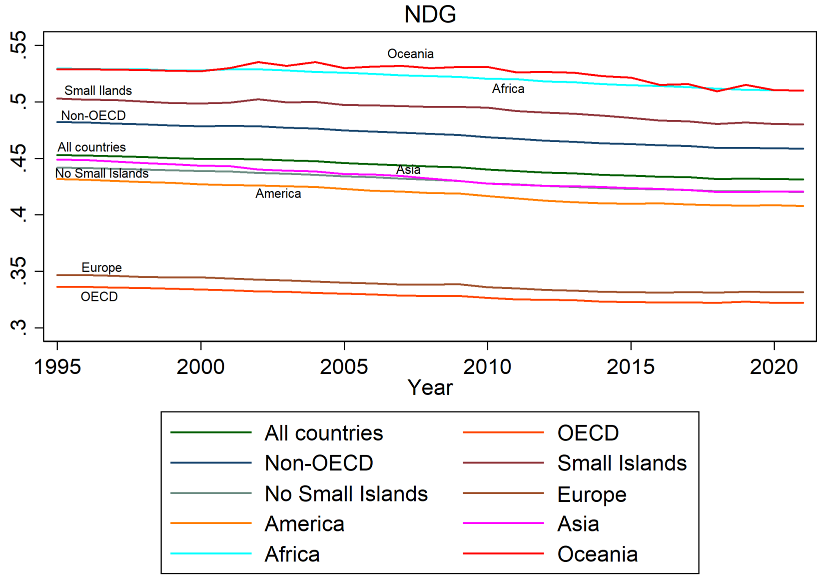


Figure 2.3: Classification of groups of countries and continents according to NDG indicator

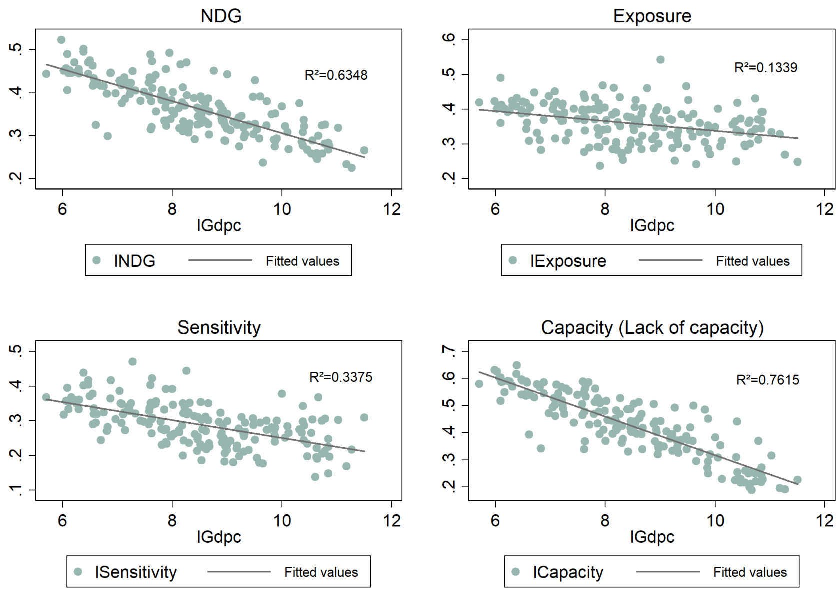


Figure 2.4: NDG and its sub-components with Gdpc

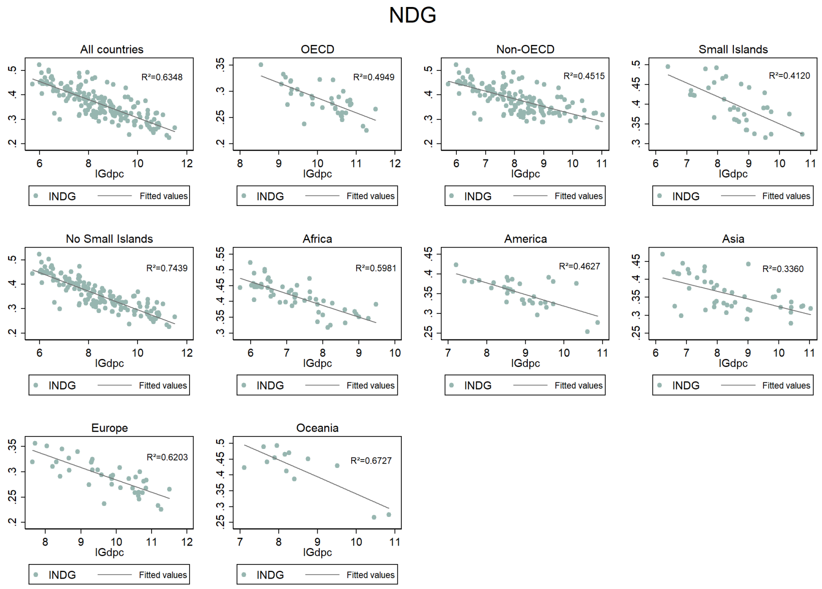


Figure 2.5: NDG and Gpdc by group of countries and continent

2.4 The "CVs" Indicators of Climate Vulnerability

To separate climate-related measures from economic factors in the ND-GAIN vulnerability indicator, we aim to create an indicator that is less likely to correlate with a country's economic conditions. Kling et al. (2021) were the first to highlight the strong relationship between the NDG indicator and economic variables. They classified the sub-indicators of NDG based on their correlation with economic variables into three categories: Low, Medium, and High. However, this classification is somewhat subjective and lacks justification (see Table 2.4). For robustness, we use their classification to evaluate two indicators: CVLM, which incorporates sub-indicators categorized as "Low" and "Medium", and CVL, which consists solely of sub-indicators classified as "Low." To achieve a more objective classification, we compute and analyze the correlation values of the sub-indicators with Gross Domestic Product per capita (GDP per capita) (see Table 2.4). Comparing their classifications with the correlation values reveals some discrepancies: certain sub-indicators classified as "Low" by Kling et al. (2021) show a high correlation with GDP per capita (e.g., Food 1), while some classified as "Medium" or "High" exhibit relatively low correlation (e.g., Water 5, Infrastructure 4). Consequently, we construct a new indicator called CV03, which consists of sub-indicators with absolute correlation values below 0.3. This threshold was chosen to ensure that at least one sub-indicator is retained for each of the six life sectors: Food, Water, Health, Ecosystems, Habitat, and Infrastructure. Additionally, we develop two other indicators (CV04 and CV02) as checks for robustness. CV04 includes sub-indicators with correlation values below 0.4, while CV02 consists of those below 0.2. We avoid focusing on correlation values below 0.1, as this would result in a very limited number of sub-indicators (only seven), leading to the exclusion of two life sectors from the original NDG indicator.

Sectors	Indicators	Link to economic variables (Kling et al. 2021)	Correlation with Gdpc	Correlation p-value
Food	1. Projected change of cereal yields	Low	-0.5387	0.0000
	2. Projected population change	Medium	-0.2755	0.0000
	3. Food import dependency	Medium	-0.3380	0.0000
	4. Rural population	High	-0.5870	0.0000
	5. Agriculture capacity	High	-0.4288	0.0000
	6. Child malnutrition	High	-0.4842	0.0000
Water	1. Projected change of annual runoff	Low	0.0971	0.0000
	2. Projected change of annual groundwater recharge	Low	-0.0538	0.0003
	3. Fresh water withdrawal rate	Low	0.0621	0.0000
	4. Water dependency ratio	Low	-0.0903	0.0000
	5. Dam capacity	High	-0.1103	0.0000
	6. Access to reliable drinking water	High	-0.6228	0.0000
Health	1. Projected change of deaths from climate induced diseases	Medium	-0.4225	0.0000
	2. Projected change in vector-borne disease	Medium	-0.1516	0.0000
	3. Dependency on external resources for health services	High	-0.3750	0.0000
	4. Slum population	High	-0.5868	0.0000
	5. Medical staff	High	-0.7179	0.0000
	6. Access to improved sanitation facilities	High	-0.6659	0.0000
Ecosystems	1. Projected change of biome distribution	Low	0.0595	0.0001
	2. Projected change of marine biodiversity	Low	0.2089	0.0000
	3. Natural capital dependency	High	-0.5505	0.0000
	4. Ecological footprint	Medium	0.4510	0.0000
	5. Projected biome	Medium	-0.5810	0.0000
	6. Engagement in international environmental conventions	Medium	-0.6019	0.0000
Habitat	1. Projected change of warm periods	Low	-0.1350	0.0000
	2. Projected change of flood hazard	Low	0.0736	0.0000
	3. Urban concentration	High	0.5870	0.0000
	4. Age dependency ratio	High	-0.4802	0.0000
	5. Quality of trade and transport infrastructure	High	-0.7903	0.0000
	6. Paved roads	High	-0.4658	0.0000
Infrastructure	1. Projected change of hydropower generation capacity	Medium	-0.1566	0.0000
	2. Projected change of sea level rise impacts	Medium	0.1870	0.0000
	3. Dependency on imported energy	Medium	0.2164	0.0000
	4. Population living under 5m above sea level	Medium	0.0979	0.0000
	5. Electricity access	High	-0.4317	0.0000
	6. Disaster preparedness	High	-0.4977	0.0000

Table 2.4: Classification of ND-GAIN Vulnerability sub-indicators to economic variables according to Kling et al. 2021 and correlation values with Gdpc

2.4.1 CVLM

The CVLM indicator consists of 20 variables and is constructed similarly to the ND-GAIN Vulnerability indicator, using the arithmetic mean of its components. Key observations regarding the CVLM indicator include:
- The CVLM shows more variation between years compared to NDG, with its declining trend being less pronounced (see Figure 2.6). The correlation between this indicator and GDP per capita is -0.3710 (p-value = 0.0000) when considering the variables in logarithmic form, and -0.3048 (p-value = 0.0000) when using levels. On average, approximately 14% of the variation in the CVLM indicator can be attributed to GDP per capita, compared to 63% for NDG (see Figure 2.7).
- Despite these differences, a hierarchical classification of countries based on their economic development level remains evident. European and OECD countries continue to be the least vulnerable, with average scores of 0.339 and 0.344, respectively, compared to 0.422 for Africa and 0.409 for Asia (see Table 2.6).

Sectors	Indicators	Related to economic variables (Kling et al. 2021)
Food	1. Projected change of cereal yields 2. Projected population change 3. Food import dependency	Low Medium Medium
Water	1. Projected change of annual runoff 2. Projected change of annual groundwater recharge 3. Fresh water withdrawal rate 4. Water dependency ratio	Low Low Low Low
Health	1. Projected change of deaths from climate induced diseases 2. Projected change in vector-borne disease	Medium Medium
Ecosystems	1. Projected change of biome distribution 2. Projected change of marine biodiversity 4. Ecological footprint 5. Projected biome 6. Engagement in international environmental conventions	Low Low Medium Medium Medium
Habitat	1. Projected change of warm periods 2. Projected change of flood hazard	Low Low
Infrastructure	1. Projected change of hydropower generation capacity 2. Projected change of sea level rise impacts 3. Dependency on imported energy 4. Population living under 5m above sea level	Medium Medium Medium Medium

Table 2.5: Sub-indicators used for CVLM

		CVLM		
Group		Mean	Std. Dev.	Observations
	Overall	0.3991	0.0667	N = 4995
All countries	Between		0.0667	n = 185
	Within		0.0048	T = 27
	Overall	0.3444	0.0492	N = 999
OECD	Between		0.0497	n = 37
	Within		0.0044	T = 27
	Overall	0.4128	0.0634	N = 3996
Non-OECD	Between		0.0634	n = 148
	Within		0.0049	T = 27
	Overall	0.4556	0.0744	N = 918
Small Islands	Between		0.0753	n = 34
	Within		0.0048	T = 27
	Overall	0.3864	0.0577	N = 4077
No Small Islands	Between		0.0577	n = 151
	Within		0.0048	T = 27
	Overall	0.4225	0.0553	N = 1431
Africa	Between		0.0556	n = 53
	Within		0.0050	T = 27
	Overall	0.3856	0.0326	N = 918
America	Between		0.0328	n = 34
	Within		0.0039	T = 27
	Overall	0.4091	0.0647	N = 1242
Asia	Between		0.0652	n = 46
	Within		0.0051	T = 27
	Overall	0.3393	0.0396	N = 1053
Europe	Between		0.0397	n = 39
	Within		0.0052	T = 27
	Overall	0.4832	0.0881	N = 351
Oceania	Between		0.0915	n = 13
	Within		0.0038	T = 27

Table 2.6: Summary statistics for CVLM

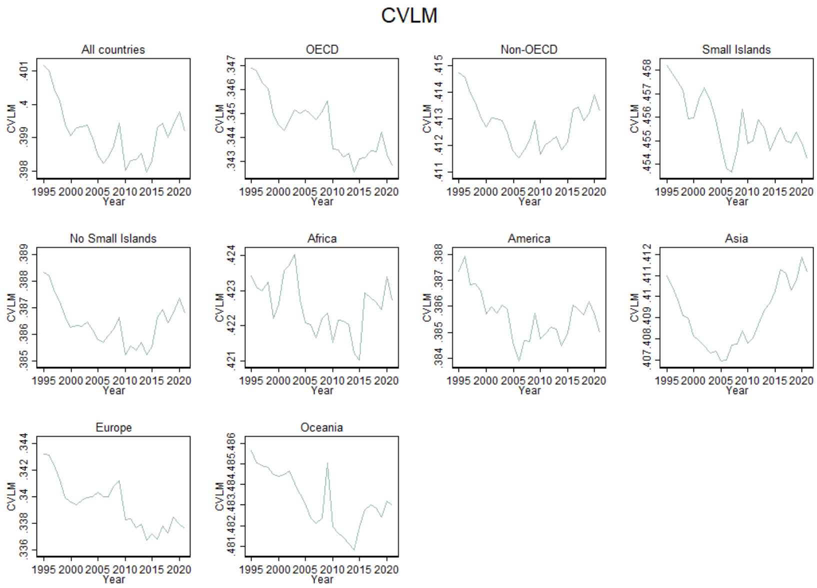


Figure 2.6: Temporal evolution of CVLM indicator

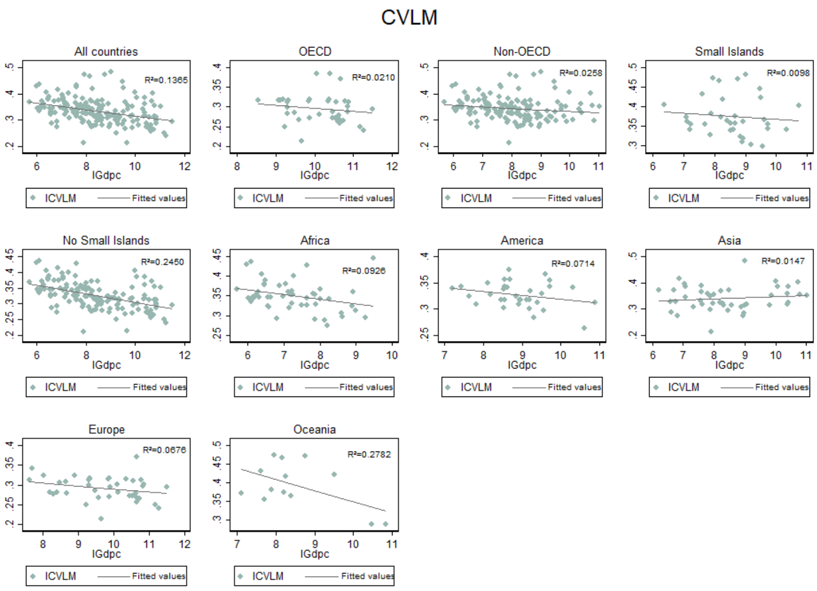


Figure 2.7: CVLM indicator and Gdpc

2.4.2 CVL

The second indicator developed following Kling et al. (2021) is referred to as CVL. This indicator exclusively uses sub-indicators that were classified as "low" by those authors (see Tables 2.4 and 2.7). Key points about the CVL indicator include:

- The CVL also shows variations over the years compared to NDG, with an observed upward

trend in vulnerability levels across all countries on average (see Figure 2.8).
- As anticipated, there is a significant decrease in correlation with GDP per capita, measuring -0.1148 (p-value = 0.0000) in logarithmic form and -0.1321 (p-value = 0.0000) in levels. On average, only 1% of the variation in this indicator is linked to GDP per capita, compared to 63% for NDG (see Figure 2.9).
- The differences in vulnerability levels among country groups are minimal; European and OECD countries remain among the least vulnerable, with average scores of 0.377 and 0.401, respectively, compared to 0.412 for Africa and 0.426 for Asia (see Table 2.8).
- Notably, the CVL indicator is based on only 9 sub-indicators, which may be insufficient for assessing the overall vulnerability of countries across multiple life sectors. The selected sub-indicators pertain to only 4 sectors, as opposed to the 6 sectors included in the original NDG indicator. This limitation could significantly affect the comprehensiveness of the CVL indicator compared to NDG.

Sectors	Indicators	Related to economic variables (Kling et al. 2021)
Food	1. Projected change of cereal yields	Low
Water	1. Projected change of annual runoff 2. Projected change of annual groundwater recharge 3. Fresh water withdrawal rate 4. Water dependency ratio	Low Low Low Low
Ecosystems	1. Projected change of biome distribution 2. Projected change of marine biodiversity	Low Low
Habitat	1. Projected change of warm periods 2. Projected change of flood hazard	Low Low

Table 2.7: Sub-indicators used for CVL

		CVL		
Group		Mean	Std. Dev.	Observations
All countries	Overall	0.4129	0.0783	N = 4995
	Between		0.0784	n = 185
	Within		0.0038	T = 27
OECD	Overall	0.4010	0.0776	N = 999
	Between		0.0785	n = 37
	Within		0.0041	T = 27
Non-OECD	Overall	0.4159	0.0782	N = 3996
	Between		0.0784	n = 148
	Within		0.0037	T = 27
Small Islands	Overall	0.4177	0.0875	N = 918
	Between		0.0887	n = 34
	Within		0.0035	T = 27
No Small Islands	Overall	0.4119	0.0761	N = 4077
	Between		0.0762	n = 151
	Within		0.0039	T = 27
Africa	Overall	0.4121	0.0721	N = 1431
	Between		0.0727	n = 53
	Within		0.0034	T= 27
America	Overall	0.4093	0.0688	N = 918
	Between		0.0697	n = 34
	Within		0.0018	T = 27
Asia	Overall	0.4262	0.0858	N = 1242
	Between		0.0867	n = 46
	Within		0.0037	T = 27
Europe	Overall	0.3770	0.0718	N = 1053
	Between		0.0724	n = 39
	Within		0.0059	T = 27
Oceania	Overall	0.4867	0.0483	N = 351
	Between		0.0502	n = 13
	Within		0.0003	T = 27

Table 2.8: Summary statistics for CVL

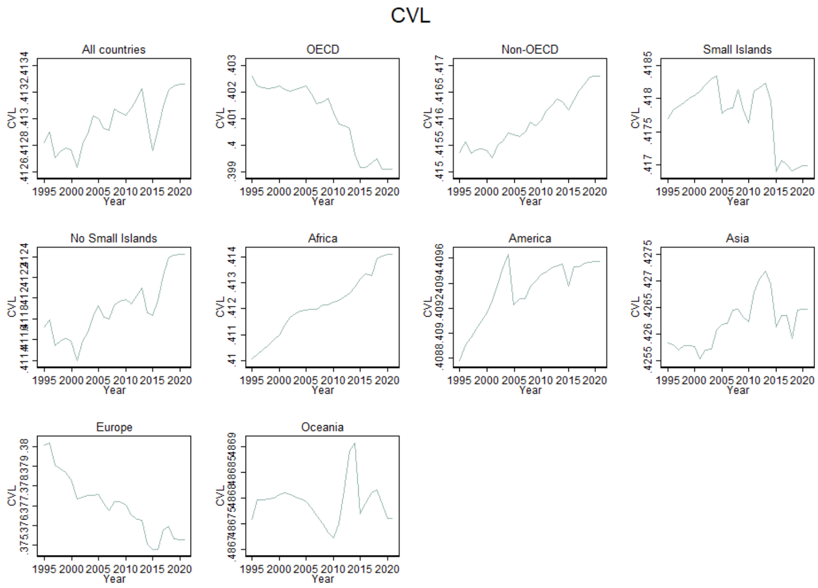


Figure 2.8: Temporal evolution of CVL indicator

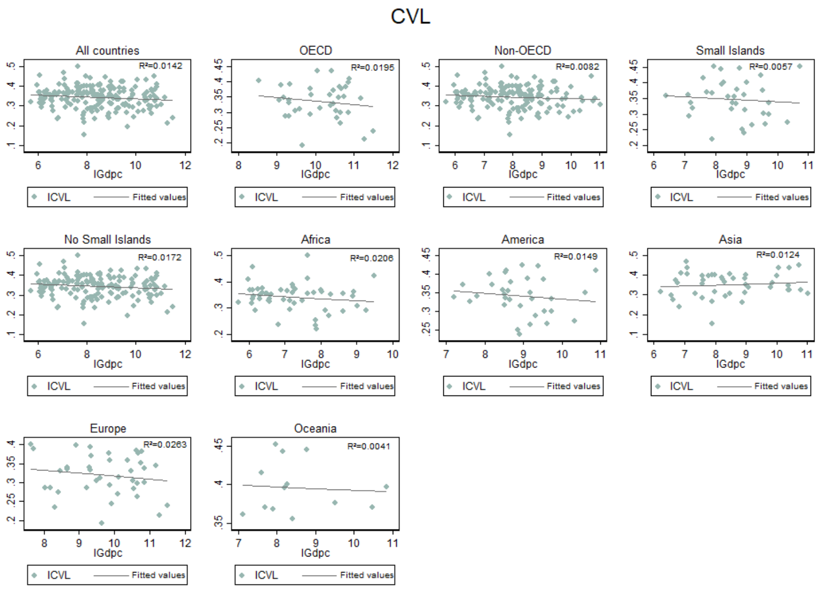


Figure 2.9: CVL indicator and Gdpc

One notable finding is that as we eliminate variables that are strongly correlated with GDP per capita, the resulting indicator exhibits a reduced downward trend. In fact, if we completely remove the correlation with GDP per capita, we can find that some regions display an upward trend in the indicators, which aligns with expectations for some regions.

2.4.3 CV03

We have now developed a new indicator, CV03, by analyzing the correlation between the original ND-GAIN vulnerability sub-indicators and GDP per capita. This indicator includes only those sub-indicators with a correlation below 0.3 in absolute value (see Tables 2.4 and 2.9) and is calculated as the arithmetic mean of 15 selected sub-indicators. In comparison to the ND-GAIN vulnerability indicator, CV03 highlights greater variability in the climate vulnerability levels among countries. Key observations include:

- On average, CV03 indicates an upward trend in vulnerability across all countries, though there are some annual variations compared to the NDG indicator (Figure 2.10).
- The correlation between CV03 and GDP per capita is positive but very low, approximately 0.0904 (p-value = 0.0000) in logarithmic terms and 0.0786 (p-value = 0.0000) in levels. Consequently, the impact of GDP per capita on the variations in this indicator is nearly negligible, accounting for only 0.53% of the variation compared to 63% for NDG (Figure 2.11).
- There is a notable diversity in vulnerability levels among different groups of countries, and the hierarchical classification based on economic levels is now much less pronounced. Interestingly, African countries show slightly less vulnerability on average (0.396) than OECD (0.408) and European countries (0.403) (Table 2.10). This may be due to certain European countries facing significant climate risks, such as extreme temperatures and flooding in Moldova, or rising sea levels in the Netherlands and Denmark.
- Despite using fewer sub-indicators than the NDG, CV03 successfully retains all six life sectors from the original NDG indicator (Table 2.9).

Sectors	Indicators	Correlation with Gdpc
Food	2. Projected population change	-0.2755
Water	1. Projected change of annual runoff 2. Projected change of annual groundwater recharge 3. Fresh water withdrawal rate 4. Water dependency ratio 5. Dam capacity	0.0971 -0.0538 0.0621 -0.0903 -0.1103
Health	2. Projected change in vector-borne disease	-0.1516
Ecosystems	1. Projected change of biome distribution 2. Projected change of marine biodiversity	0.0595 0.2089
Habitat	1. Projected change of warm periods 2. Projected change of flood hazard	-0.1350 0.0736
Infrastructure	1. Projected change of hydropower generation capacity 2. Projected change of sea level rise impacts 3. Dependency on imported energy 4. Population living under 5m above sea level	-0.1566 0.1870 0.2164 0.0979

Table 2.9: sub-indicators used for CV03

		CV03		
Group		Mean	Std. Dev.	Observations
All countries	Overall	0.4026	0.0697	N = 4995
	Between		0.0697	n = 185
	Within		0.0054	T = 27
OECD	Overall	0.4080	0.0556	N = 999
	Between		0.0561	n = 37
	Within		0.0056	T = 27
Non-OECD	Overall	0.4013	0.0728	N = 3996
	Between		0.0728	n = 148
	Within		0.0054	T = 27
Small Islands	Overall	0.4403	0.0969	N = 918
	Between		0.0983	n = 34
	Within		0.0038	T = 27
No Small Islands	Overall	0.3942	0.0588	N = 4077
	Between		0.0587	n = 151
	Within		0.0058	T = 27
Africa	Overall	0.3968	0.0691	N = 1431
	Between		0.0695	n = 53
	Within		0.0056	T = 27
America	Overall	0.3741	0.0457	N = 918
	Between		0.0461	n = 34
	Within		0.0045	T = 27
Asia	Overall	0.4079	0.0739	N = 1242
	Between		0.0745	n = 46
	Within		0.0054	T = 27
Europe	Overall	0.4031	0.0533	N = 1053
	Between		0.0536	n = 39
	Within		0.0067	T = 27
Oceania	Overall	0.4817	0.0886	N = 351
	Between		0.0920	n = 13
	Within		0.0025	T = 27

Table 2.10: Summary statistics for CV03

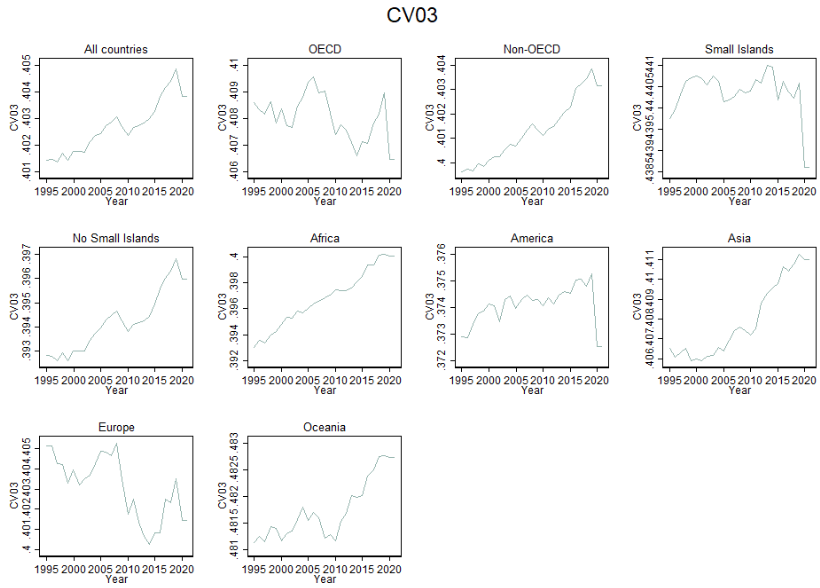


Figure 2.10: Temporal evolution of CV03 indicator

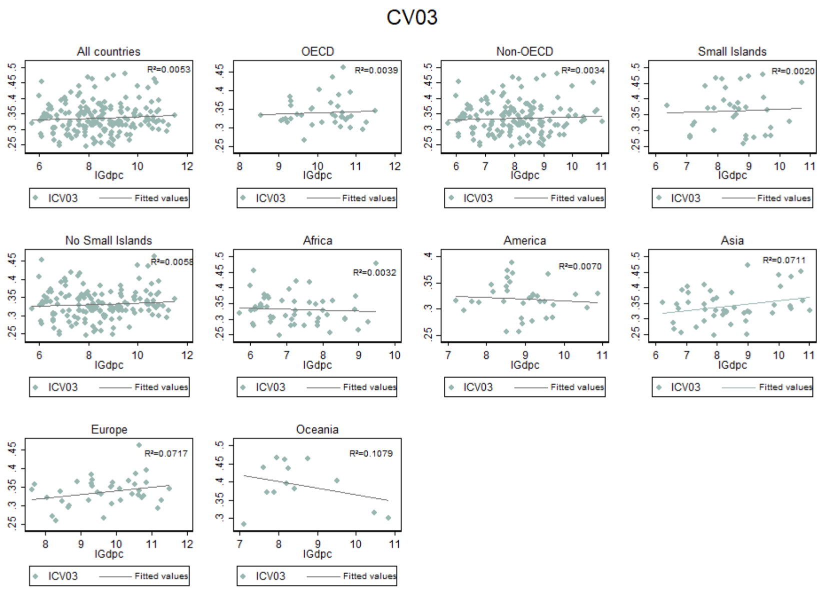


Figure 2.11: CV03 indicator and Gdpc

2.4.4 CV04

As a robustness check, we created another indicator, CV04, by analyzing the correlation between the original ND-GAIN vulnerability sub-indicators and GDP per capita. This new indicator includes only those sub-indicators with a correlation below 0.4 in absolute value (see Tables 2.9 and 2.11) and is calculated as the arithmetic mean of 17 selected sub-indicators. Key observations for this indicator include:

- On average, CV04 shows an upward trend in climate vulnerability, which aligns with the ongoing global warming, although there are slight variations from year to year compared to the NDG indicator (Figure 2.12).
- The correlation between CV04 and GDP per capita is negative but weaker than that of NDG, at approximately -0.1552 (p-value = 0.0000) in logarithmic terms and -0.0732 (p-value = 0.0000) in levels. Overall, about 2.93% of the variations in this indicator can be attributed to GDP per capita, compared to 63% for NDG (Figure 2.13).
- There is not a significant difference in climate vulnerability levels between various groups of countries and continents. However, similar to the NDG indicator, European and OECD countries tend to be less vulnerable on average, with means of 0.369 and 0.372, respectively, compared to 0.399 for Africa and 0.378 for Asia (Table 2.12).
- Despite using fewer sub-indicators than the NDG, CV04 successfully retains all six life sectors from the original NDG indicator (Table 2.11).

Sectors	Indicators	Correlation with Gdpc
Food	2. Projected population change 3. Food import dependency	-0.2755 -0.3380
Water	1. Projected change of annual runoff 2. Projected change of annual groundwater recharge 3. Fresh water withdrawal rate 4. Water dependency ratio 5. Dam capacity	0.0971 -0.0538 0.0621 -0.0903 -0.1103
Health	2. Projected change in vector-borne disease 3. Dependency on external resources for health services	-0.1516 -0.3750
Ecosystems	1. Projected change of biome distribution 2. Projected change of marine biodiversity	0.0595 0.2089
Habitat	1. Projected change of warm periods 2. Projected change of flood hazard	-0.1350 0.0736
Infrastructure	1. Projected change of hydropower generation capacity 2. Projected change of sea level rise impacts 3. Dependency on imported energy 4. Population living under 5m above sea level	-0.1566 0.1870 0.2164 0.0979

Table 2.11: Sub-indicators used for CV04

		CV04		
Group		Mean	Std. Dev.	Observations
	Overall	0.3843	0.0697	N = 4995
All countries	Between		0.0689	n = 185
	Within		0.0114	T = 27
	Overall	0.3724	0.0501	N = 999
OECD	Between		0.0505	n = 37
	Within		0.0051	T = 27
	Overall	0.3873	0.0735	N = 3996
Non-OECD	Between		0.0726	n = 148
	Within		0.0125	T = 27
	Overall	0.4291	0.0984	N = 918
Small Islands	Between		0.0986	n = 34
	Within		0.0153	T = 27
	Overall	0.3742	0.0567	N = 4077
No Small Islands	Between		0.0559	n = 151
	Within		0.0103	T = 27
	Overall	0.3997	0.0666	N = 1431
Africa	Between		0.0655	n = 53
	Within		0.0149	T = 27
	Overall	0.3465	0.0422	N = 918
America	Between		0.0422	n = 34
	Within		0.0069	T = 27
	Overall	0.3784	0.0617	N = 1242
Asia	Between		0.0618	n = 46
	Within		0.0082	T = 27
	Overall	0.3697	0.0478	N = 1053
Europe	Between		0.0481	n = 39
	Within		0.0059	T = 27
	Overall	0.4853	0.1021	N = 351
Oceania	Between		0.1037	n = 13
	Within		0.0217	T = 27

Table 2.12: Summary statistics for CV04

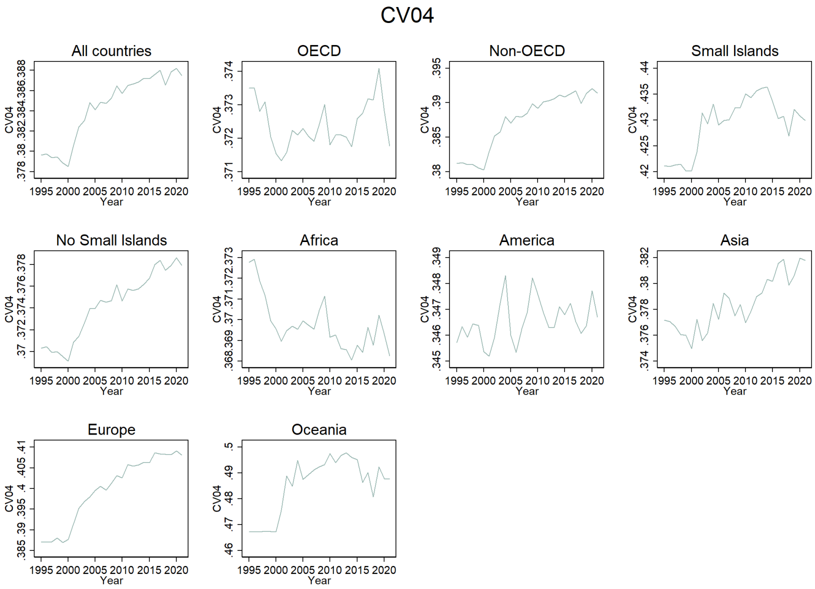


Figure 2.12: Temporal evolution of CV04 indicator

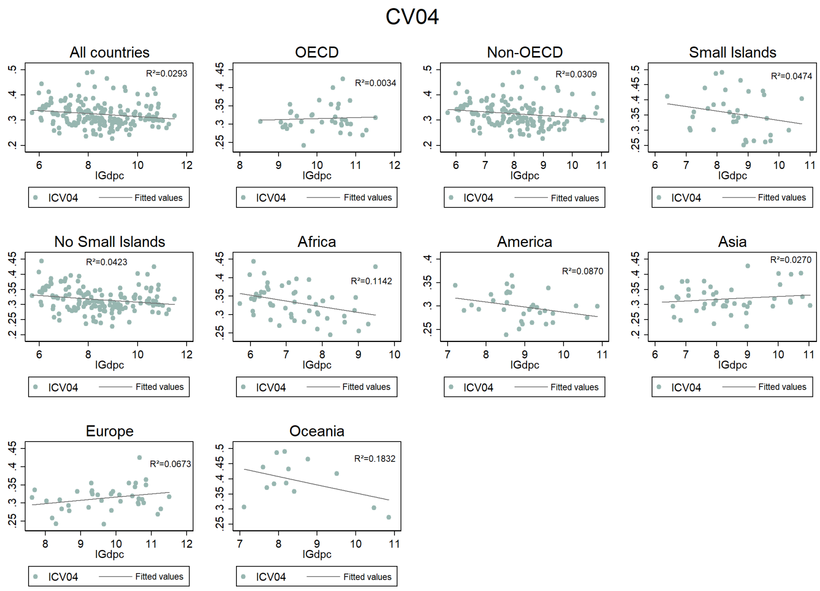


Figure 2.13: CV04 indicator and Gdpc

2.4.5 CV02

Finally, we constructed a second robustness check indicator, CV02, by including only those sub-indicators with a correlation level below 0.2 in absolute value (see Table 2.9). This new indicator comprises 12 sub-indicators (Table 2.13). Key observations for CV02 include:

- On average, the indicator shows an upward trend in vulnerability across all countries, although

the year-to-year variations are less pronounced compared to the CV03 indicator (Figure 2.14).
- The correlation between CV02 and GDP per capita is minimal, at -0.0120 (p-value = 0.4026) in logarithmic terms and -0.0063 (p-value = 0.6594) in levels. Overall, the variations linked to GDP per capita are nearly zero percent, similar to CV03 (Figure 2.15).
- There is a heterogeneous distribution of vulnerability levels, akin to CV03, with a less distinct hierarchical classification of countries based on their economic development. Notably, European countries (mean of 0.415) appear more vulnerable than African countries (mean of 0.411) (Table 2.14).
- Unlike the initial NDG indicator, CV02 comprises sub-indicators related to only five life sectors instead of six, which may be a limitation of this indicator.

Sectors	Indicators	Correlation with Gdpc
Water	1. Projected change of annual runoff 2. Projected change of annual groundwater recharge 3. Fresh water withdrawal rate 4. Water dependency ratio 5. Dam capacity	0.0971 -0.0538 0.0621 -0.0903 -0.1103
Health	2. Projected change in vector-borne disease	-0.1516
Ecosystems	1. Projected change of biome distribution	0.0595
Habitat	1. Projected change of warm periods 2. Projected change of flood hazard	-0.1350 0.0736
Infrastructure	1. Projected change of hydropower generation capacity 2. Projected change of sea level rise impacts 4. Population living under 5m above sea level	-0.1566 0.1870 0.0979

Table 2.13: Sub-indicators used in CV02

		CV02		
Group		Mean	Std. Dev.	Observations
	Overall	0.4172	0.0775	N = 4995
All countries	Between		0.0776	n = 185
	Within		0.0041	T = 27
	Overall	0.4070	0.0691	N = 999
OECD	Between		0.0699	n = 37
	Within		0.0038	T = 27
	Overall	0.4197	0.0793	N = 3996
Non-OECD	Between		0.0794	n = 148
	Within		0.0042	T = 27
	Overall	0.4518	0.1040	N = 918
Small Islands	Between		0.1054	n = 34
	Within		0.0031	T = 27
	Overall	0.4094	0.0678	N = 4077
No Small Islands	Between		0.0679	n = 151
	Within		0.0044	T = 27
	Overall	0.4117	0.0798	N = 1431
Africa	Between		0.0803	n = 53
	Within		0.0049	T = 27
	Overall	0.3774	0.0442	N = 918
America	Between		0.0447	n = 34
	Within		0.0027	T = 27
	Overall	0.4343	0.0785	N = 1242
Asia	Between		0.0793	n = 46
	Within		0.0036	T = 27
	Overall	0.4153	0.0625	N = 1053
Europe	Between		0.0631	n = 39
	Within		0.0049	T = 27
	Overall	0.4883	0.1032	N = 351
Oceania	Between		0.1073	n = 13
	Within		0.0028	T = 27

Table 2.14: Summary statistics for CV02

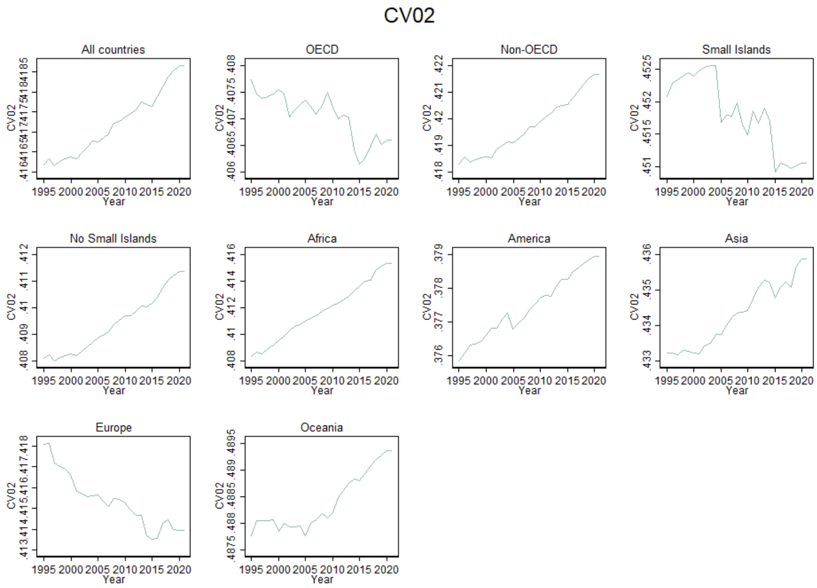


Figure 2.14: Temporal evolution of CV02 indicator

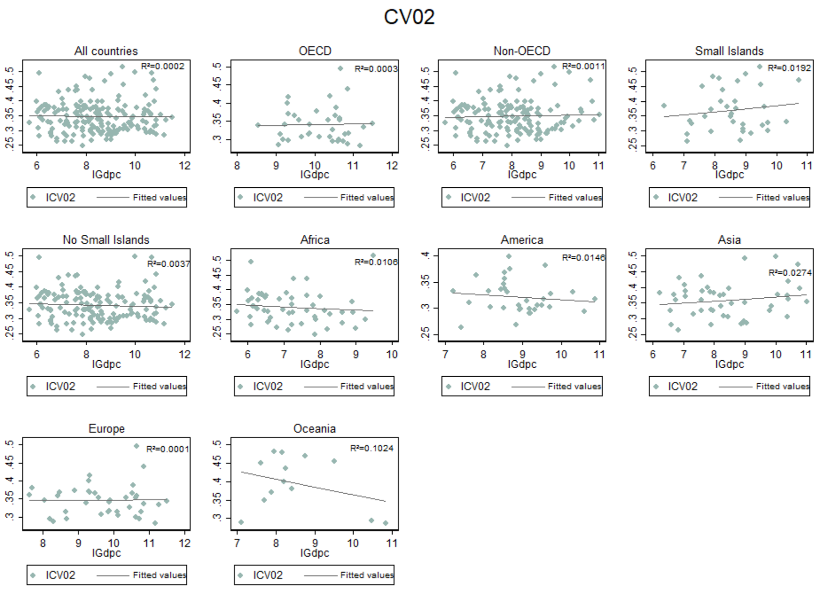


Figure 2.15: CV02 indicator and Gdpc

2.5 Econometric Estimation

In the previous section, we examined the correlation between the various vulnerability indicators (NDG, CVLM, CVL, CV03, CV04, and CV02) and GDP per capita. In this section, we will apply an econometric framework to estimate the link between these vulnerability indicators and GDP per capita.

2.5.1 Data

We use data from 1995 to 2020 for 163 countries, due to missing values and in order to have the largest strongly balanced panel. The dependent variables are NDG, CVLM, CVL, CV04, CV03, and CV02. Each dependent variable is estimated separately in relation to GDP per capita. The main explanatory variable is GDP per capita (Gdpc) measured in US dollars. The control variables include the frequency of natural disasters (storms, extreme temperatures, droughts, and floods), denoted as NDisaster, and the temperature level in degrees Celsius (Temperature). GDP data is sourced from the World Bank's Worldwide Indicators, while data on natural disasters comes from the IMF's Climate Change Portal, and temperature data is from the World Bank Climate Change Portal. In the following sections, all variables are logged.

Variables	Observations	Mean	St.Dev	Min	Max
NDG	4238	0.43821	0.09428	0.24416	0.66402
CVLM	4238	0.39571	0.06549	0.22518	0.62721
CVL	4238	0.41390	0.07889	0.16619	0.65058
CV04	4238	0.38362	0.06723	0.24453	0.63571
CV03	4238	0.40415	0.06873	0.27393	0.61426
CV02	4238	0.41743	0.07702	0.27872	0.67434
Gdpc	4238	11887.11	16914.37	217.625	112417.9
NDisaster	4238	1.79471	3.38231	0	34
Temperature	4238	19.15494	8.00463	-4.88	29.78

Table 2.15: Summary Statistics

2.5.2 Stationarity Tests

Economic relationships among variables can change over time. In a regression analysis, the dependent variable, regressors, or disturbance term may be either stationary or non-stationary. Stationary variables tend to revert to a fixed mean after a shock, while non-stationary variables do not. Understanding the stationarity or non-stationarity of variables is crucial for accurate econometric model estimation. Various tests have been developed to assess the stationarity of variables. The first generation of stationarity tests, which assumes independence among units, includes tests such as the Levin-Lin-Chu (LLC) unit-root test, the Im-Pesaran-Shin (IPS) test, the Fisher test, and the Hadri test (Mignon and Hurlin, 2005). In contrast, second-generation tests, which consider cross-sectional dependence, include methods like those proposed by Bai and Ng (2004), Philips and Sul (2003), Choi (2000), and Pesaran (2003) (Mignon and Hurlin, 2005). We denote stationary variables as I(0) and non-stationary variables as I(1). We conduct tests on variables at level (Table 16) and their first differences (Table 17), utilizing the LLC, IPS, and Pesaran (2003) tests. Since the LLC test often rejects the null hypothesis of non-stationarity (Mignon and Hurlin, 2005), we will primarily rely on the results from the IPS and Pesaran (2003) tests. These results indicate that NDG, CVLM, CVL, CV04, CV03, CV02, and Gdpc are non-stationary at level, while NDisaster and Temperature are stationary.

Variables	Test	Lags(1)		Lags(2)		Lags(3)		Lags(4)	
		No Trend	Trend	No Trend	Trend	No Trend	Trend	No Trend	Trend
NGD	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(1)	I(0)	I(1)
	IPS	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	Pesaran 2003	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
CVLM	LLC	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	IPS	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	Pesaran 2003	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
CVL	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(1)
	IPS	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	Pesaran 2003	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)
CV04	LLC	I(0)	I(0)	I(0)	I(0)	I(1)	I(0)	I(0)	I(1)
	IPS	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	Pesaran 2003	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)
CV03	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(1)
	IPS	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	Pesaran 2003	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)
CV02	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(1)
	IPS	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	Pesaran 2003	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Gdpc	LLC	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
	IPS	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	Pesaran 2003	I(1)	I(1)	I(0)	I(1)	I(0)	I(1)	I(1)	I(1)
NDisaster	LLC	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	I(0)	I(0)	I(1)	I(0)	I(0)
Temperature	LLC	I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

Table 2.16: Stationarity tests with variables in level

Variables	Test	Lags(1)		Lags(2)		Lags(3)		Lags(4)	
		No Trend	Trend	No Trend	Trend	No Trend	Trend	No Trend	Trend
NGD	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CVLM	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CVL	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CV04	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	(0)	I(0)	I(0)	I(0)	I(0)
CV03	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	(0)	I(0)	I(0)	I(0)	I(0)
CV02	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	(0)	I(0)	I(0)	I(0)	I(0)
Gdpc	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
NDisaster	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Temperature	LLC	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	IPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
	Pesaran 2003	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

Table 2.17: Stationarity tests with variables in first difference

2.5.3 Cointegration Tests

Since both the dependent variables and Gdpc (our primary explanatory variable) are non-stationary at level, we will perform a cointegration test. When the dependent variable and the regressor are I(1), yet the error term in their relationship is stationary, we say that these variables are cointegrated. A cointegration test assesses the stationarity of the error term in the cointegration equation. If variables are non-stationary, using standard estimation methods on them can yield misleading results. Cointegration techniques help identify the presence of a long-run relationship between integrated variables, guiding the choice of the appropriate estimation method. We employ the Westerlund ECM Panel cointegration test to investigate the existence of a cointegration relationship between the vulnerability indicators and Gross Domestic Product per capita (Gdpc). The results indicate that the vulnerability indicators are indeed cointegrated with Gdpc. All statistical tests [2], except for the group average Ga for some variables, support the presence of cointegration. Therefore, we can proceed with an error correction model.

[2] Gt and Ga are group mean tests, while Pt and Pa are panels tests. Gt and Ga examine the alternative hypothesis that at least one unit is cointegrated and the panels test examine the hypothesis that the panel is cointegrated as a whole.

	Statistic	Value	Z-value	P-value
NDG	Gt	-1.914	-1.932	0.027
	Ga	-7.081	0.145	0.558
	Pt	-23.071	-4.616	0.000
	Pa	-5.902	-4.809	0.000
CVLM	Gt	-2.321	-7.724	0.000
	Ga	-8.179	-2.432	0.008
	Pt	-24.775	-6.330	0.000
	Pa	-6.182	-5.612	0.000
CVL	Gt	-2.203	-6.046	0.000
	Ga	-7.868	-1.702	0.044
	Pt	-20.982	-2.514	0.000
	Pa	-5.578	-3.875	0.000
CV04	Gt	-1.190	-2.629	0.004
	Ga	-2.680	3.150	0.999
	Pt	-15.339	-7.557	0.000
	Pa	-2.220	-5.266	0.000
CV03	Gt	-2.350	-8.132	0.000
	Ga	-7.618	-1.116	0.132
	Pt	-28.573	-10.150	0.000
	Pa	-6.403	-6.249	0.000
CV02	Gt	-2.385	-8.632	0.000
	Ga	-7.673	-1.245	0.107
	Pt	-41.569	-23.221	0.000
	Pa	-9.402	-14.873	0.000

Table 2.18: Cointegration test

2.5.4 Cross-Sectional Dependence Test

Before estimating the econometric model, it is essential to determine whether the variables exhibit cross-sectional dependence. Unobserved common factors can create this dependence, and failing to account for it may lead to biased results. Therefore, we will assess if the selected variables show signs of cross-sectional dependence. Pesaran (2015) introduced a test for weak cross-sectional dependence. This involves considering the following equation with heterogeneous coefficients (Pesaran, 2006):

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it} \tag{2.1}$$

With $u_{it} = \gamma_i' f_t + e_{it}$
Where x_{it} is a K $\times$ 1 vector of regressors, f_t is an unobserved common factor, γ_i a heterogeneous factor loading, α_i a unit specific fied effect and e_{it} a cross section unit specific error term. Estimating Equation 1 without considering the error structure can result in unobserved common factors and heterogeneous loadings being incorporated into the error term u_{it}. Consequently, this error term may exhibit correlation across units (cross-sectionally dependent), making it no longer IID (independent and identically distributed). This correlation can introduce omitted variable bias if the observed explanatory variables are correlated with the unobserved common factors, leading to inconsistencies in OLS (Ordinary Least Squares) estimates (Everaert and Groote, 2016).
Chudik et al. (2011) describe two types of cross-sectional dependence: weak and strong. Following Equation 1, cross-sectional independence is defined as $\gamma_i = 0 \; \forall \; i$. The two types cross-sectional dependence are defined as following:
Weak cross-sectional dependence: $\lim_{N \longrightarrow \infty} \frac{1}{N} \Sigma_{i=1}^{N} |\gamma_i| = 0$.
Strong cross-sectional dependence: $\lim_{N \longrightarrow \infty} \frac{1}{N} \Sigma_{i=1}^{N} |\gamma_i| \geq K > 0$.
Pesaran (2015) proposes a method for testing weak cross-sectional dependence, which serves as the null hypothesis for the test. The test statistic is calculated as follows:
$CD = \sqrt{\frac{2T}{N(N-1)}} (\Sigma_{j=i+1} \widehat{p}_{ij})$
Where $\widehat{p}_{ij}$ is the correlation coefficient and $\widehat{p}_{ij} = \widehat{p}_{ji} = \frac{\Sigma_{t=1}^{N-1} \widehat{u}_{it} \widehat{u}_{jt}}{(\Sigma_{t=1}^{T} \widehat{u}_{it}^2)^{1/2})(\Sigma_{t=1}^{T} \widehat{u}_{jt}^2)^{1/2})}$

Due to the tendency of the Pesaran CD test to diverge when many period-specific parameters are included (the incidental parameter problem), an alternative weighted CD test (CDw) is also utilized, as proposed by Juodis and Reese (2021). Both CD tests are applied to each variable (including both dependent and explanatory variables) and to the residuals from estimating Equation (1). In this context, NDG, CVLM, CVL, CV03, and CV02 are treated as dependent variables, while Gdpc, NDisaster, and Temperature are considered explanatory variables. The results presented in Tables 2.19 and 2.20 indicate that both the Pesaran CD test and the weighted CD test (CDw) reject the null hypothesis of weak cross-sectional dependence for all variables and residuals from the estimations, with p-values less than 0.1. This suggests that an estimation method that accounts for cross-sectional dependence is necessary.

	CD (Pesaran, 2015, 2021)		CDw (Juodis and Reese, 2021)	
Variables	CD Value	p-value	CDw Value	p-value
NDG	323.76	0.000	-2.06	0.039
CVLM	28.49	0.000	4.26	0.000
CVL	27.37	0.000	9.79	0.000
CV04	16.15	0.000	3.64	0.000
CV03	21.01	0.000	3.11	0.002
CV02	23.99	0.000	-2.91	0.004
Gdpc	363.38	0.000	-3.29	0.001
NDisaster	20.36	0.000	-2.05	0.043
Temperature	257.58	0.000	-2.29	0.022

Table 2.19: Cross-sectional dependence test for each variable

	CD (Pesaran, 2015, 2021)		CDw (Juodis and Reese, 2021)	
Variables	CD Value	p-value	CDw Value	p-value
Residuals-NDG	576.926	0.000	-2.94	0.003
Residuals-CVLM	549.076	0.000	-2.97	0.003
Residuals-CVL	334.723	0.000	-2.19	0.029
Residuals-CV04	485.103	0.000	7.16	0.000
Residuals-CV03	513.741	0.000	2.09	0.037
Residuals-CV02	537.042	0.000	-3.02	0.003

Table 2.20: Cross-sectional dependence test for residuals

2.5.5 Cross-Sectional Error Correction Model Estimation (CS-ECM)

Theoretical Framework

Given the cointegration relationship between the vulnerability indicators and GDP per capita (Gdpc), we estimate this relationship using an error correction model. We consider a dynamic ARDL (1,1)[3] panel model with heterogeneous coefficients, as outlined by Chudik et al. (2011) and Chudik and Pesaran (2015), represented by the following equation:

$$y_{i,t} = u_i + \lambda_i y_{i,t-1} + \beta_{0,i} x_{i,t} + \beta_{1,i} x_{i,t-1} + u_{i,t} \tag{2.2}$$

Where $y_{i,t}$ is the dependent variable and $x_{i,t}$ is an observed independent variable which includes unobserved common factors. u_i is a unit-specific fixed effect and $u_{i,t}$ includes both factor loadings related to the unobserved common factors and the cross-section unit-specific IID error term denoted $e_{i,t}$. i=1,...,N and t=1,...,T

Estimating this equation without accounting for unobserved common factors in the presence of cross-sectional dependence may result in inconsistent estimates (Everaert and De Groote, 2016). To achieve consistent estimation, Equation 2 can be modified by approximating the common factors using cross-sectional averages, as demonstrated by Pesaran (2006) and Chudik and Pesaran (2015). Consequently, following the approaches of Lee et al. (1997) and Pesaran (1999), we transform Equation 2 into an error correction model with cross-sectional averages (CS-ECM) to account for common correlated factors. This error correction model enables the estimation of both short- and long-run dynamics between the dependent variable and the explanatory variable.

$$\Delta y_{i,t} = u_i - \phi_i [y_{i,t-1} - \theta 1, i x_{i,t}] - \beta_{1,i} \Delta x_{i,t} + \Sigma_{l=0}^{\eta} \gamma'_{i,l} \overline{z}_{t-l} + e_{i,t} \tag{2.3}$$

Where Δ is the first difference operator, θ_i is the long run effect of variable x and is defined as: $\theta_i = \frac{\beta_{0,i}+\beta_{1,i}}{1-\lambda_i}$. $\phi_i = (1 - \lambda_i)$ is the error correction speed of adjustment parameter and $[y_{i,t-1} - \theta_{1,i} x_{i,t}]$ is the error correction term. There is a long run relationship if $\phi_i \neq 0$ (Pesaran et al., 1999). The long-run effect assesses how the equilibrium between the dependent and independent variables shifts, while ϕ reflects the speed at which this adjustment occurs. The term $\beta_{0,i}$ represents the short run effect of $x_{i,t}$ on $y_{i,t}$.

Where $\overline{z} = (\overline{y_t}, \overline{x}_t)' = (1/N\Sigma_{i=1}^{N} y_{i,t}, 1/N\Sigma_{i=1}^{N} x_{i,t})'$ are the cross sectional averages of the dependent and independent variables. $\gamma'_{i,l} = (\gamma_{y,i,l}, \gamma_{y,i,l})'$ are the estimated coefficients of these averages, typically considered nuisance parameters (Ditzen, 2018). Estimation is performed using both the Mean Group (MG) and Pooled Mean Group (PMG) approaches, as detailed by

[3]We tried to estimate other models with more lags but they were not convergent.

Ditzen (2018). The mean group estimation allows for heterogeneity in both short- and long-run coefficients. Individual coefficients for each panel member i are estimated, and the mean group coefficients are computed as the average of these unit-specific coefficients for both short- and long-run estimates. In contrast, the pooled mean group (PMG) assumes homogeneous long-run coefficient ($\theta_i = \theta \; \forall i$) and heterogeneous short run coefficients.

The general ECM representation between climate vulnerability indicators and Gdpc is expressed as follows:

$$\Delta y_{i,t} = u_i - \phi_i(NDG_{i,t-1} - \theta_{1,i}Gdpc_{i,t} - \theta_{2,i}NDisaster_{i,t} - \theta_{3,i}Temperature_{i,t}) - \beta_{1,i}\Delta Gdpc_{i,t} - \beta_{2,i}\Delta NDisaster_{i,t} - \beta_{3,i}\Delta Temperature_{i,t} + \epsilon_{i,t}$$

Where $y_{i,t}$ refers to the vulnerability indicators, which include NDG, CVLM, CVL, CV04, CV03 and CV02.
Each indicator is estimated separately, following the methodologies outlined by Ditzen (2018, 2021). Results are presented in Tables 21 and 22.

Results and Analysis

The estimation results for each vulnerability indicator are presented in Tables 2.21 and 2.22. The Mean Group (MG) estimation can be found in Table 21, while the Pooled Mean Group (PMG) estimation is detailed in Table 2.22. The findings are summarized as follows:

NDG Vulnerability indicators:

In the MG estimation reported in Table 2.21, the adjustment parameter is negative and significant, indicating a stable long-run relationship between the ND-GAIN Vulnerability indicator (NDG) and economic development, as proxied by GDP per capita (Gdpc). The adjustment term of -0.6362 suggests that 63% of the disequilibrium is corrected each year. This stability implies a consistent long-run relationship between NDG and economic development. The long-run coefficient associated with Gdpc is negative and significant at the 5% level, indicating that in the long run, an increase in Gdpc is associated with a decrease in climate vulnerability. As for the other variables, natural disasters and temperature levels show a positive association with vulnerability, but these relationships are not statistically significant.

In the PMG estimation detailed in Table 2.22, the adjustment parameter remains negative and significant, again supporting the conclusion of a stable long-run relationship between the NDG indicator and economic development. Here, too, 63% of the disequilibrium is adjusted annually. The long-run coefficient related to Gdpc is negative and significant at the 10% level, suggesting that an increase in Gdpc over the long run reduces climate vulnerability. However, the frequency of natural disasters and temperature levels are also positively associated with climate vulnerability in the long run, although these relationships are not statistically significant.

CVLM:

In the MG estimation, the adjustment parameter is -0.936 and significant, indicating a rapid correction of disequilibrium. However, in contrast to NDG, the long-run coefficient associated with Gdpc is positive but not significant, suggesting that in the long run, increases in GDP do not influence vulnerability levels. The effects of the control variables are also not significant in the long run.

The PMG estimation yields similar conclusions to the MG, indicating that increases in GDP do not significantly affect climate vulnerability levels.

CVL:

In the Mean Group (MG) estimation, the adjustment parameter is -0.3608 and significant, indicating an adjustment of the disequilibrium; however, the speed of adjustment is relatively low compared to the previous indicators (NDG and CVulnLM). Additionally, there is a positive and significant relationship between vulnerability levels and GDP per capita (Gdpc) in the long run, suggesting that as a country develops, it may become more vulnerable to climate change, which is not always the case. The effects of other variables are not significant in the long run.

In the Pooled Mean Group (PMG) estimation, the adjustment speed is also low, with the adjustment parameter at -0.0854 and significant. Similar to the MG estimation, a positive and significant long-run relationship between vulnerability levels and Gdpc is observed.

CV04:

In the Mean Group estimation (MG), the adjustment coefficient is -0.8184 and significant. This negative value lies between -1 and 0, indicating convergence towards long-run equilibrium following a short-run imbalance. There is a significant relationship at the 10% level between vulnerability levels and economic income in the long run, suggesting that developing countries may be more adversely affected than developed ones. The effects of control variables (natural disasters and temperature) are positive but not significant in the long run.

The PMG estimation reveals an adjustment coefficient of -0.6273, which is significant, indicating a stable long-run relationship between vulnerability levels and the explanatory variables. Similar to the MG results, a significant relationship between climate vulnerability and income level (Gdpc) is found in the long run. This suggests that economic development tends to influence vulnerability levels according to the CV04 indicator. The p-value of the CD statistic supports the null hypothesis of weak cross-sectional dependence in the results.

CV03:

In the Mean Group estimation (MG), the adjustment coefficient related to the speed of convergence towards long-run equilibrium is -0.6026 and significant. In the short run, variables may deviate from their long-run relationship, and the adjustment coefficient indicates the speed at which these deviations are corrected. Its negative value, which lies between -1 and 0, shows that deviations are not explosive and do not drift indefinitely or far from the long-run equilibrium. Thus, there is convergence towards long-run equilibrium following a short-run imbalance. Furthermore, there is no significant relationship between vulnerability levels and economic income in the long run, indicating that both developing and developed countries can be vulnerable to climate change. The effects of the control variables (natural disasters and temperature) are positive but not significant in the long run. The p-value of the CD statistic accepts the null hypothesis of weak cross-sectional dependence in the estimation.

The Pooled Mean Group (PMG) estimation shows a non-significant adjustment coefficient, indicating that there is no stable long-term relationship between vulnerability levels and the explanatory variables. This suggests that the level of economic development (Gdpc) does not significantly influence vulnerability in the long run, meaning that both developing and developed countries exhibit similar levels of vulnerability. The p-value of the CD statistic supports the null hypothesis of weak cross-sectional dependence in the results.

CV02:

In the Mean Group (MG) estimation, the adjustment coefficient is negative and significant, indicating a stable long-term relationship between vulnerability levels and the explanatory variables. There is a positive and significant relationship between Gdpc and vulnerability, suggesting that countries with different levels of economic development have varying vulnerability levels.

However, in the Pooled Mean Group (PMG) estimation, the adjustment coefficient is not significant, indicating a lack of a stable long-term relationship between vulnerability levels and Gdpc.

The indicators CVLM and CV03 appear to be the strongest indicators, as they show a non-significant long-term relationship between vulnerability and Gdpc in both the Mean Group (MG) and Pooled Mean Group (PMG) estimations. However, CVLM demonstrates a significant short-term relationship with Gdpc in the PMG estimation, making CV03 seem to be the most effective indicator overall.

	Δ NDG	Δ CVLM	Δ CVL	Δ CV04	Δ CV03	ΔCV02
Short run Estimation						
Δ Gdpc	-0.00498**	-0.02022	-0.01172**	0.00043	-0.00076	-0.00383*
	(0.00232)	(0.01399)	(0.00543)	(0.00507)	(0.00829)	(0.00216)
Δ NDisaster	-0.00013	0.00048	-0.00021	-0.00034	-0.00004	-0.00002
	(0.00014)	(0.00061)	(0.00024)	(0.003096)	(0.00033)	(0.00015)
Δ Temperature	-0.00527	0.09898**	0.00351	0.01329	0.00646	-0.00072
	(0.005818)	(0.03487)	(0.00835)	(0.01393)	(0.01044)	(0.00345)
Adjustment Term	-0.63629***	-0.93664***	-0.36087***	-0.81844***	-0.60268***	-0.33063***
	(0.02631)	(0.04882)	(0.03225)	(0.03504)	(0.03695)	(0.02647)
Long run Estimation						
Gdpc	-0.005**	0.00092	0.00824**	-0.00103*	0.01302	0.00447**
	(0.00248)	(0.01354)	(0.00363)	(0.00098)	(0.08028)	(0.00197)
NDisaster	0.0004	-0.00097	0.00021	0.00084	0.00005	0.00013
	(0.00025)	(0.0014)	(0.00027)	(0.00095)	(0.00055)	(0.00022)
Temperature	0.008	0.06482	-0.00834	0.00511	0.00959	-0.00156
	(0.00875)	(0.0529)	(0.01425)	(0.02219)	(0.01662)	(0.00783)
Observations	4075	4075	4075	4075	4075	4075
Number of countries	163	163	163	163	163	163
R-squared	0.37	0.17	0.38	0.28	0.32	0.44
CD Statistic	0.32	-0.15	1.23	0.13	-1.56	0.91
p-value CD Statistic	0.747	0.8812	0.2191	0.8966	0.122	0.3626
CDw Statistic	-0.86	-0.04	-1.22	0.79	1.43	-1.403
p-value CDw Statistic	0.390	0.965	0.222	0.439	0.171	0.177
Fixed and Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 2.21: Mean Group Estimation (MG) between climate vulnerability indicators and Gdpc

	Δ NDG	Δ CVLM	Δ CVL	Δ CV04	Δ CV03	Δ CV02
Short run Estimation						
Δ Gdpc	-0.00066	-0.01829**	-0.00901*	0.00018	0.00642	-0.00451
	(0.00257)	(0.00763)	(0.00537)	(0.00458)	(0.00585)	(0.00387)
Δ Disaster	0.00013	0.00012	-0.00345*	0.00016	0.00004	0.00005
	(0.00014)	(0.00022)	(0.00018)	(0.00017)	(0.00015)	(0.00016)
Δ Temperature	-0.00037	-0.00998	-0.00834	0.01328	0.00647	0.0031
	(0.00382)	(0.0105)	(0.00594)	(0.06628)	(0.00487)	(0.00313)
Adjustment Term	-0.62568***	-0.62323***	-0.08543***	-0.62733***	-0.15645	-0.00878
	(0.02659)	(0.02672)	(0.02836)	(0.02859)	(0.20849)	(0.20288)
Long run Estimation						
Gdpc	-0.00455*	0.00574	0.00194*	-0.00217*	0.0041	0.00232
	(0.00261)	(0.0059)	(0.00189)	(0.00202)	(0.00453)	(0.00271)
NDisaster	0.0002	0.00042	0.00037	0.00055	0.00013	0.00008
	(0.00027)	(0.00066)	(0.00035)	(0.00058)	(0.00048)	(0.00022)
Temperature	0.00105	-0.00124	-0.00012	0.00054	0.00175	0.00026
	(0.0056)	(0.03233)	(0.00535)	(0.00059)	(0.00336)	(0.00273)
Observations	4075	4075	4075	4075	4075	4075
Number of countries	163	163	163	163	163	163
R-squared	0.48	0.46	0.53	0.43	0.49	0.41
CD Statistic	-1.13	-1.30	1.44	-0.13	-0.53	0.59
p-value CD Statistic	0.2605	0.1949	0.1492	0.8980	0.5939	0.5549
CDw Statistic	-0.35	1.35	-0.92	0.801	0.87	0.77
p-value CDw statistic	0.726	0.176	0.364	0.414	0.385	0.442
Fixed and Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 2.22: Pooled Mean Group Estimation (PMG) between climate vulnerability indicators and Gdpc

2.5.6 Robustness Check

Alternative Estimation With Fractional Response Model

Since the dependent variables (NDG and "CVs" indicators) are restricted to the [0,1] interval, we employ a fractional response model, which is particularly suitable for bounded continuous dependent variables (Papke and Wooldridge, 1996, 2008). This model is appropriate when the dependent variable is between 0 and 1. It utilizes either a probit or logit model for the conditional mean. Papke and Wooldridge (2008) introduced the fractional response model for panel data, employing a quasi-maximum likelihood estimator along with robust estimators for the conditional mean parameters. One key advantage of the fractional response model is that it helps prevent model misspecification and ensures that predictions remain within the specified bounds of the dependent variable (Papke and Wooldridge, 2008). The basic model is :

$$E(y_{it}|x_{it}, c_i) = G(x_{it}\beta + c_i) \tag{2.4}$$

Where y_{it} is the dependent variable, x_{it} the explanatory variables and c_i accounts for the fixed effects of countries. $G(\cdot)$ is a logistic function and $G(z) \equiv exp(z)/(1+exp(z))$. We introduced fixed and year effects in the estimations and correct for heteroskedasticity. Additionally, we estimated the model with variables in first differences (see Appendix D). The results presented in Table 2.23 indicate that the NDG and CV04 indicators exhibit a significant relationship with GDP per capita. In contrast, the CVLM, CVL, CV03, and CV02 indicators do not show a significant influence from the level of GDP per capita. Concerning the control variables, the coefficient for Natural Disasters (NDisaster) is significant for the CVLM indicator, while temperature has a positive and significant association with CV03. This suggests that an increase in temperature correlates with a heightened level of vulnerability as indicated by CV03, aligning with trends of global warming. Since there is no significant relationship between CV03 and GDP per capita, yet temperature significantly affects CV03, it appears that CV03 remains the most reliable indicator for assessing vulnerability to climate change.

	NDG	CVLM	CVL	CV04	CV03	CV02
Gdpc	-0.03584***	-0.00039	-0.00157	-0.02081**	0.00814	0.00371
	(0.00756)	(0.00513)	(0.00347)	(0.01079)	(0.05423)	(0.00384)
NDisaster (Lagged)	0.00088	0.00122**	0.00048	0.00336	0.00071	0.00052
	(0.00107)	(0.00063)	(0.00058)	(0.00459)	(0.00069)	(0.00053)
Temperature (Lagged)	0.0062	-0.02105	-0.01496*	0.03764**	0.02404**	-0.01699
	(0.00877)	(0.09721)	(0.00856)	(0.01573)	(0.01177)	(0.08762)
Observations	4238	4238	4238	4238	4238	4238
Number of countries	163	163	163	163	163	163
Log pseudolikelihood	-2731.7869	-2674.003	-2699.6967	-2647.1453	-2690.3945	-2711.3204
Fixed and Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 2.23: Fractional Response model estimation with climate vulnerability indicators

Focus on the World Risk Index (WRI)

Among macro-scale indicators, the World Risk Index (WRI) stands out as a noteworthy metric due to its availability over a relatively long period (2000-2023) and its coverage of a large panel of countries. We focused on this indicator to examine its temporal trends and its relationship with GDP per capita. The WRI comprises sub-indicators that encompass aspects of poverty, inequality, and governance, which are closely correlated with GDP per capita (e.g., extreme poverty, GDP per capita, the share of undernourished populations, and public health expenditure) (Birkmann and Welle, 2016; Birkmann et al., 2022). The WRI is calculated as a product of two components: Exposure (E-WRI) and Vulnerability (V-WRI). The Exposure component is determined by a weighted average of five sub-indicators related to the number of people exposed to natural hazards such as earthquakes, storms, floods, droughts, and rising sea levels. The Vulnerability component is derived from a weighted average of three sub-components: susceptibility (composed of five sub-indicators), coping capacity (seven sub-indicators), and adaptive capacity (eleven sub-indicators). These sub-components are also calculated as weighted averages of their respective sub-indicators. More details about the vulnerability sub-components are as follows:

Susceptibility: This relates to the likelihood of the population suffering harm in the event of natural hazards. Examples of indicators in this sub-component include the share of the population lacking access to improved sanitation, extreme poverty measured by the proportion of the population living on less than 1.25 USD per day, and GDP per capita.

Coping Capacity: This measures a population's or country's ability to respond immediately to the impacts of hazard events. Its sub-indicators focus on the quality of existing medical services, government effectiveness, and material protection (e.g., corruption perception index, number of physicians per 10 000 population, and number of hospital beds per 10 000 population).

Adaptive Capacity: This focuses on long-term strategies that enable countries to adapt to and transform in response to the anticipated negative effects of natural hazards. Sub-indicators relate to education, research, environmental protection, and health investments (e.g., adult literacy rate, biodiversity and habitat protection, public health expenditure).

Compared to the NDG indicator, the WRI exhibits fluctuations with both decreasing and increasing trends (Figure 2.16). Its correlation with the CV03 indicator is 0.0659 (p-value = 0.0000), which is relatively lower than its correlation with NDG, which is 0.1385 (p-value = 0.0000). Descriptive statistics (Table 2.24) indicate that, on average, European countries exhibit the lowest risk of being impacted by climate change, with a mean of 3.1952, significantly lower than other regions. This finding appears unrealistic, as European countries also face potential climate change impacts (e.g., sea level rise, extreme temperatures, floods) similar to those in Asia and the Americas. Additionally, small island nations show, on average, lower risk levels compared to non-small island nations, which is also counterintuitive given their high exposure to sea level rise and flooding. To investigate the causal relationship between WRI and GDP per capita, we employed an econometric framework focusing on 163 countries over the period from 2000 to 2021. Since the WRI and its components (E-WRI and V-WRI) are stationary at level, we utilized a classical linear model incorporating fixed and year effects, correcting for heteroskedasticity and cross-sectional dependence bias. The estimation results indicate a causal link between WRI and GDP per capita (Table 2.25). Although the correlation between WRI and GDP per capita is relatively lower than that of NDG (Figure 2.17), WRI is still influenced by the economic development level of countries. This suggests that an increase in GDP per capita tends to lower the likelihood of being affected by climate change events, which does not align well with global warming trends. Regarding its components, E-WRI is not significantly influenced by GDP per capita, whereas V-WRI is affected in a similar manner to WRI.

		WRI			E-WRI			V-WRI		
Group		Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations
All countries	Overall	8.5421	9.4444	N = 3586	5 .8961	10.7015	N = 3586	23.8972	16.1063	N = 3586
	Between		9.4121	n = 163		10.7325	n = 163		15.2106	n = 163
	Within		0.0109	T = 22		0.09971	T = 22		5.4225	T =22
OECD	Overall	8.2597	9.4721	N = 792	8.9493	13.70076	N = 792	11.4559	7.8799	N=792
	Between		9.5529	n = 36		13.8861	n = 36		7.7081	n = 36
	Within		0.9407	T = 22		0.0781	T = 22		2.0632	T = 22
Non-OECD	Overall	8.6221	9.4367	N = 2794	5.0306	9.5101	N = 2794	27.4239	16.0951	N = 2794
	Between		9.5529	n = 148		9.5455	n = 127		14.9734	n = 127
	Within		1.0951	T = 22		0.1051	T = 22		6.0445	T = 22
Small Islands	Overall	5.7067	5.1605	N = 638	2.4836	3.8073	N = 638	17.2019	8.4634	N = 638
	Between		5.2012	n = 29		3.8712	n = 29		7.4976	n = 29
	Within		0.6856	T = 22		0.0529	T = 22		4.1556	T = 22
No Small Islands	Overall	9.0631	9.8542	N = 2838	6.6256	11.6231	N = 2838	25.2551	17.0103	N = 2838
	Between		9.8269	n = 129		11.6658	n = 129		16.0883	n = 129
	Within		1.1192	T = 22		0.1041	T = 22		5.6951	T = 22
Africa	Overall	6.2159	5.5717	N = 968	1.9776	3.8262	N = 968	36.7096	17.2629	N=968
	Between		5.5719	n = 44		3.8678	n = 44		15.7654	n = 44
	Within		0.8197	T= 27		0.0718	T = 22		7.4065	T = 22
America	Overall	11.9788	9.4817	N = 704	9.5118	12.0569	N = 704	20.9835	9.0457	N = 704
	Between		9.5537	n = 32		12.2408	n = 321		8.4094	n =32
	Within		1.1649	T = 22		0.0915	T = 22		3.6358	T = 22
Asia	Overall	12.9832	13.2799	N = 770	11.1052	15.9788	N = 770	25.8495	16.0735	N = 770
	Between		13.3706	n = 35		16.2007	n = 35		14.8765	n = 35
	Within		13.3706	T = 22		0.1607	T = 22		6.5641	T = 22
Europe	Overall	3.1952	2.4279	N = 814	1.5161	2.1967	N = 814	10.5183	5.0291	N = 814
	Between		2.4259	n = 37		2.2256	n = 37		4.4395	n = 37
	Within		0.4024	T = 22		0.0183	T = 22		2.4681	T = 22
Oceania	Overall	10.5183	7.3554	N = 220	9.0558	10.0338	N = 220	17.6156	7.7688	N = 220
	Between		7.6627	n = 10		10.5521	n = 10		7.3256	n = 10
	Within		1.0072	T = 22		0.0828	T = 22	3.4402	T = 22	

Table 2.24: Summary statistics for WRI and its components

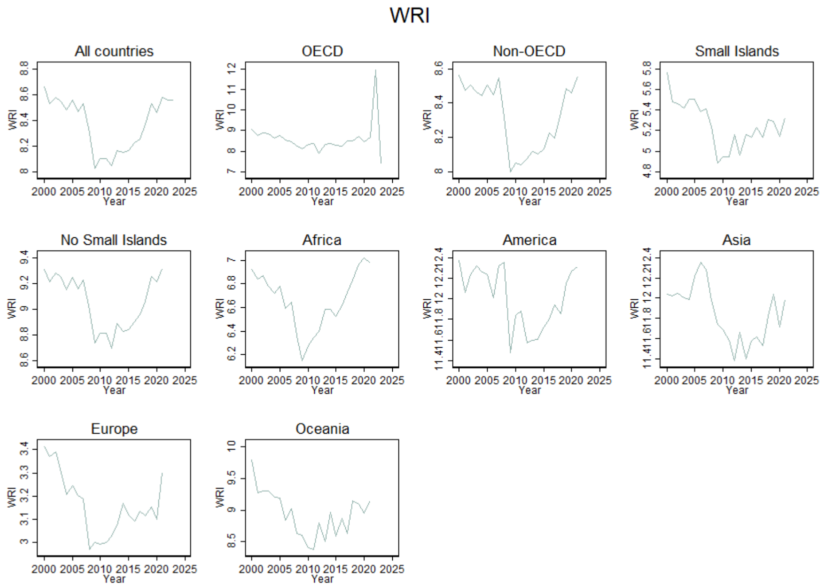


Figure 2.16: Temporal evolution of WRI by group of countries and continent

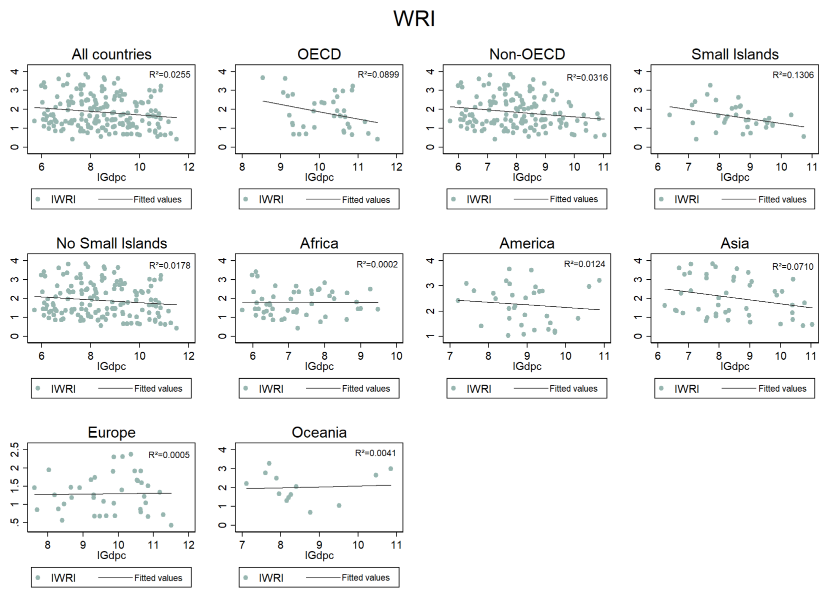


Figure 2.17: WRI and Gpdc by group of countries and continent

	WRI	E-WRI	V-WRI
Gdpc	-0.11046**	-0.01427	-0.25692***
	(0.0301151)	(0.01156)	(0.06993)
NDisaster	0.03019***	0.00039	0.07736***
	(0.00347)	(0.00519)	(0.00892)
Temperature	0.00047	0.00677	0.02187
	(0.02498)	(0.00441)	(0.06821)
Observations	3260	3260	3260
Number of countries	163	163	163
R-squared	0.3119	0.3238	0.3767
Fixed and Year effects	Yes	Yes	Yes
Cross-sectional dependence correction	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 2.25: Econometric estimation with WRI indicator

Spearman Correlation Test

We compared the classification of countries based on NDG, CVLM, CV03, WRI, and E-WRI using the Spearman correlation test. This test provides Spearman's rank correlation for all pairs of variables (Table 2.26). The results indicate that the classification of countries using CVLM is very similar to that of NDG, with a correlation value of 0.7899. In contrast, the correlation between NDG and CV03 is much lower, at 0.2614. When looking at the correlation with WRI, CV03 again shows the lowest value (0.1353), suggesting that CV03 diverges the most from the other indicators in terms of country classification. Thus, it appears that CV03 is less aligned with NDG, CVLM, and WRI.

	NDG	CVLM	CV03	WRI	E-WRI
NDG	1.0000				
CVLM	0.7899 (0.0000)	1.0000			
CV03	0.2614 (0.0000)	0.6247 (0.0000)	1.0000		
WRI	0.1736 (0.0000)	0.2253 (0.0000)	0.1353 (0.0000)	1.0000	
E-WRI	-0.0455 (0.0000)	0.1107 (0.0000)	0.1678 (0.0000)	0.9446 (0.0000)	1.0000

p-value in parentheses

Table 2.26: Spearman's rank correlation

2.6 Overview of Distribution of Countries According to the Selected Indicator: "CV03"

2.6.1 Regional and Country Group Comparison Based on the "CV03" Indicator

Among the newly constructed indicators, we use the CV03 indicator to provide an overview of the distribution of countries based on their climate vulnerability levels. This indicator is considered the best choice, as it is less correlated with GDP per capita (Gdpc) and shows no significant relationship with economic development in econometric analyses. The world map [4] of climate vulnerability (Figure 2.18) illustrates the variation in vulnerability levels across regions. Many countries in Oceania, Asia, Europe, and Africa are classified as having critically high vulnerability. Unlike the NDG indicator (Figure 2.19), the CV03 indicator reflects a less pronounced hierarchy of climate vulnerability tied to economic development. Oceania (mean of 0.481), small island nations (mean of 0.440), and Asia (mean of 0.407) are the regions most vulnerable to climate change (Table 2.12 and Figure 2.18). These areas are frequently impacted by natural disasters such as storms, droughts, and floods. Small island nations are especially susceptible due to their proximity to sea level, increasing their exposure to floods and rising sea levels. Asia, with its high population density, is particularly sensitive to the effects of climate change as natural disasters can impact large numbers of people. Although Africa, on average, appears less vulnerable than Oceania or Asia, certain African countries, such as Niger and Somalia, experience significant damage from droughts.

[4] On the maps (Figures 2.18 and 2.19), a more red color stands for higher level of climate vulnerability.

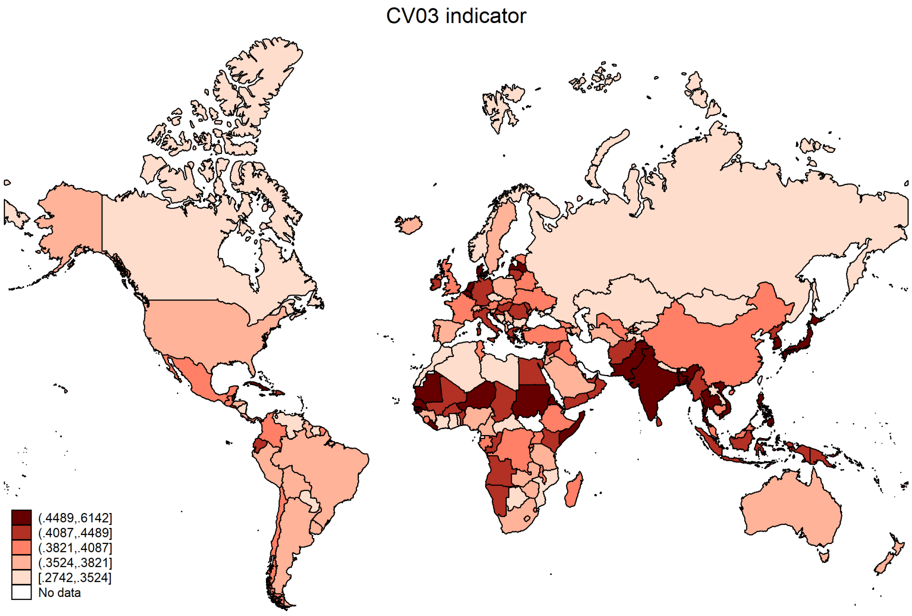


Figure 2.18: World map of countries's vulnerability level according to CV03 indicatior

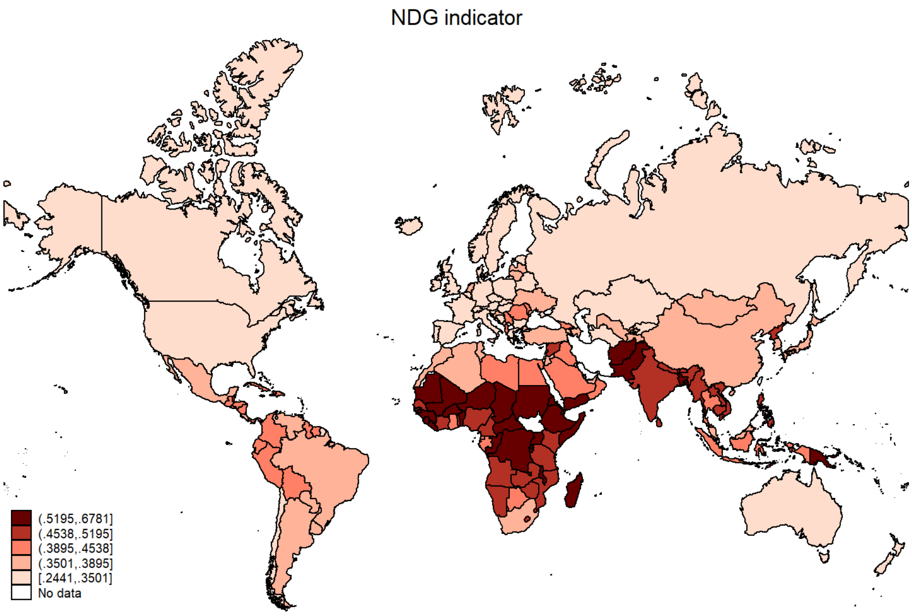


Figure 2.19: World map of countries's vulnerability level according to NDG indicator

2.6.2 Most Vulnerable Countries Within Groups According to the "CV03" Indicator

In Africa, countries like Niger, Chad, and Guinea-Bissau appear to be highly vulnerable to climate change. These countries are particularly susceptible to climate events such as droughts, floods, and heat waves, which cause significant damage to both populations and infrastructure. For instance, Niger is already experiencing food insecurity due to frequent droughts and floods. Niger has also faced rapid population growth, epidemics, and severe food crises caused by droughts, notably in 2005, 2008, 2010, and 2012. In 2015, 20 million people were at risk of food insecurity, with 6 million children suffering from malnutrition (World Bank, 2015).

In the Americas, countries like Belize, Jamaica, and Haiti rank as some of the most vulnerable. These nations face frequent climate hazards, including storms and floods. Haiti, for example, has been repeatedly hit by hurricanes and floods, which have caused widespread devastation. Interestingly, the United States is also among the most vulnerable countries according to the CV03 indicator, facing regular climate impacts such as hurricanes, floods, and extreme temperatures that disrupt daily life (IPCC, 2021).

In Asia, countries such as the Maldives, Bangladesh, and India are more vulnerable to climate change. These nations are particularly affected by extreme temperatures, heat waves, floods, and droughts, which have severe impacts on both their populations and economies. The Maldives, one of the world's lowest-lying countries, is especially vulnerable to sea-level rise and is predicted to experience increased storms and coastal flooding, threatening its population and infrastructure (UN Climate Change Secretariat, 2022).

In Europe, the Netherlands, Denmark, and Moldova stand out as the most vulnerable countries. The Netherlands, in particular, faces significant risks from coastal impacts such as sea-level rise and flooding, due to its geographic position relative to sea level (European Commission, 2021).

In Oceania, nations like Micronesia, Nauru, and the Solomon Islands are among the most vulnerable to climate change. These countries are highly exposed to coastal impacts, such as sea-level rise, coastal flooding, and damage to coastal infrastructure. For instance, Tonga faces risks from tropical cyclones, rising sea levels, storms, and droughts, with major droughts recorded in 1983, 1998, and 2006 (World Bank, 2016).

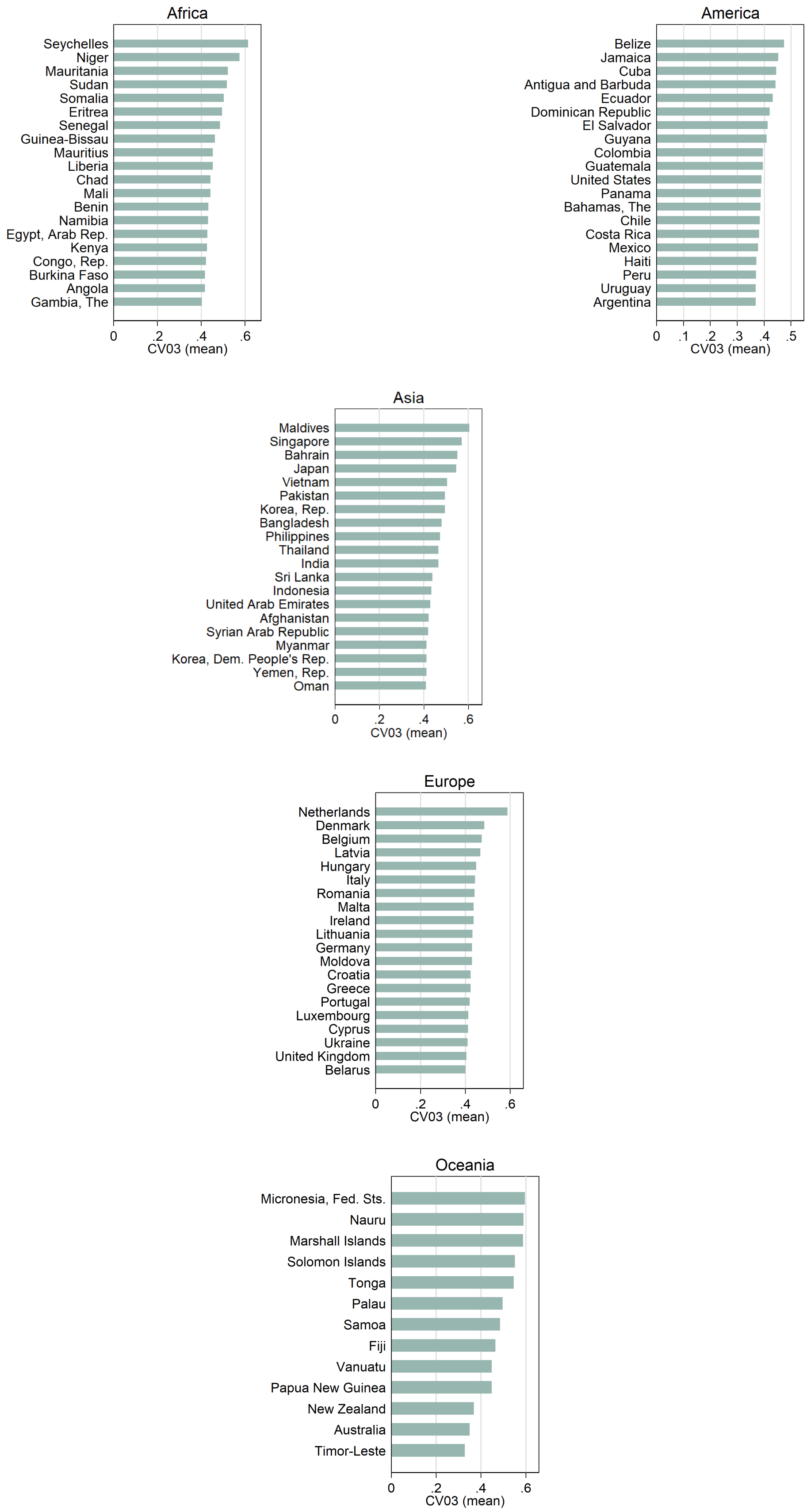


Figure 2.20: Most vulnerable countries by group of countries according to CV03 indicator

2.7 Focus on Resource-rich countries

A particular focus is now placed on resource-rich countries. These countries are defined by the World Bank Group as countries whose average total natural resources rent (% of GDP) for the last three years is at least ten percent. These countries hold a significant strategic advantage in the global economy. Their wealth in natural resources offers considerable potential for economic development. However, this wealth is not without challenges. They are so particular as in addition of their vulnerability to climate change events such as droughts, flood or extreme temperature, they are for several of them major producers of natural resources such as oil, gas or minerals which are often pointed out as drivers of greenhouse gas emissions (Mason and Williams, 2020; Bardoux et al. 2016) contributing to the global warming and can also exacerbate their climate vulnerability through environmental degradation (Afolabi, 2023; Agboola et al., 2021). They find themselves in a kind of dilemma because reducing the exploitation or the production of these resources can lead to a significant drop in revenue for those most dependent on them.This group of countries shows a heterogeneity as we notice high income countries (e.g. Saudi Arabia or Bahrain), middle income countries (e.g. Ecuador or Angola) and low income countries (Somalia or Yemen) and are all susceptible to be impacted by climate events independently of their economic development level. Several of them are often located in regions that are particularly exposed to climate extremes. For example, countries in the Middle East which are susceptible to extreme heatwaves and prolonged droughts (Hegerl et al. 2016) and countries in Oceania, which are susceptible to sea level rise. In addition of their likelihood to experience climate events due to their geographical location, the environmental impacts from natural resources in these countries are also significant challenges. Indeed, in addition of the increased greenhouse gas emissions resulting from resource extraction activities, these countries, particularly in tropical regions, are often exposed to deforestation and biodiversity loss which can further intensify climate risks by reducing the planet's carbon sequestration capacity (Achard et al., 2014). Hence, the loss of forests can disrupts local climate in these countries. Similarly, mining activities in Arctic regions can exacerbate the impacts of climate change by accelerating ice melting and altering local weather (Holloway et al., 2015). Natural resources exploitation can also lead to water depletion and communities displacement affecting population sensitivity to climate events. Moreover, several of these countries are exposed to bad governance, corruption, rent-seeking and political influence in natural resources management which hinder adoption of climate-friendly policies. Indeed, a significant amount of research indicates that resource-rich countries are more prone to corruption because the influx of resources wealth encourages their governments to pursue rent-seeking (Van der Ploeg, 2011; Torvik, 2002; Leite and Weidmann, 2002). According to Van der Ploeg (2011), reliance on natural resource lead to corruption and rent-seeking through the exclusive allocation of resource licenses by the political elite and their associates, aiming to amass wealth an political influence. Others studies found that oil windfalls correlate with higher levels of corruption (James and Rivera, 2022; Arezki and Bruckner, 2011). On the other hand, empirical research suggest that corruption weakens the enforcement of environmental policies (Fredriksson and Svensson, 2003). Corruption results in the mismanagement of public funds, which hampers the effectiveness of environmental policies and the adoption of green technologies. The low level of democracy is also underlined as an obstacle in the implementation of environmental policies as democracy is posited to be positively correlated with political commitment to climate change mitigation (Battig and Bernauer, 2009). This argument is supported by studies showing that democracies are more likely to ratify international environmental agreements such as Kyoto Protocol and the UNFCCC (Fredriksson and Gaston, 2000; Fredriksson et al., 2007). Hence, the extraction of natural resources can heighten climate vulnerability level in resource-rich countries by contributing to greenhouse gas emissions, disrupting local ecosystems and communities, and providing economic incentives that prioritize extraction over cleaner alternatives. Therefore, due to their particular case, these countries really need attention from international institutions and need to implement policies for a resilient, inclusive and adaptive economic development (Tadadjeu et al. 2023, Li et al. 2023). These policies include protecting and restoring natural habitats, facilitating the shift to renewable energy, supporting sustainable extraction methods, involving local communities in decision making, fostering international partnerships and promoting circular economy practices. According to the indicator CV03, about 35% of resource-rich countries have a level of climate vulnerability higher than the overall mean of all countries. These countries are among others, Solomon Islands, Mauritania, Somalia or Papua New Guinea (Figure 2.21). This proportion rises to about 60% for the indicator NDG, but is mainly due to the NDG's tendency to posit countries with low GDP per capita as more vulnerable to climate change. According to the indicator WRI, this proportion rises to about 47%. We notice that for all three indicators CV03, NDG and WRI, countries such as Solomon Islands, Papa New Guinea, Somalia, Ecuador, Myanmar or Mauritania are among the most vulnerable with a level of climate vulnerability higher than the overall mean of all countries (Figure 2.21 to 2.24). Indeed, Solomon Islands located in Oceania, are particularly vulnerable to extreme weather events such as cyclones, storms, and rising sea levels which threatens soil salinization and saltwater intrusion, affecting agriculture and freshwater sources (Mimura et al., 2007; IPCC, 2014). Similarly, Papua New Guinea located in the same region is also exposed to cyclones, floods and droughts affecting agriculture, causing crop losses and disrupting water supply systems (Piggott-McKellar et al., 2019). Myanmar located in Asia is also exposed to severe cyclones, floods and droughts, worsened by deforestation affecting populations with impacts on food security, public health, and living conditions (Myint et al., 2016; UNDP, 2017). Regarding Somalia, this country located in Africa, is highly exposed to prolonged droughts and floods which lead to food crises, disruption of water supply systems and damage of crops (FAO, 2020b).

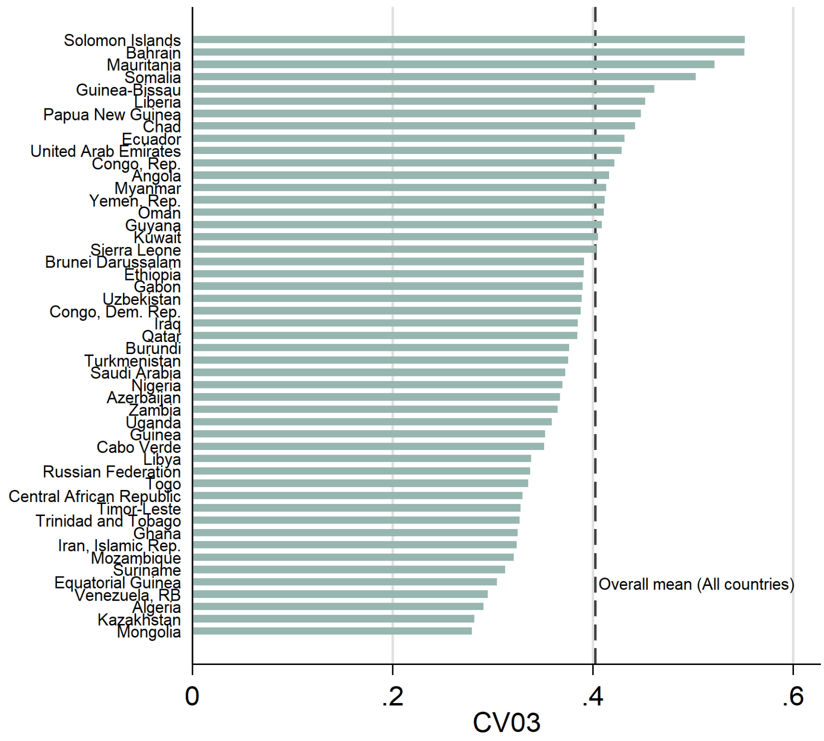


Figure 2.21: Resource-rich countries's vulnerability level according to CV03 indicator

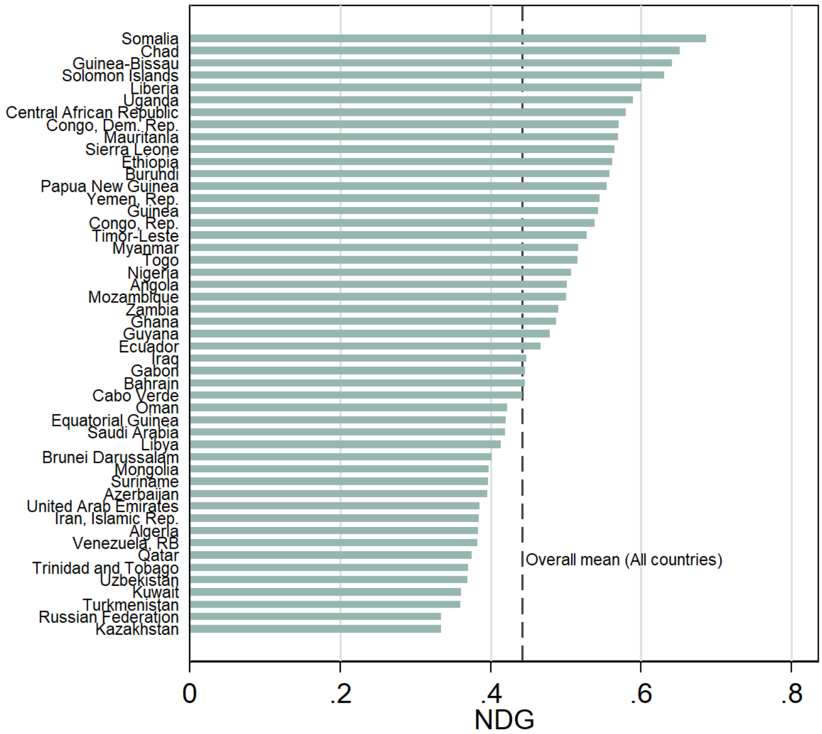


Figure 2.22: Resource-rich countries's vulnerability level according to NDG indicator

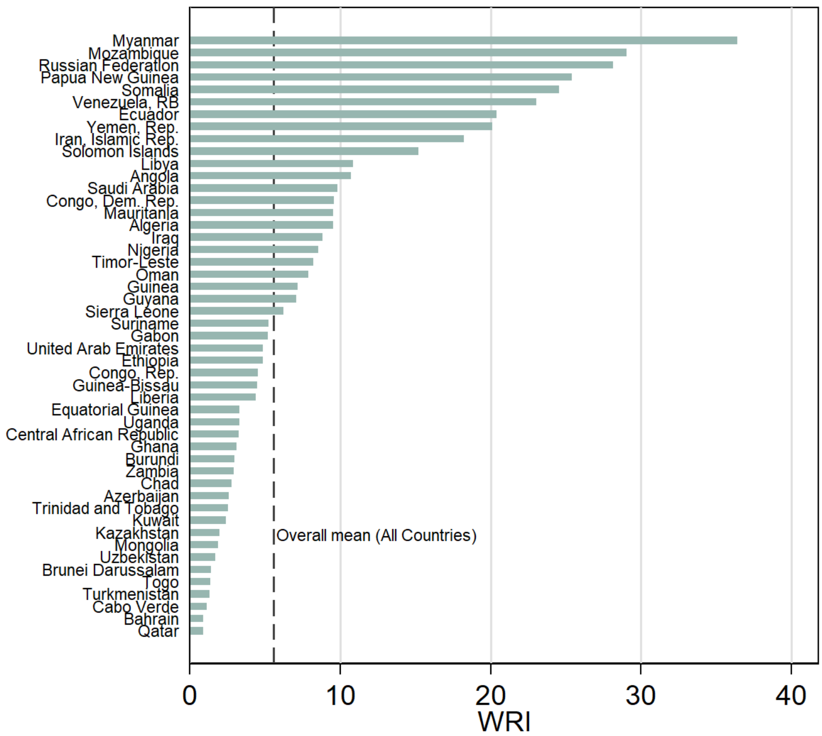


Figure 2.23: Resource-rich countries's vulnerability level according to WRI indicator

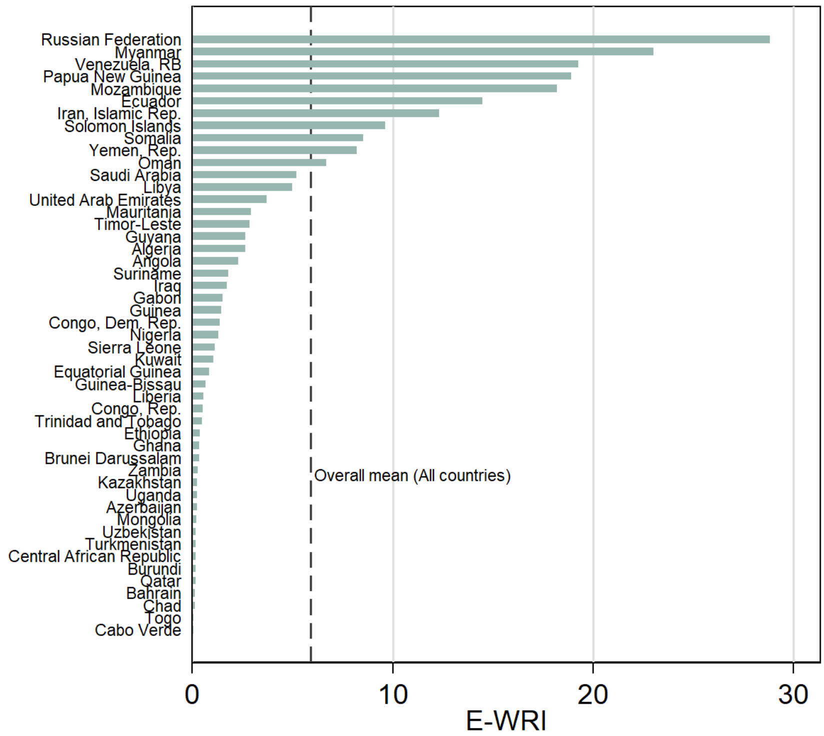


Figure 2.24: Resource-rich countries's vulnerability level according to E-WRI indicator

2.8 Conclusion

This chapter aimed to examine the extent to which countries are vulnerable to the effects of climate change. Due to this phenomenon, numerous extreme climate events such as heat waves, storms, floods, or droughts frequently occur worldwide, causing significant damage to human, economic, and natural systems. Therefore, assessing countries' vulnerability to climate change has become crucial, with a realistic evaluation being essential for adaptation planning, reliable forecasting, and empirical studies. While various indicators are used to measure climate change vulnerability, many of them are strongly linked to economic development and may suffer from endogeneity bias, which affects forecasts and economic studies. Consequently, after highlighting the potential impacts of climate change on natural, economic, and human systems, this paper sought to assess the level of countries' vulnerability using a set of corrected indicators that reduce correlation with economic development and account for endogeneity bias in empirical studies. The new indicator, less correlated with economic development, reveals heterogeneity in the distribution of countries' climate vulnerability compared to the basic indicator used, and it can be utilized in future empirical studies.

Appendix

A Comparaison NDG, CV indicators and WRI

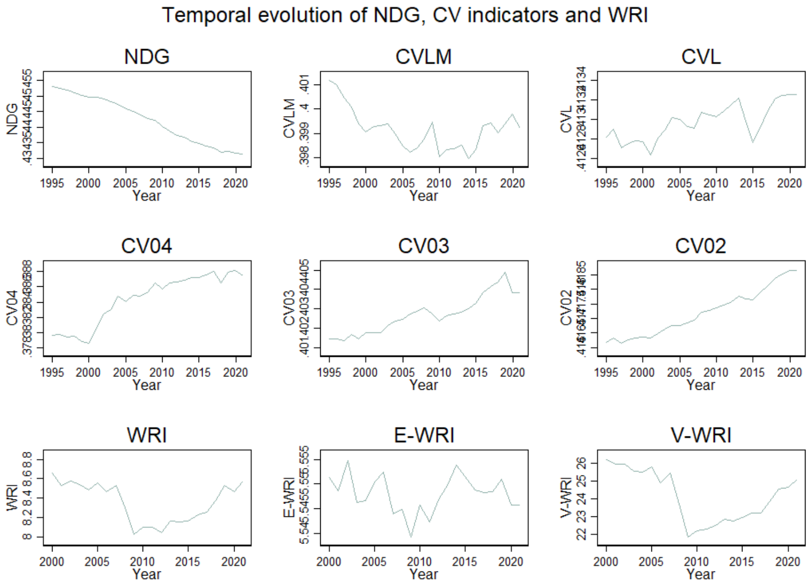


Figure A1: Temporal evolution of NDG, CV indicators and WRI

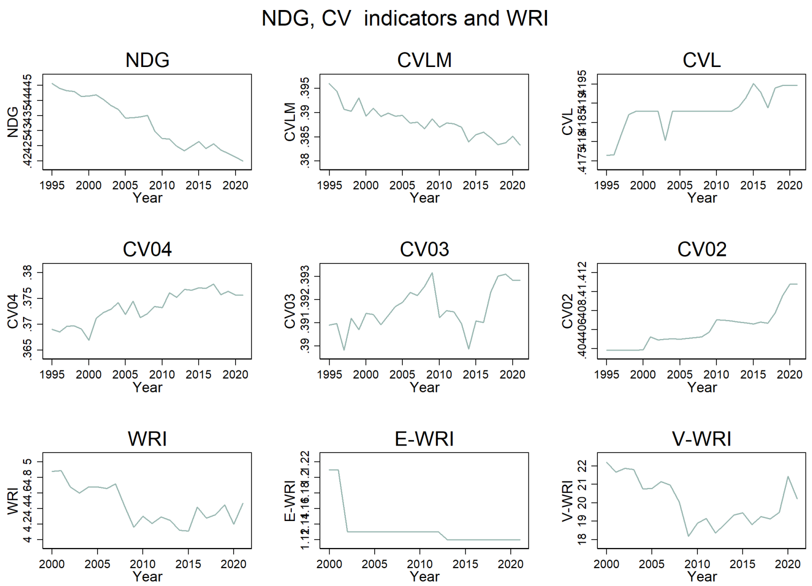


Figure A2: Temporal evolution of NDG, CV indicators and WRI with median values

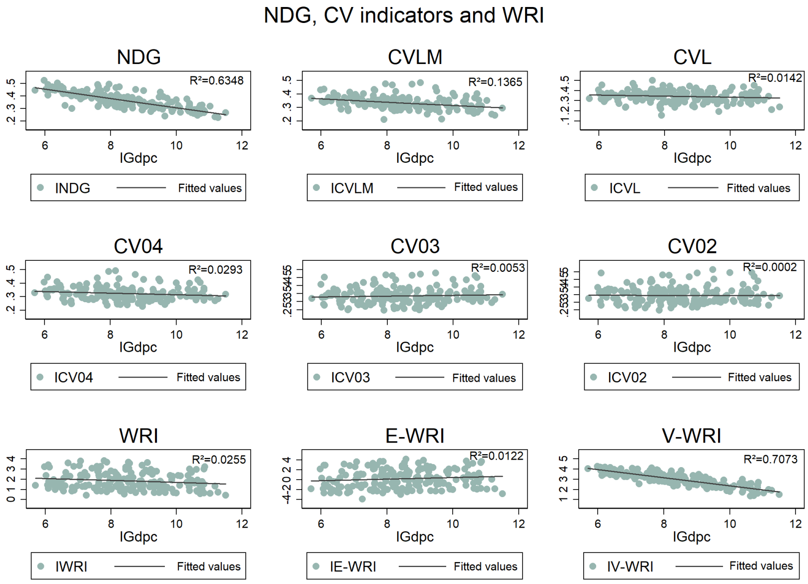


Figure A3: NDG, CV indicators, WRI and Gdpc

B Temporal evolution of NDG and CV indicators by considering median values by year

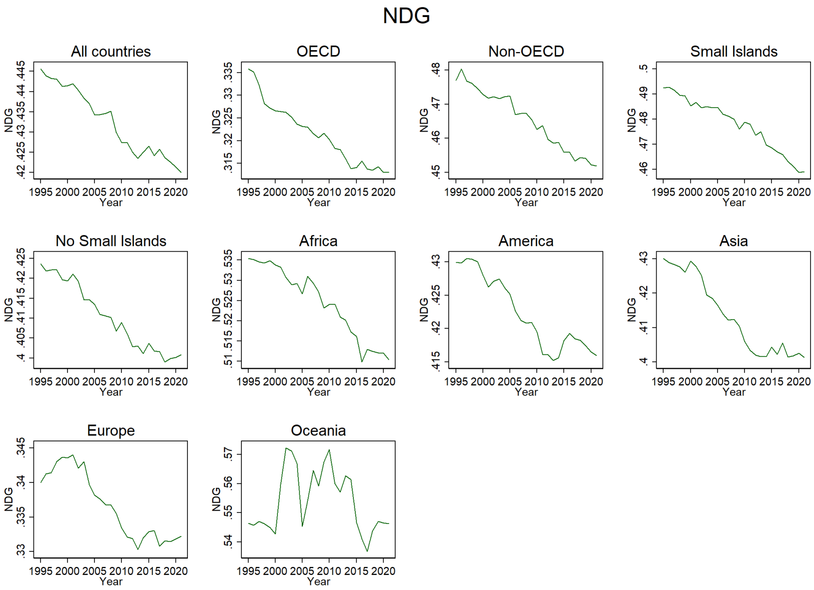


Figure B1: Temporal evolution of NDG with median values by year

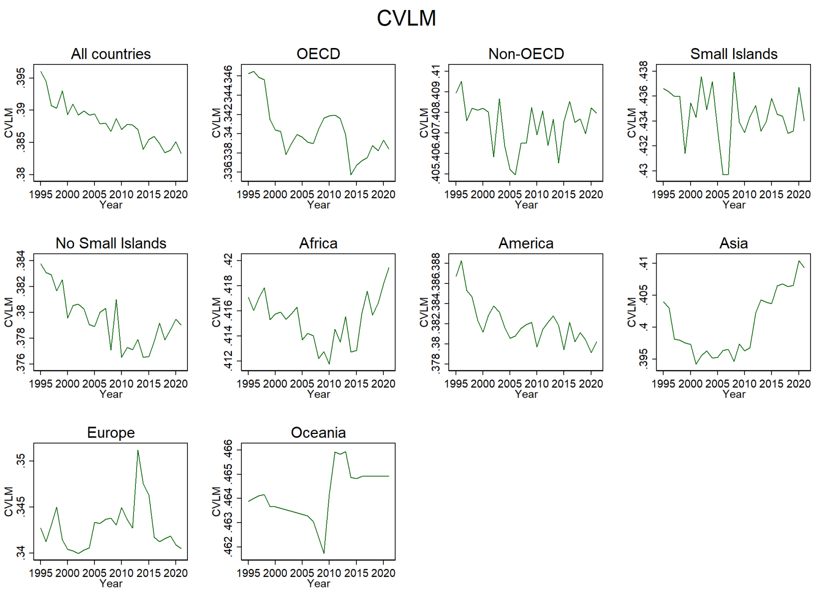


Figure B2: Temporal evolution of CVLM with median values by year

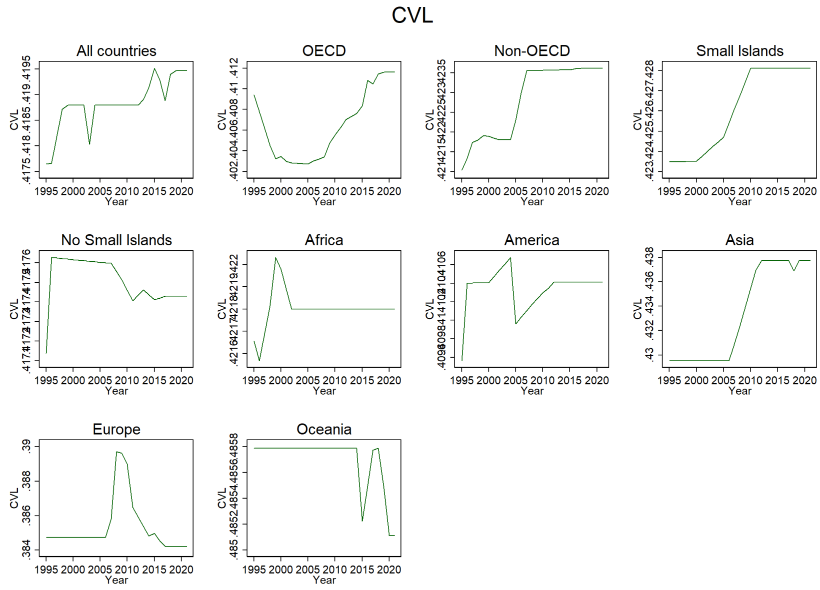


Figure B3: Temporal evolution of CVL with median values by year

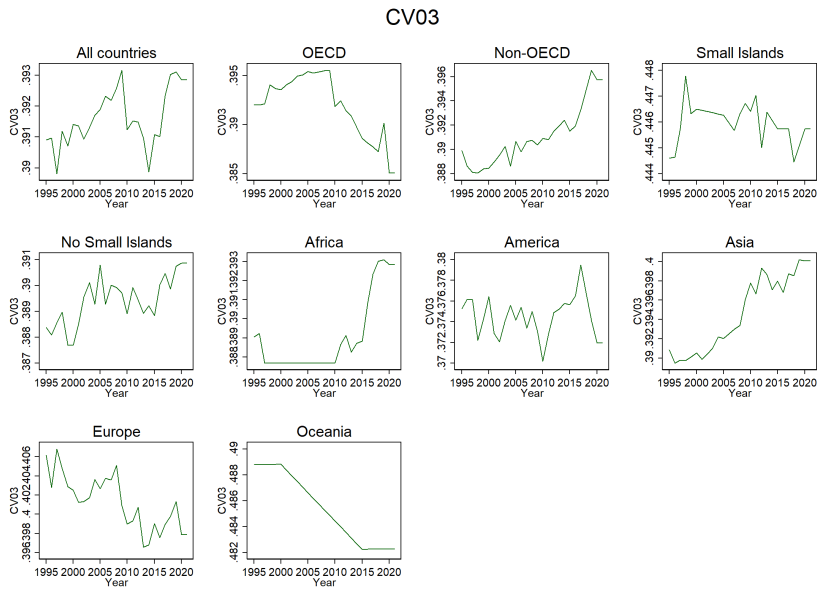


Figure B4: Temporal evolution of CV03 with median values by year

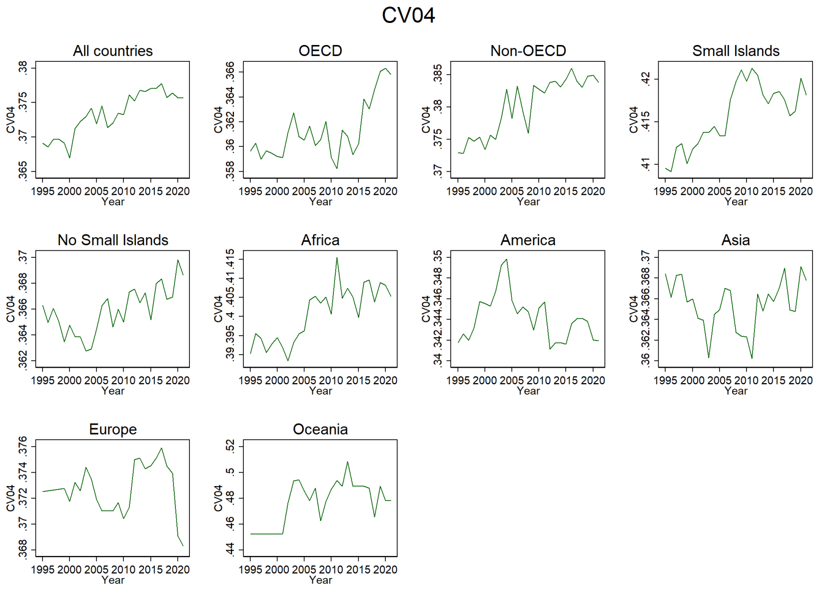


Figure B5: Temporal evolution of CV04 with median values by year

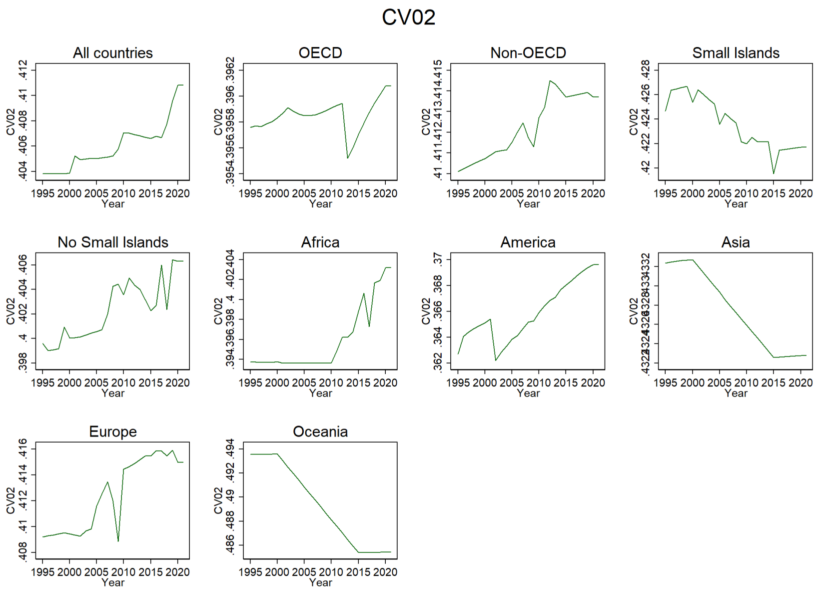


Figure B6: Temporal evolution of CV02 with median values by year

C Temporal evolution of WRI and its components

Figure C1: Temporal evolution of WRI with median values by year

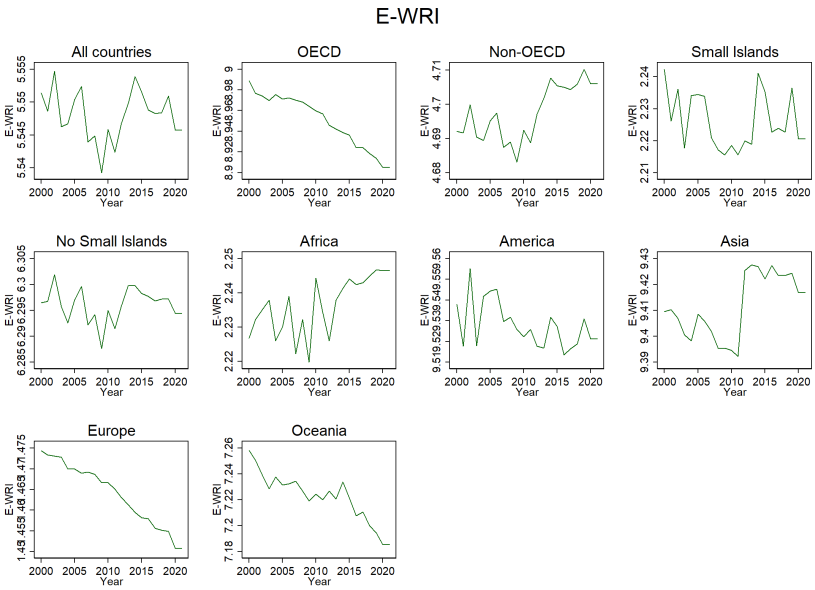


Figure C2: Temporal evolution of E-WRI with mean values by year

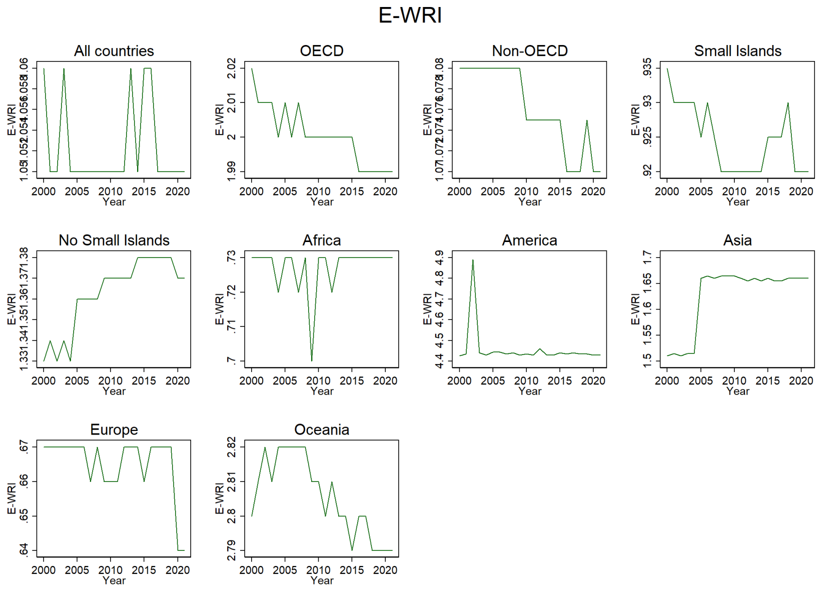


Figure C3: Temporal evolution of E-WRI with median values by year

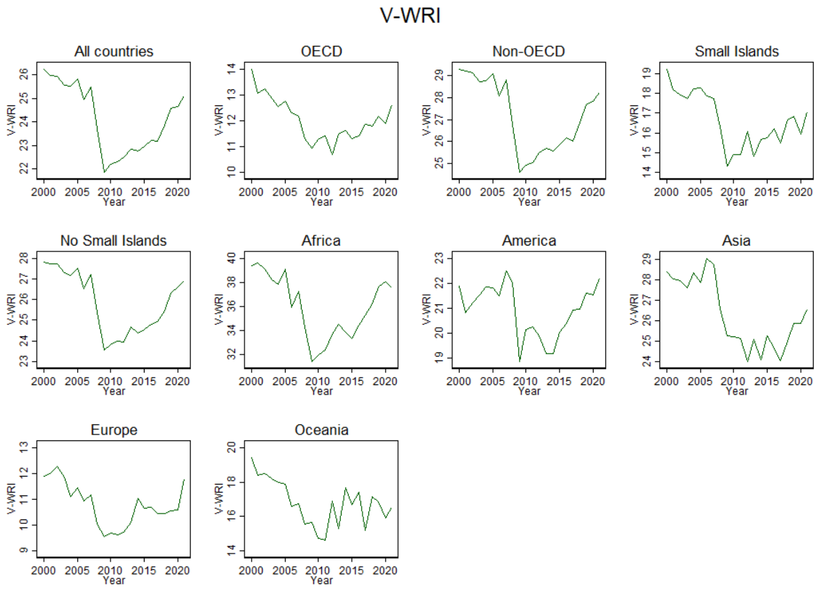


Figure C4: Temporal evolution of V-WRI with mean values by year

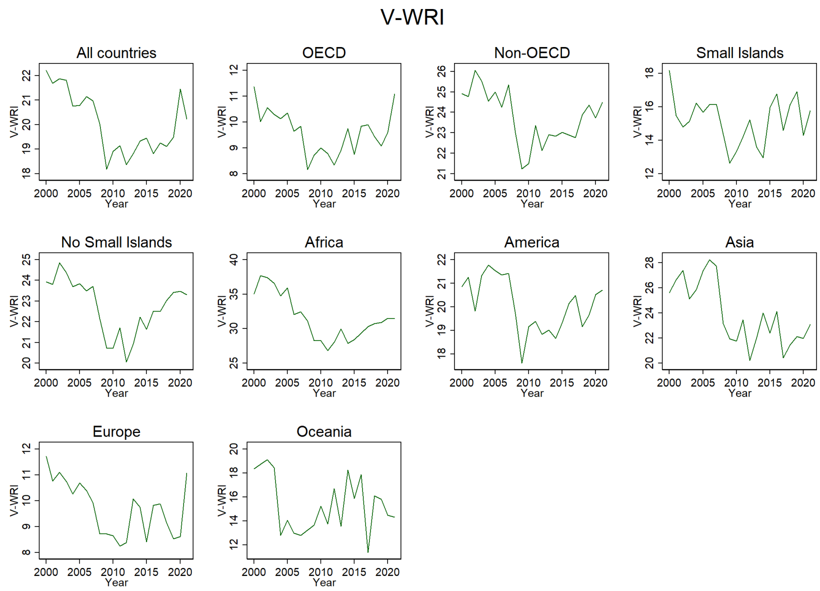


Figure C5: Temporal evolution of V-WRI with median values by year

D Additional estimations with Fractional Response Model

	NDG	CVLM	CVL	CV04	CV03	CV02
Gdpc	-0.03361***	-0.00163	0.00135	-0.02104**	0.00744	0.00358
	(0.00791)	(0.00463)	(0.00324)	(0.01066)	(0.00822)	(0.00363)
NDisaster	0.00101	0.00118**	0.00037	0.00337	0.00069	0.00054
	(0.00108)	(0.00062)	(0.00055)	(0.00692)	(0.00067)	(0.00055)
Temperature	0.00063	-0.02333	-0.01659*	0.04361**	0.02461**	-0.01898
	(0.00881)	(0.06226)	(0.00943)	(0.01739)	(0.01207)	(0.09966)
Observations	4238	4238	4238	4238	4238	4238
Number of countries	163	163	163	163	163	163
Log pseudolikelihood	-2733.154	-2674.2231	-2699.6548	-2646.6681	-2690.2158	-2711.1188
Fixed and Year effects	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table D1: Fractional Response model estimation without lags of NDisaster and Temperature

	Δ NDG	Δ CVLM	Δ CVL	Δ CV04	Δ CV03	Δ CV02
Δ Gdpc	-0.43318**	-0.36924	0.08001**	-0.50061*	0.09143	0.06873**
	(0.17396)	(0.25267)	(0.02271)	(0.30585)	(0.30044)	(0.03349)
Δ NDisaster (Lagged)	0.00467	0.00725*	0.00012	0.00948	0.00254	-0.00085
	(0.00436)	(0.00435)	(0.00157)	(0.00842)	(0.00401)	(0.00165)
Δ Temperature (Lagged)	0.00851	0.00228	-0.00068	0.00628	0.00933*	0.00023
	(0.00591)	(0.00792)	(0.00222)	(0.00895)	(0.00808)	(0.00201)
Observations	4074	4074	4074	4074	4074	4074
Number of countries	163	163	163	163	163	163
Log pseudolikelihood	-2819.2414	-2782.6487	-2823.3852	-2823.7608	-2823.8344	-2819.4252
Fixed and Year effects	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table D2: Fractional Response model estimation with variables in difference and lags of NDisaster and Temperature

	Δ NDG	Δ CVLM	Δ CVL	Δ CV04	Δ CV03	Δ CV02
Δ Gdpc	-0.44803**	-0.39574*	0.05913**	-0.50023*	0.14969	0.04792*
	(0.17078)	(0.24581)	(0.03198)	(0.30348)	(0.29905)	(0.02733)
Δ NDisaster	0.00156	0.01066**	0.00113	0.00738	0.00139	0.00216
	(0.00452)	(0.00516)	(0.00117)	(0.00926)	(0.00352)	(0.00989)
Δ Temperature	0.00158	0.00326	-0.00141	0.00543	0.01834*	-0.00107
	(0.00704)	(0.01201)	(0.00228)	(0.01026)	(0.01143)	(0.00211)
Observations	4075	4075	4075	4075	4075	4075
Number of countries	163	163	163	163	163	163
Log pseudolikelihood	-2819.2392	-2782.6982	-2823.386	-2823.7655	-2823.8336	-2819.4291
Fixed and Year effects	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table D3: Fractional Response model estimation with variables in difference without lags of NDisaster and Temperature

E Sub-components of ND-GAIN Vulnerability indicator

Sector	Exposure Component
Food	Projected change of cereal yields Projected Population Change
Water	Projected change of annual runoff Projected change of annual groundwater recharge
Health	Projected change of deaths from climate change induced diseases Projected change of length of transmission season of vector-borne diseases
Ecosystem services	Projected change of biome distribution Projected change of marine biodiversity
Human habitat	Projected change of warm period Prjoected change of flood hazard
Infrastructure	Projected changeof hydropower generation capacity Projection of sea level rise impacts

Table E1: Indicators of ND-GAIN Vulnerability, Exposure Component

Sector	Sensitivity Component
Food	Food import Dependency Rural Population
Water	Freshwater withdrawal rate Water dependency ratio
Health	Slum population Dependency on external resource for health services
Ecosystem services	Dependency on natural capital Ecological footprint
Human habitat	Urban concentration Age dependency ratio
Infrastructure	Dependency on imported energy Population living under 5m above sea level

Table E2: Indicators of ND-GAIN Vulnerability, Sensitivity Component

Sector	Adaptative Capacity Component
Food	Agriculture capacity Child malnutrition
Water	Access to reliable drinking water Dam capacity
Health	Medical staffs Access to improved sanitation facilities
Ecosystem services	Protected biomes Engagement in International environmental conventions
Human habitat	Quality of trade and transport-related infrastructure Paved roads
Infrastructure	Electricity access Disaster preparedness

Table E3: Indicators of ND-GAIN Vulnerability, Adpatative Capacity Component

F Mean of NDG and CV03 variables for each country

Table F1: Less vulnerable to most vulnerable countries according to ND-GAIN vulnerability indicator

Rank	Country	NDG (Mean)
1.	Switzerland	0.2527372
2.	Norway	0.2629083
3.	Czechia	0.267803
4.	United Kingdom	0.2785709
5.	Finland	0.2871245
6.	Canada	0.288309
7.	Germany	0.2949811
8.	Sweden	0.2953054
9.	Austria	0.2962297
10.	Luxembourg	0.3042618
11.	New Zealand	0.3051535
12.	Ireland	0.3067668
13.	France	0.3069363
14.	Spain	0.3083934
15.	Australia	0.3153859
16.	Poland	0.3159333
17.	Slovenia	0.3170821
18.	United States	0.3180094
19.	Israel	0.3188832
20.	Iceland	0.3246639
21.	Denmark	0.3277434
22.	Italy	0.3316136
23.	Greece	0.3322321
24.	Kazakhstan	0.3342133
25.	Russian Federation	0.3344396

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Table F1 – *Continued from previous page*

Rank	Country	NDG (Mean)
26.	Belgium	0.3354335
27.	Portugal	0.3373225
28.	Belarus	0.3380551
29.	Malta	0.3408104
30.	Estonia	0.3415367
31.	Chile	0.3441839
32.	Kyrgyz Republic	0.3482895
33.	Netherlands	0.3496721
34.	Bulgaria	0.3535386
35.	Slovak Republic	0.3547711
36.	Hungary	0.3548637
37.	Turkmenistan	0.3592386
38.	Kuwait	0.3604568
39.	Cyprus	0.3608693
40.	Bosnia and Herzegovina	0.3637935
41.	Turkiye	0.3679048
42.	Uzbekistan	0.369297
43.	Trinidad and Tobago	0.3702385
44.	Malaysia	0.3729598
45.	Tunisia	0.373934
46.	Qatar	0.3747377
47.	Latvia	0.3754472
48.	Ukraine	0.3769
49.	North Macedonia	0.3769194
50.	Lithuania	0.377576
51.	Japan	0.3797733
52.	Korea, Rep.	0.380237

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Table F1 – *Continued from previous page*

Rank	Country	NDG (Mean)
53.	Armenia	0.3808177
54.	Barbados	0.3827093
55.	Venezuela, RB	0.3828114
56.	Singapore	0.3830861
57.	Algeria	0.3836091
58.	Tajikistan	0.3836276
59.	Brazil	0.3838192
60.	Croatia	0.3838256
61.	St. Lucia	0.3843299
62.	Iran, Islamic Rep.	0.3846415
63.	Argentina	0.3848861
64.	United Arab Emirates	0.3853987
65.	Costa Rica	0.3862391
66.	Montenegro	0.386669
67.	Uruguay	0.3873707
68.	Paraguay	0.3887421
69.	Jordan	0.3891578
70.	South Africa	0.3933482
71.	Mexico	0.3943063
72.	Azerbaijan	0.3953511
73.	Suriname	0.3969663
74.	Grenada	0.3970738
75.	Mongolia	0.3976582
76.	Morocco	0.3984922
77.	China	0.3988533
78.	Brunei Darussalam	0.4009854
79.	Georgia	0.4027183
80.	Romania	0.4045569

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Table F1 – *Continued from previous page*

Rank	Country	NDG (Mean)
81.	Panama	0.4078716
82.	Serbia	0.4124361
83.	Libya	0.4137295
84.	Saudi Arabia	0.4191103
85.	Colombia	0.4195735
86.	Equatorial Guinea	0.4202
87.	Albania	0.4202457
88.	Lebanon	0.4207107
89.	Oman	0.421775
90.	Cuba	0.4272935
91.	Moldova	0.4276162
92.	Egypt, Arab Rep.	0.4299971
93.	Mauritius	0.4329723
94.	Dominican Republic	0.4333992
95.	Jamaica	0.4363104
96.	Thailand	0.4380625
97.	El Salvador	0.4399943
98.	Peru	0.4415627
99.	Cabo Verde	0.4418378
100.	Bahrain	0.4455028
101.	Gabon	0.4457851
102.	Iraq	0.4474028
103.	Botswana	0.4531525
104.	Dominica	0.4541902
105.	Syrian Arab Republic	0.4552295
106.	Bahamas, The	0.4553248
107.	Indonesia	0.4567781

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Table F1 – *Continued from previous page*

Rank	Country	NDG (Mean)
108.	Guatemala	0.4584948
109.	Honduras	0.4621001
110.	St. Kitts and Nevis	0.4629874
111.	Nicaragua	0.4645303
112.	Ecuador	0.466693
113.	Bolivia	0.4672078
114.	Sri Lanka	0.4673282
115.	Cameroon	0.470755
116.	Belize	0.4717674
117.	Fiji	0.4727555
118.	Seychelles	0.4777711
119.	Djibouti	0.4779382
120.	Guyana	0.4789999
121.	Antigua and Barbuda	0.4793292
122.	Philippines	0.479564
123.	Vietnam	0.4822088
124.	Korea, Dem. People’s Rep.	0.4828686
125.	Namibia	0.4828762
126.	Ghana	0.4868902
127.	Lesotho	0.4880646
128.	Zambia	0.4896846
129.	Eswatini	0.4946268
130.	Cote d’Ivoire	0.4958963
131.	Lao PDR	0.4988582
132.	Mozambique	0.5005335
133.	Angola	0.5012678
134.	Nigeria	0.5071521
135.	Zimbabwe	0.5101894

Continued on next page

Table F1 – *Continued from previous page*

Rank	Country	NDG (Mean)
136.	Samoa	0.5104582
137.	Cambodia	0.5152994
138.	Togo	0.5155674
139.	Myanmar	0.5164239
140.	India	0.5181269
141.	Nepal	0.5228124
142.	Tanzania	0.5229527
143.	Kenya	0.5256203
144.	Sao Tome and Principe	0.5256582
145.	Haiti	0.5264104
146.	Bhutan	0.5276319
147.	Timor-Leste	0.5276836
148.	Pakistan	0.534196
149.	Senegal	0.5356418
150.	Palau	0.5358545
151.	Congo, Rep.	0.5386375
152.	Guinea	0.5430971
153.	Yemen, Rep.	0.5452334
154.	Comoros	0.5452902
155.	Papua New Guinea	0.5545973
156.	Maldives	0.5568011
157.	Burundi	0.5582139
158.	Gambia, The	0.5593881
159.	Rwanda	0.5600213
160.	Bangladesh	0.561089
161.	Malawi	0.5620177
162.	Ethiopia	0.5620924

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Table F1 – *Continued from previous page*

Rank	Country	NDG (Mean)
163.	Benin	0.5633428
164.	Sierra Leone	0.5645084
165.	Mauritania	0.5695372
166.	Nauru	0.5702968
167.	Congo, Dem. Rep.	0.5703783
168.	Madagascar	0.5716895
169.	Burkina Faso	0.5762408
170.	Vanuatu	0.5763735
171.	Central African Republic	0.5797404
172.	Uganda	0.5891392
173.	Marshall Islands	0.5931967
174.	Liberia	0.6005529
175.	Tonga	0.6006656
176.	Afghanistan	0.60134
177.	Sudan	0.6048245
178.	Eritrea	0.605814
179.	Mali	0.6088444
180.	Solomon Islands	0.6310018
181.	Niger	0.6325684
182.	Micronesia, Fed. Sts	0.6369188
183.	Guinea-Bissau	0.6414376
184.	Chad	0.6516595
185.	Somalia	0.6870268

Table F2: Less vulnerable to most vulnerable countries according to CV03 indicator

Rank	Country	CV03 (Mean)
1	Mongolia	0.2792158
2	Kazakhstan	0.2815055
3	Lesotho	0.2821034
4	Algeria	0.2907739
5	Kyrgyz Republic	0.2915313
6	Paraguay	0.2929179
7	Dominica	0.2934856
8	Venezuela, RB	0.2953084
9	North Macedonia	0.2974942
10	Tajikistan	0.3033339
11	Equatorial Guinea	0.3043399
12	Czechia	0.3061774
13	Lao PDR	0.3109372
14	Bosnia and Herzegovina	0.3115473
15	Suriname	0.3124027
16	St. Lucia	0.3180715
17	Mozambique	0.3211021
18	Cote d'Ivoire	0.3215345
19	Comoros	0.3215745
20	Morocco	0.3216459
21	Iran, Islamic Rep.	0.3238123
22	Ghana	0.3249958
23	Grenada	0.325487
24	Trinidad and Tobago	0.3267032
25	Timor-Leste	0.3280899
26	Barbados	0.3282261

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Table F2 – *Continued from previous page*

Rank	Country	CV03 (Mean)
27	Central African Republic	0.3296489
28	Nepal	0.3297978
29	Togo	0.3357997
30	Russian Federation	0.3373641
31	Djibouti	0.337626
32	Bhutan	0.3378063
33	Libya	0.3386352
34	Norway	0.3417927
35	Montenegro	0.3433837
36	Nicaragua	0.3458312
37	Cameroon	0.3478939
38	South Africa	0.3497072
39	Australia	0.3498412
40	Bulgaria	0.3505698
41	Botswana	0.3512404
42	Cabo Verde	0.3515449
43	Guinea	0.3524108
44	Canada	0.3526286
45	Tanzania	0.3569579
46	Slovenia	0.3579405
47	Uganda	0.3590853
48	St. Kitts and Nevis	0.3596441
49	Armenia	0.361734
50	Zambia	0.3648681
51	Brazil	0.3648837
52	Bolivia	0.3658392
53	Serbia	0.3660253
54	Azerbaijan	0.3675041

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Table F2 – *Continued from previous page*

Rank	Country	CV03 (Mean)
55	Tunisia	0.3685499
56	Honduras	0.3688103
57	Switzerland	0.3689665
58	Argentina	0.3690638
59	Spain	0.369079
60	Uruguay	0.3691813
61	New Zealand	0.3692046
62	Poland	0.3694538
63	Zimbabwe	0.3695653
64	Nigeria	0.369856
65	Peru	0.3699356
66	Haiti	0.3713005
67	Saudi Arabia	0.3724664
68	Lebanon	0.3726011
69	Turkmenistan	0.3753593
70	Turkiye	0.3760383
71	Burundi	0.3765668
72	Mexico	0.3779463
73	Sweden	0.3791167
74	Albania	0.3795013
75	Malaysia	0.3798537
76	Costa Rica	0.3819261
77	Jordan	0.3825197
78	Chile	0.3838811
79	Qatar	0.3848254
80	Iraq	0.3851833
81	Georgia	0.3858345

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Table F2 – *Continued from previous page*

Rank	Country	CV03 (Mean)
82	Sao Tome and Principe	0.3859567
83	Eswatini	0.3860543
84	Iceland	0.3866268
85	Bahamas, The	0.3867882
86	Congo, Dem. Rep.	0.3877724
87	Austria	0.3879445
88	Panama	0.3883079
89	Uzbekistan	0.3888056
90	Finland	0.389703
91	Gabon	0.3899703
92	United States	0.3908229
93	Ethiopia	0.3910454
94	Brunei Darussalam	0.3914118
95	France	0.3922541
96	Cambodia	0.3940912
97	Estonia	0.3942757
98	Guatemala	0.3951951
99	Colombia	0.3957315
100	China	0.395824
101	Malawi	0.3966012
102	Israel	0.4006026
103	Slovak Republic	0.4006279
104	Belarus	0.4016735
105	Rwanda	0.4029199
106	Madagascar	0.4033343
107	Sierra Leone	0.4033692
108	Gambia, The	0.4034662
109	Kuwait	0.4051891

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Table F2 – *Continued from previous page*

Rank	Country	CV03 (Mean)
110	United Kingdom	0.4057153
111	Guyana	0.4089816
112	Ukraine	0.4105311
113	Oman	0.4107936
114	Yemen, Rep.	0.4119768
115	Cyprus	0.4122699
116	Korea, Dem. People's Rep.	0.4129671
117	Myanmar	0.4132893
118	El Salvador	0.4133544
119	Luxembourg	0.4139224
120	Angola	0.4163481
121	Burkina Faso	0.4165058
122	Portugal	0.4202673
123	Dominican Republic	0.4207648
124	Syrian Arab Republic	0.4209211
125	Congo, Rep.	0.4216112
126	Afghanistan	0.4229806
127	Greece	0.4234954
128	Croatia	0.4242527
129	Kenya	0.4260747
130	Egypt, Arab Rep.	0.4274849
131	United Arab Emirates	0.428963
132	Moldova	0.4296853
133	Germany	0.4304369
134	Namibia	0.4307203
135	Ecuador	0.4316443
136	Lithuania	0.4325978

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Table F2 – *Continued from previous page*

Rank	Country	CV03 (Mean)
137	Benin	0.4331215
138	Indonesia	0.434583
139	Ireland	0.4374382
140	Malta	0.4377975
141	Sri Lanka	0.4404669
142	Romania	0.4410992
143	Mali	0.4420281
144	Chad	0.4421045
145	Antigua and Barbuda	0.4422262
146	Italy	0.4437454
147	Cuba	0.4450533
148	Papua New Guinea	0.4478705
149	Vanuatu	0.447871
150	Hungary	0.4487334
151	Liberia	0.4522601
152	Mauritius	0.4522672
153	Jamaica	0.4523232
154	Guinea-Bissau	0.4614133
155	Fiji	0.4646338
156	India	0.465334
157	Thailand	0.4665444
158	Latvia	0.4674543
159	Philippines	0.4731812
160	Belgium	0.4733343
161	Belize	0.4738722
162	Bangladesh	0.4813089
163	Denmark	0.4849504
164	Senegal	0.4849799

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Table F2 – *Continued from previous page*

Rank	Country	CV03 (Mean)
165	Samoa	0.4854176
166	Eritrea	0.4943444
167	Korea, Rep.	0.4950728
168	Pakistan	0.4955297
169	Palau	0.4969896
170	Somalia	0.5028813
171	Vietnam	0.5048432
172	Sudan	0.5174565
173	Mauritania	0.5214769
174	Japan	0.5458058
175	Tonga	0.5466288
176	Bahrain	0.5512246
177	Solomon Islands	0.5519783
178	Singapore	0.570639
179	Niger	0.5747461
180	Marshall Islands	0.5880709
181	Netherlands	0.5882567
182	Nauru	0.5902588
183	Micronesia, Fed. Sts.	0.5958696
184	Maldives	0.6046106
185	Seychelles	0.6142354

Chapter 3

Climate Change Vulnerability and International Climate Finance: A Gravity Panel Model Approach

Introduction

Which countries receive more international climate finance? Do vulnerable nations receive more international climate finance? What are the characteristics of countries that receive more international climate finance? What factors determine its allocation? Do the interests of donor countries play a key role in the flow of this finance ?

Over the past two decades, governments, international institutions and researchers have placed particular emphasis on the effects of climate change (IPCC, 2014). Climate change is expected to impact fundamental aspects of people's life around the world through natural disasters such as droughts, floods, sea level rise, storms or extreme temperatures. The potential effects of climate change on human, economic and natural systems are extensive, including ecosystem degradation, destruction of infrastructures and human habitat, famine, migration from rural areas, conflicts over arable lands, high urban concentration, food insecurity, effects on business production, reduced economic growth, declining of incomes and increased poverty (IPCC, 2021; Dunne et al., 2020; Diffenbaugh and Burke, 2019; Dai, 2013; Diffenbaugh and Field, 2013; Stern, 2007). Given the urgent need for action to address climate change across countries and to assist nations in building resilient economies and fostering greener growth, developed countries have been providing financial assistance to several nations since the 2000s. Following the 15th Conference of Parties (COP 15) of the United Nations Framework Convention on Climate Change (UNFCCC) in Copenhagen in 2009, this financial support significantly increased, with a commitment to mobilize USD 100 billion annually by 2020 for climate action in more vulnerable countries (UNFCCC, 2009). This goal was reiterated and extended to 2025 during the 21th Conference of Parties (UNFCCC, 2015). The importance of climate finance is underscored by its critical role in the global response to climate change. It is expected to help countries cope with the effects of climate change and enhance their adaptation capacity by foster investments in climate-resilient infrastructures, research and development, renewable energy and human habitat, as well as by reducing income inequality to avoid exacerbating poverty, which can increase population sensitivity. Given the pivotal role of climate finance in addressing climate change and following the Copenhagen summit in 2009, research has increasingly focused on international climate finance and sought to explore its determinants (Barrett, 2014; Doku et al., 2021; Bayramoglu et al., 2023). Some studies have highlighted some similar determinants, such as the income level of recipients countries or colonial ties, but ambiguous responses still remain regarding whether more vulnerable or less vulnerable countries receive a greater share of climate finance. In this context, Barrett, 2014 argued that climate finance is not directed towards vulnerable areas, whereas Bayramoglu et al., 2023 argued that international climate finance is indeed targeted toward vulnerable countries. To better understand the characteristics of countries that receive more climate finance and to address this ambiguous issue, this chapter focuses on the allocation of international climate finance by investigating empirically its potential determinants using a Gravity Panel Model.

This chapter contributes to the literature on the international climate finance in three key ways. First, it applies a gravity model, commonly used in trade studies, to climate finance flows which has been less frequently used in previous studies. Second, it uses a large panel of countries, which allows for a more stable and generalized estimation of the results. Finally, it employs disaggregated climate finance data, distinguishing between grants and loans which may provide more detailed insights compared to previous studies. The main finding of this work is that vulnerable countries are not likely to receive international climate finance, either in the form of grants or loans, with economic interests and political ties playing a significant role in the provision of climate aid. The chapter is organized as follows: The first section provides a summary review of potential determinants of climate finance, highlighting the needs of recipient countries and the self-interests of donor countries. Section 2 presents stylized facts related to climate finance allocation, while section 3 outlines the econometric framework. The last section discusses the conclusion and policy implications.

3.1 Potential determinants of Bilateral Climate Finance: A review of the literature

The provision of aid is generally explained as being altruistic in nature, but the self-interests of donors and the characteristics of recipients can influence the effectiveness of the aid provided (Alesinar and Dollar, 2000; Berthelemy and Tichit, 2004; Younas, 2008). By analogy, it is reasonable to expect that the allocation of international climate finance follows a similar pattern to that of development aid. Therefore, the following subsections discuss the potential determinants of international climate finance, drawing from the development aid literature, which emphasizes both the needs of recipient countries and the interests of donor countries.

3.1.1 Recipient Countries View: Needs and Merits

Previous studies on the allocation of development aid suggest that donor countries take into account the needs of recipient nations, often providing more financial assistance to less developed countries (Alesinar and Dollar, 2000). These countries typically lack the economic and financial resources needed to address social, economic, or environmental challenges. Providing assistance to these nations can help strengthen their economic and financial capacities. Population size is also highlighted as a factor in the allocation of development aid (Trumbull and Wall, 1994; Tezano Vasquez, 2004). An increase in population can heighten a country's needs in areas suchs as housing, food, energy, education (including human capital development and research), and healthcare. In this study, which focuses on climate aid allocation, another characteristic relevant to recipient countries is considered: climate vulnerability. This characteristic is identified as a key factor in determining which countries receive climate aid (Robertsen et al., 2015, Barrett, 2014). Climate change vulnerability, in the context of climate finance, serves as an equivalent to poverty in the literature on development aid. Given the varied impacts and potential damages of climate change, vulnerable countries are likely to suffer more severely, facing issues such as the destruction of housing, famine, economic losses, reduced production, rural migration, urban concentration, and land conflicts. Therefore, providing financial assistance to vulnerable countries can help them improve their adaptation capacity and manage the effects of climate change. Another important determinant of aid is the quality of a country's economic and political institutions. Countries with strong political and economic institutions are expected to use financial assistance more effectively to achieve the intended objectives (Doku et al., 2015; Persson and Remling, 2014).

3.1.2 Provider Countries View: Self Interests and Economic Wealth

The interests of donor countries are also expected to influence aid allocation. Balla and Reinhard (2008) argue that recipients with strong political alignment with donor countries are more likely to receive increased development aid. Economic relationships such as trade partnerships, can also affect aid distribution, with recipient countries that import a significant amount of goods from donor countries receiving more aid (Berthelemy and Tichit, 2004; Younas, 2008). Hicks et al. (2010) suggest that donor countries might use environmental aid as a tool for export promotion. Similarly, Robinson and Dornan (2017) and Weiler et al.(2018) find a link between higher trade volumes and the allocation of development aid, indicating that aid may be used to strengthen trade ties with recipient countries. Alesinar and Dollar (2000) also contend that bilateral aid patterns are shaped by political and strategic considerations, such as colonial history and voting behavior in the United Nations, and that donor countries vary significantly in their levels of altruism. They argue that a former colony that maintains friendly political relations with its former colonizer is more likely to receive greater aid compared to another country with a similar poverty level. Collier and Dollar (2002) further assert that aid allocation is often inefficient from a poverty-reduction perspective. The economic wealth of donor countries also tends to influence the provision of aid in general and climate assistance in particular. Wealthier countries are more likely to provide climate finance. Fuchs et al. (2014) find that aid budgets generally increase as the wealth of donor countries rises. Higher income levels in donor countries make aid allocation more feasible and easier to implement. In line with this, faini (2006) argues that development aid tends to decrease with rising public debt, declining economic growth, and larger fiscal deficits in donor countries.

3.1.3 Previous Studies on the Determinants of Climate Finance

Following the Copenhagen summit in 2009, research has increasingly focused on tracking climate finance and exploring the factors that determine its allocation. Several studies have sought to define the motivations behind the provision of climate finance. Regarding donors characteristics, Fuchs et al. (2014) argued that climate aid is positively correlated with the wealth of donor countries. On the other hand, with respect to recipient needs, Barrett (2014) found that climate vulnerability is not a determining factor in receiving climate finance in Malawi and that climate finance tends to go to regions with higher income levels, which appear equipped to use the funding efficiently. Halimanjaya (2015) showed that developing countries with lower GDP per capita, higher CO_2 intensity and good governance are more likely to be selected as recipients of climate mitigation finance. Using ordinary least squares and the 4P framework for Sub-Saharan African countries from 2010 to 2013 and focusing on seven donors (Canada, France, Japan, United Kingdom, Netherlands, Germany and Sweden), Robertsen et al. (2015) found that climate vulnerability, measured by the exposure component of the ND-GAIN index is positively but not significantly associated with climate finance for adaptation. They identified political regime (Polity2), language and development aid as positively and significantly affecting the provision of climate adaptation finance. Weiler et al. (2018), using a two stage Cragg's model over the period 2010-2015, argued that trade ties, as measured by donors exports to recipient countries, drive adaptation aid. They also found that vulnerable countries, as measured by the exposure component of ND-GAIN Vulnerability index and the Climate Risk Index of Germanwatch tend to receive more adaptation aid. Additionally, they reported that colonial ties, development aid and population are positively and significantly associated with adaptation aid. Similarly, Weiler and Sanubi (2019), applying the same model and focusing on African countries from 2010-2016, argued that governance framework of recipients, as measured by worldwide governance indicators, and colonial ties are positively and significantly linked to both climate adaptation finance and climate mitigation finance. They also found that climate vulnerability, measured by the ND-GAIN exposure component, is positively and significantly associated with climate adaptation finance, albeit only at the 10 percent confidence level. Regarding Sub-Saharan African countries and using a Generalized Method of Moments (GMM), Doku et al. (2021) analyzed a panel of 43 countries over the period 2006-2017, finding that countries with stronger rule of law, higher population growth rates, higher poverty levels, better ease of doing business, deeper social inequality, and better ICT usage attracted more climate finance. In a more recent study using IV-2SLS estimation on bilateral climate aid from 2002 to 2017, Bayramoglu et al. (2023) found that donor exports, recipient population size, colonial ties, geographical proximity (measured by the distance between the capitals of donor and recipient countries), and donor GDP are positively and significantly associated with climate aid. They also argued that vulnerable countries, as measured by the ND-GAIN Vulnerability index, are likely to receive climate aid.

Most of theses previous studies focused on aggregated and unilateral climate finance data and small sample of countries. In our study, we focus on bilateral data and extend the analysis to a large sample of countries over a longer period (2000 to 2021). Moreover, compared to previous studies, particularly Bayramoglu et al. (2023), we use a climate vulnerability indicator that is less correlated with economic conditions of recipient countries, which allows for less biased results. The higher correlation of the ND-GAIN Vulnerability index (used in their paper) with the economic conditions of recipients countries [1] might explain the positive and significant

[1] In Chapter 2, we show that the ND-GAIN Vulnerability indicator is highly correlated with a country's GDP per capita. Additionally, the correlation between the ND-GAIN Vulnerability index and economic variables is also noted by Kling et al. (2021).

association between Climate aid and vulnerability, as most recipient countries are developing nations with lower GDP per capita, and are therefore automatically and hierarchically classified by the ND-GAIN indicator as more vulnerable to climate change. Another contribution of this chapter to the literature on climate aid determinants is our disaggregation of climate finance into grants and loans, which provides more detailed information than aggregated data.

3.2 International Climate Finance

Financial assistance is a key ingredient of the global response to climate change. The climate resilient-development of countries depends on the amount of funding available to support their efforts. Climate finance is seen as a tool to help vulnerable countries cope with the effects of climate change and climate related-risks through disaster prevention, preparedness, and capacity building (OECD, 2011). The United Nations Framework Convention on Climate Change (UNFCCC) defines Climate finance as "local, national or transnational financing drawn from public, private and alternative sources of funding that aims to support adaptation and mitigation actions to address climate change". Climate finance flows are typically categorized into national climate finance (financing within a country from public or private sources) and international climate finance, which includes bilateral and multilateral climate finance. Bilateral climate finance refers to financial assistance provided by one country to another, while multilateral climate finance involves funding from international institutions to a country. In this study, we focus exclusively on bilateral climate finance.

3.2.1 General View

Data on climate finance were sourced from the OECD DAC statistics database. The initial dataset includes information such as the year of provision, the type and specific name of the donor, the recipient countries, the amount of climate finance, and the type of financial instrument used (grant or debt instrument). The providers may be multilateral donors (such as the World Bank, regional development banks, or other international institutions), private donors, or DAC (Development Assistance Committee) and Non-DAC donors, which correspond to donor countries. For this study, we focused on DAC and Non-DAC donors, representing donor countries, specifically examining bilateral climate finance (from a donor country to a recipient country). We created a new dataset by retaining only the DAC and Non-DAC donors, the year of provision, the amount of climate finance in 2021 USD thousand (referred to as “climate-related development finance" in the original database) and the type of financial instrument (grants or loans). Using coding techniques such as data combination and merging, we reconstructed a bilateral dataset that details donor countries, recipient countries, the total amount of climate finance allocated per year to each recipient by each donor country, and the breakdown of climate finance into grants and loans. The initial dataset comprised 36 donor countries and 154 recipient countries for the period 2000-2021. We excluded 6 donor countries (Azerbaijan, Estonia, Hungary, Latvia, Liechtenstein and Romania) because they provided climate finance only one to four times to one or a few recipients throughout the entire period. Additionally, we removed 3 recipients countries (Anguilla, Bahrain and Slovenia) due to insufficient observations (only one to three climate finance flows) and 11 other countries [2] due to the absence of observations for the Vulnerability indicator (CV03). The final dataset consists of 30 donor countries and 140 recipient countries.

A graphical analysis of bilateral climate finance trend reveals that following the Copenhagen summit (2009), bilateral climate finance nearly doubled in the year immediately after the summit and increased by approximately sixfold between 2009 and 2021 (Figure 3.1). As previously mentioned, we focus on bilateral climate finance (funds transferred from one country to another) to better understand both the needs of recipient countries and the motivations behind the allocation of these funds. We also distinguish between two type of financial instruments: grants and loans. Grants account for a smaller portion of bilateral climate finance (about 30 %), while loans make up around 70%. Additionally, the overall trend in total climate finance closely follows the trend in loans (Figure 3.1), indicating that loans are a critical component of international climate finance. Japan emerges as the largest provider, contributing around 42% of total bilateral climate finance, followed by Germany (24%), France (14%) and United States (4%). The six major donor countries (Japan, Germany, France, United States Norway and United Kingdom) collectively account for about 83% of total bilateral climate finance (Figure 3.2). Japan and France primarily offer their climate aid in the forms of loans (approximately 92% of Japan's climate aid and 94% of France's). These two countries, along with Germany, are the larger providers of loans, representing over 60% of the total climate finance from all providers (Figure 3.6). On the other hand, while their total climate aid is relatively small, United States, Norway and United Kingdom primarily provide their climate aid in form of grants (Figure 3.2). These three countries are among the top five grant providers, with Germany being the largest (Figure 3.4). Regarding recipient countries, India is the largest recipient, receiving around 17% of total bilateral climate finance, with about 93% of this aid in the form of loans (Figure 3.3). The five largest recipient countries are in Asia (India, Indonesia, Bangladesh, Philippines and Vietnam), and they are also the top recipients of loans (Figure 3.7). The largest African recipient is a North African country, Morocco, which receives about 4% of total bilateral climate

[2] These countries include Cook Islands, Kiribati, Kosovo, Montserrat, Niue, Saint Helena, South Sudan, St. Vincent and the Grenadines, Tokelau, Tuvalu and Wallis and Futuna.

finance. In the Americas, Brazil is the largest recipient, receiving about 3% of total bilateral climate finance (Figure 3.3). Most of the major recipient countries primarily receive climate aid in the form of loans, with the exception of Brazil and Kenya. Additionally, the countries that receive the most grants are predominantly in Africa and Asia (Figure 3.5).

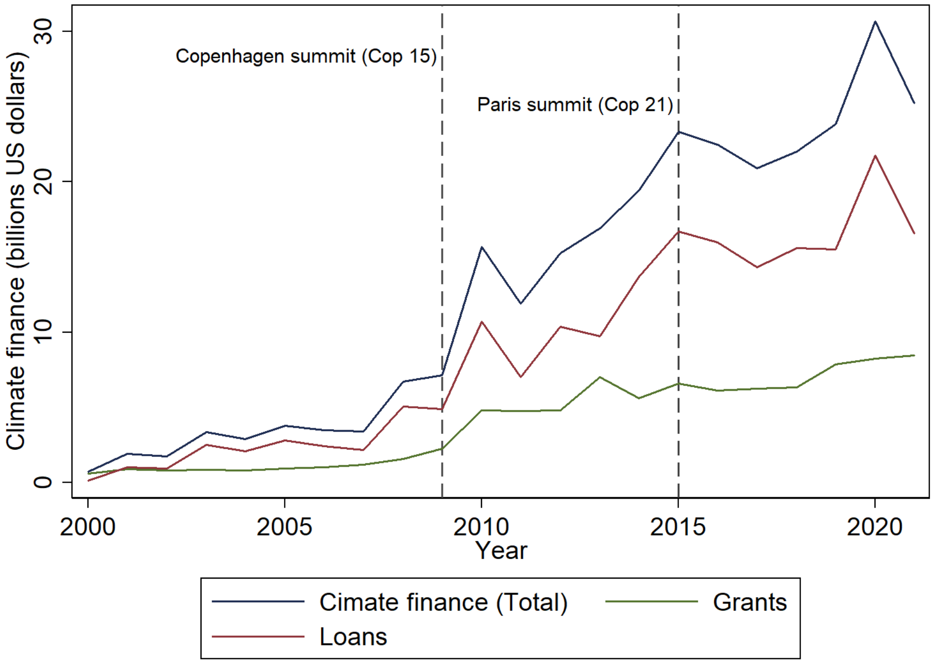

Figure 3.1: Evolution of Bilateral Climate Finance

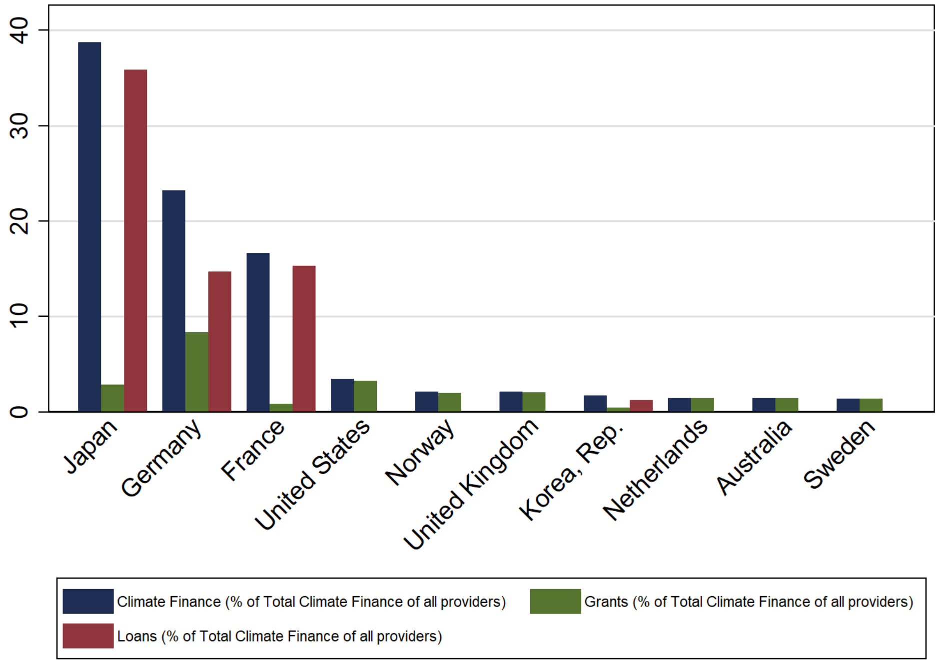

Figure 3.2: Most provider countries of Bilateral Climate finance (% of Total Climate Finance of all providers)

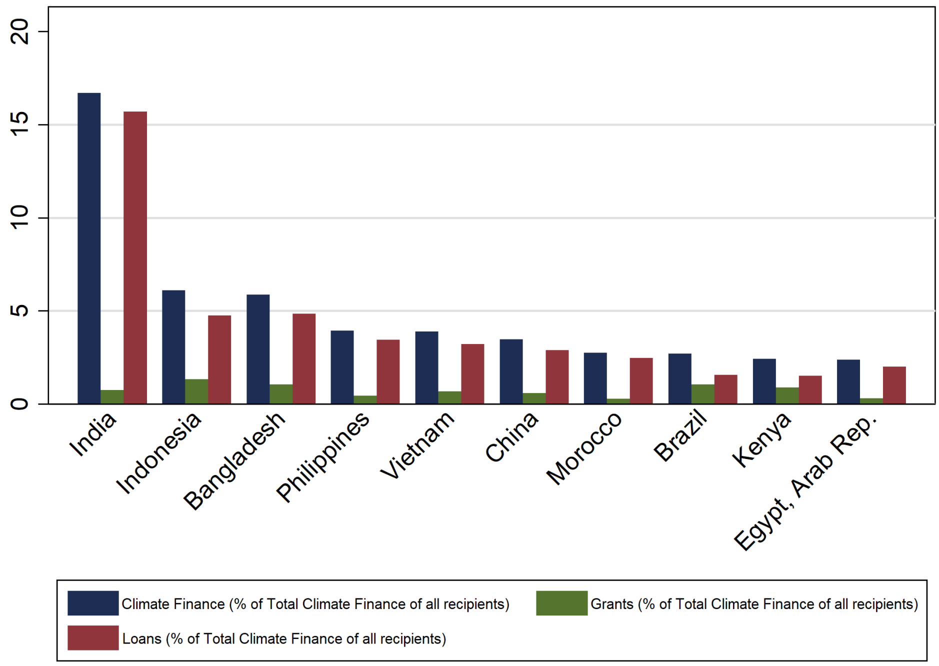

Figure 3.3: Most recipient countries of Bilateral Climate finance (% of Total Climate Finance of all recipients)

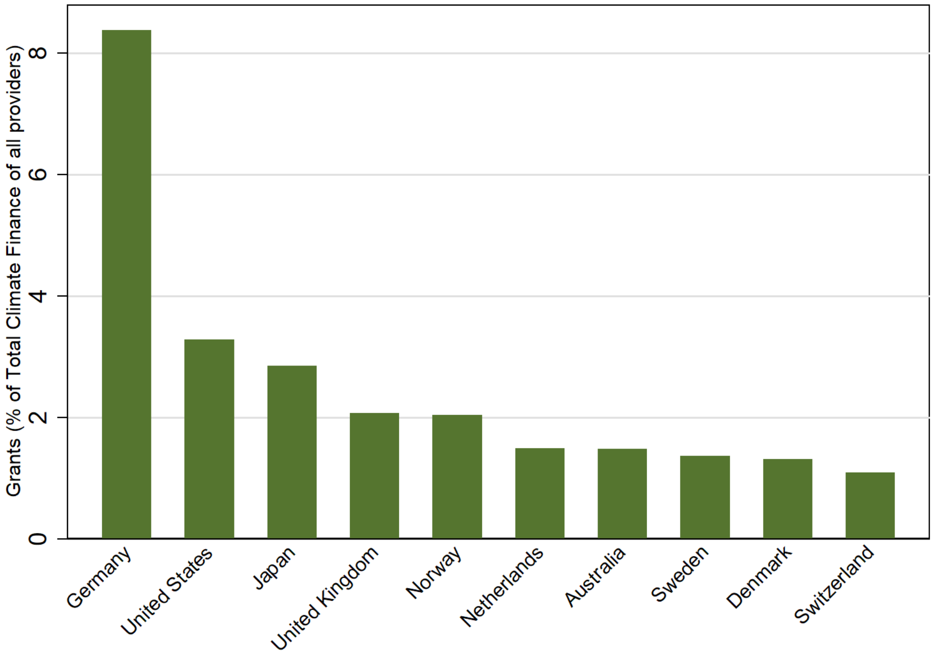

Figure 3.4: Most provider countries of Grants (% of Total Climate Finance of all providers)

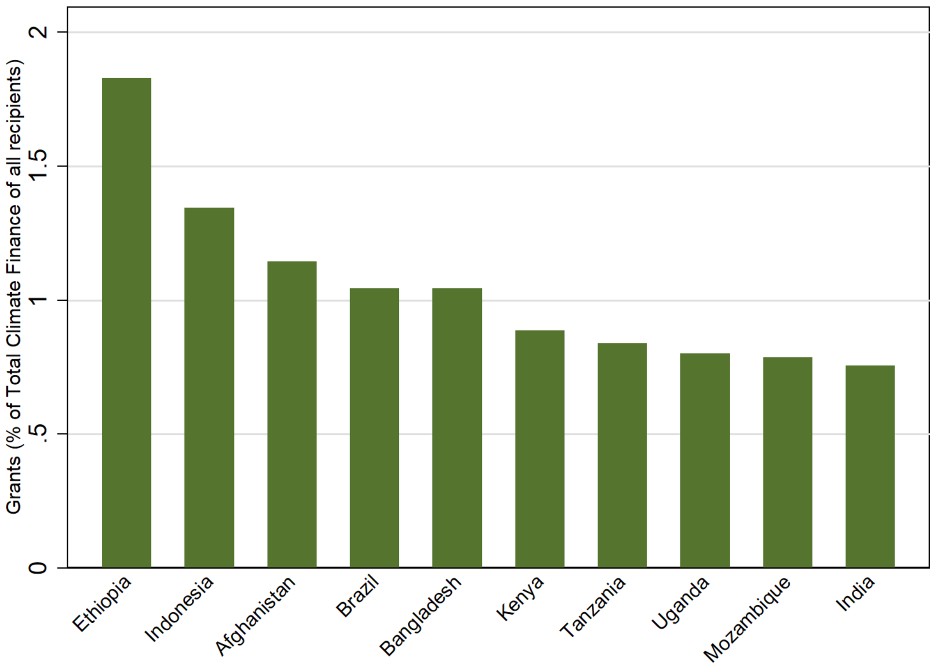

Figure 3.5: Most recipient countries of Grants (% of Total Climate Finance of all recipients)

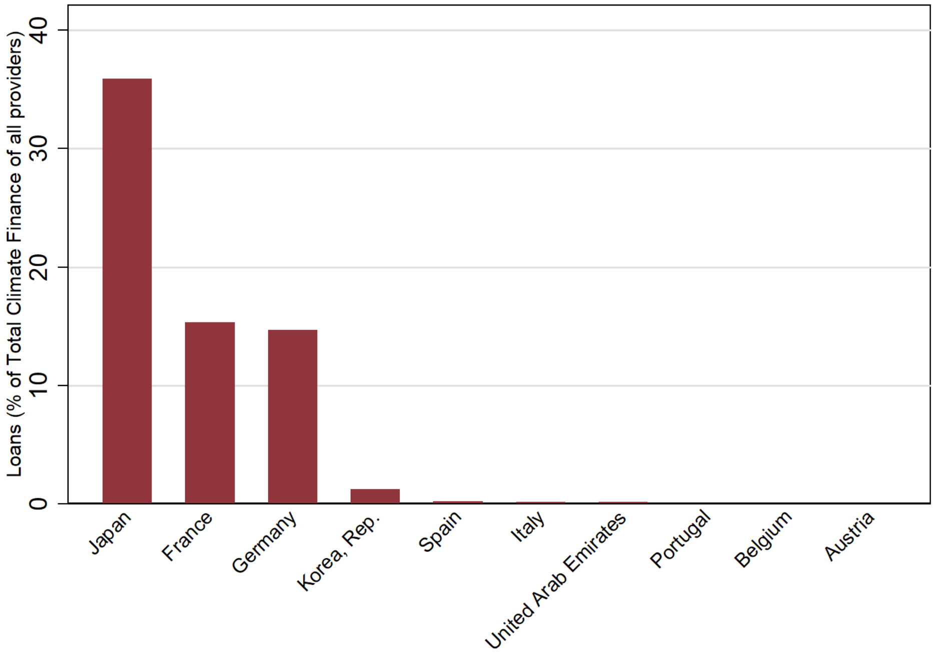

Figure 3.6: Most provider countries of Loans (% of Total Climate Finance of all providers)

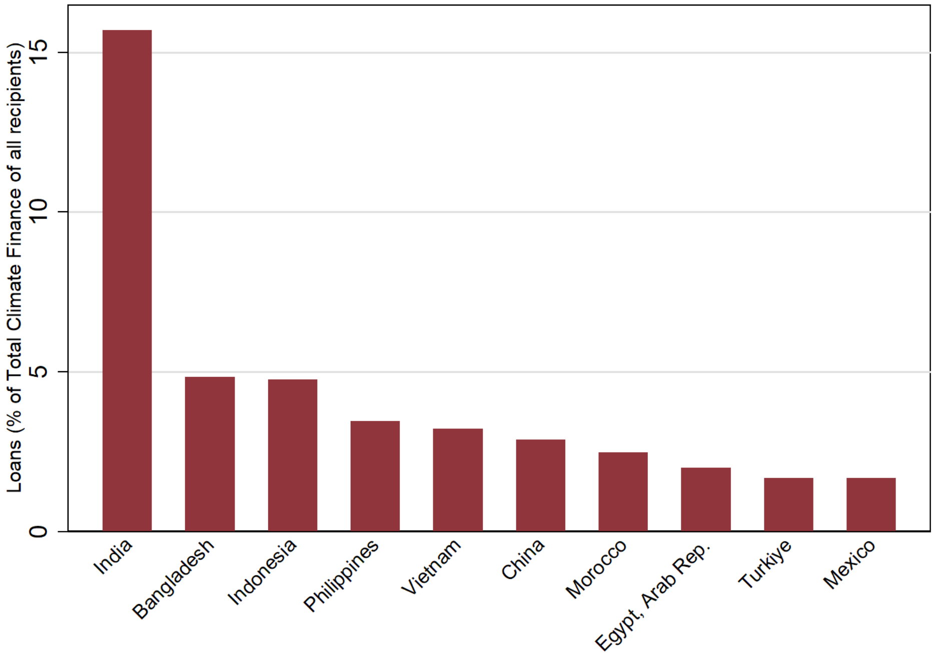

Figure 3.7: Most recipient countries of Loans (% of Total Climate Finance of all recipients)

3.2.2 Distribution by Region of Recipient Countries

This section provides an additional overview of bilateral climate finance by comparing the regions of Africa, the Americas, Asia, Europe and Oceania. We analyze total international climate finance as well finance distributed in the form of grants and loans. Notably, Asian countries receive the largest share of international climate finance, accounting for about 56% of the total flows (Figure 3.9). This region also receives the majority of its climate aid in the form of loans, with approximately 79% of the aid provided as loans. African countries are the second-largest recipients of bilateral climate finance, receiving about 23% of the total climate finance. The African region is also the largest recipient of grants, with more than 60% of its aid provided as grants. In contrast, countries in Oceania, which are among the most vulnerable to climate change (as discussed in Chapter 2), receive the smaller share of climate finance (less than 3% of the total) and predominantly in the form of grants. American and European countries receive less climate finance compared to Asia and Africa, and also receive a higher proportion of their climate aid in the form of loans rather than grants.

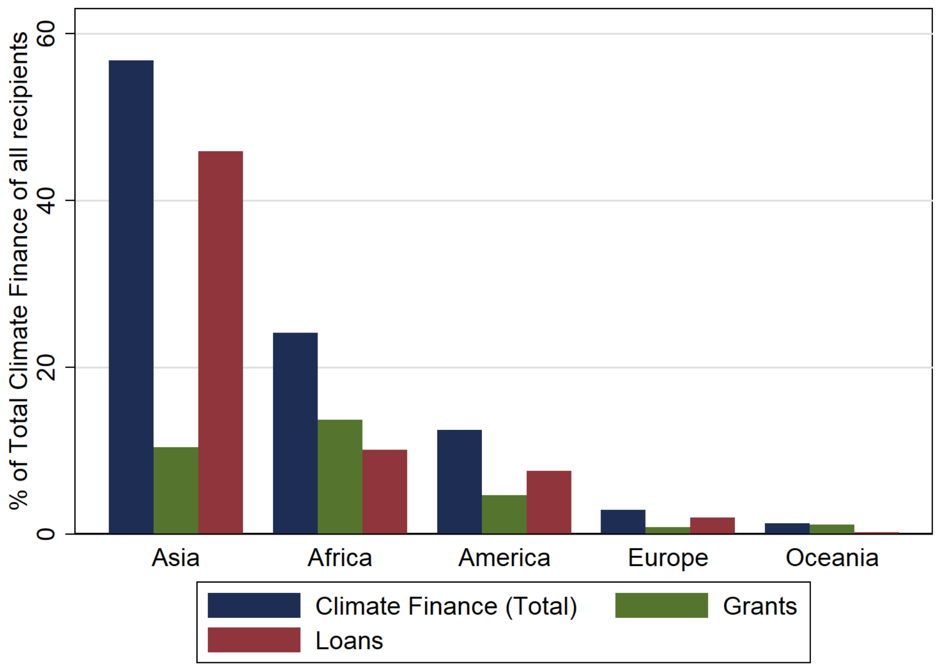

Figure 3.8: Climate Finance (Total), Grants and Loans by region (% of Total Climate Finance of all recipients)

3.2.3 Provider Countries View

Figures 3.12 and 3.14 reveal that donor countries often direct climate finance to their former colonies. For example, Portugal allocates about 70% of its climate aid to its former colonies, such as Cabo Verde, Mozambique, Sao Tome and Principe, and Angola (Figure 12). Similarly, Spain directs around 50% of its climate aid to its former colonies, including Peru, Bolivia, Nicaragua, Colombia, Ecuador, and Guatemala (Figure 3.14). This indicates that colonial ties are likely to influence the distribution of climate finance. Donor countries also tend to support countries within the same region or continent. In other words, donor countries are inclined to assist their neighboring countries (e.g., Australia, Japan, New Zealand or Slovenia, see Figures 3.9, 3.10, 3.11 and 3.13). For instance, more than 70% of Japan's climate aid is directed towards Asian countries, over 60% of New Zealand's climate aid is allocated to Oceania, and more than 70% of Slovenia's climate aid is focused on European countries. This pattern supports the notion that geographical proximity may significantly influence the allocation of bilateral climate finance.

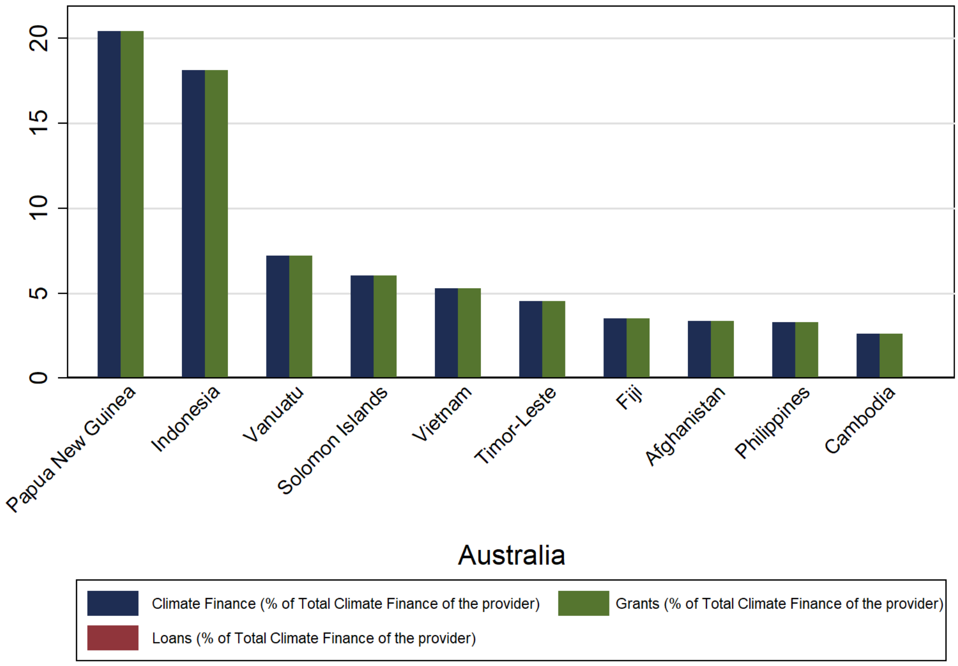

Figure 3.9: Australia and its most recipients (% of the Total Climate Finance of the provider)

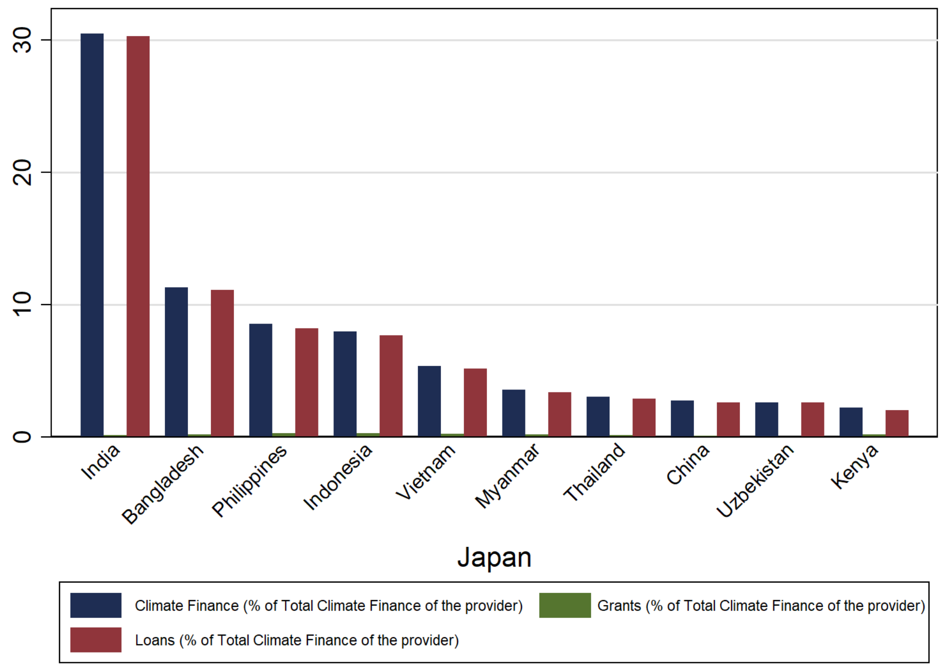

Figure 3.10: Japan and its most recipients (% of the Total Climate Finance of the provider)

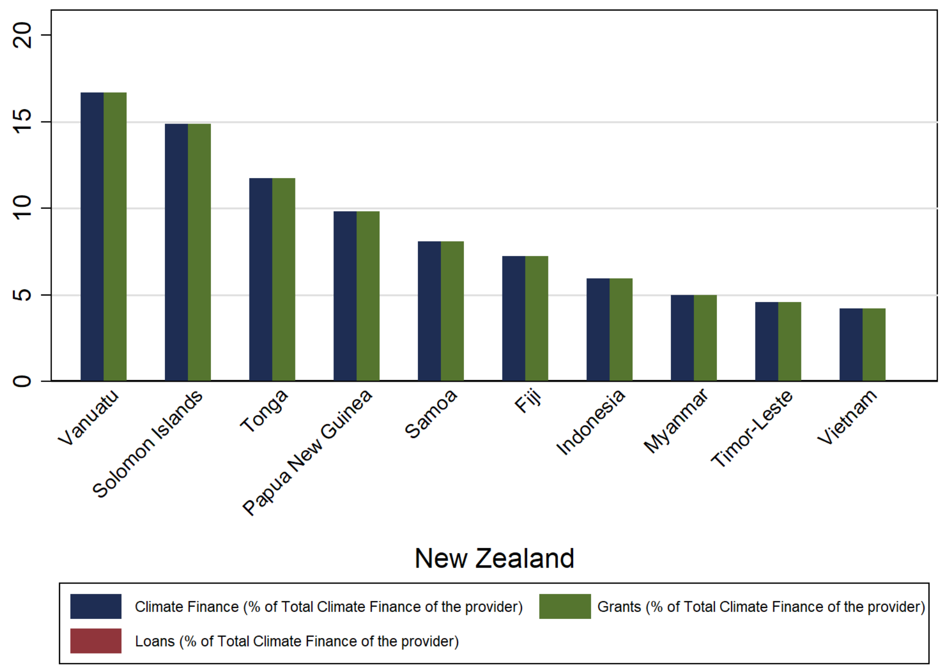

Figure 3.11: New Zealand and its most recipients (% of the Total Climate Finance of the provider)

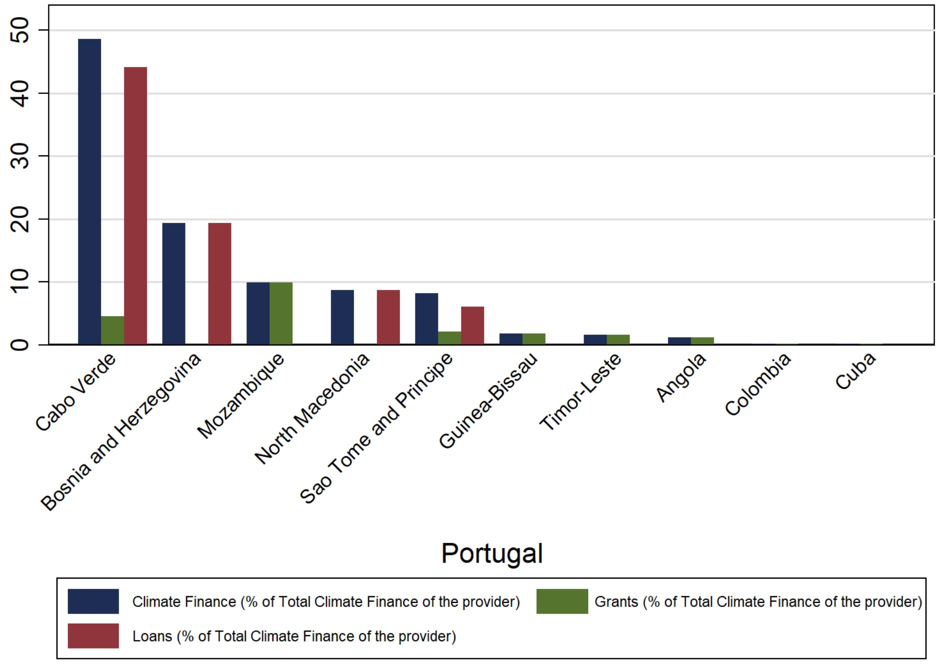

Figure 3.12: Portugal and its most recipients (% of the Total Climate Finance of the provider)

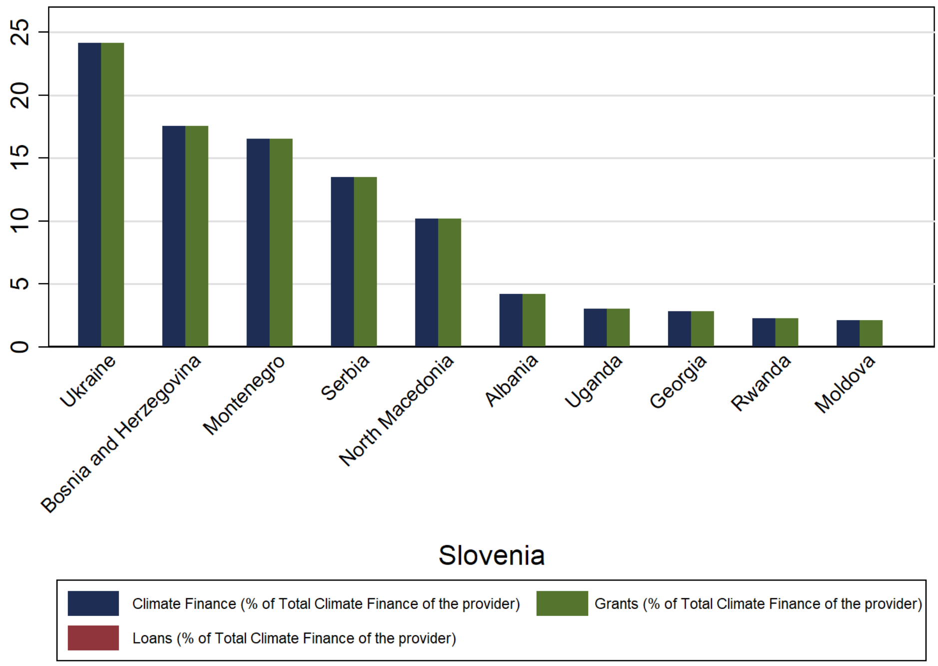

Figure 3.13: Slovenia and its most recipients (% of the Total Climate Finance of the provider)

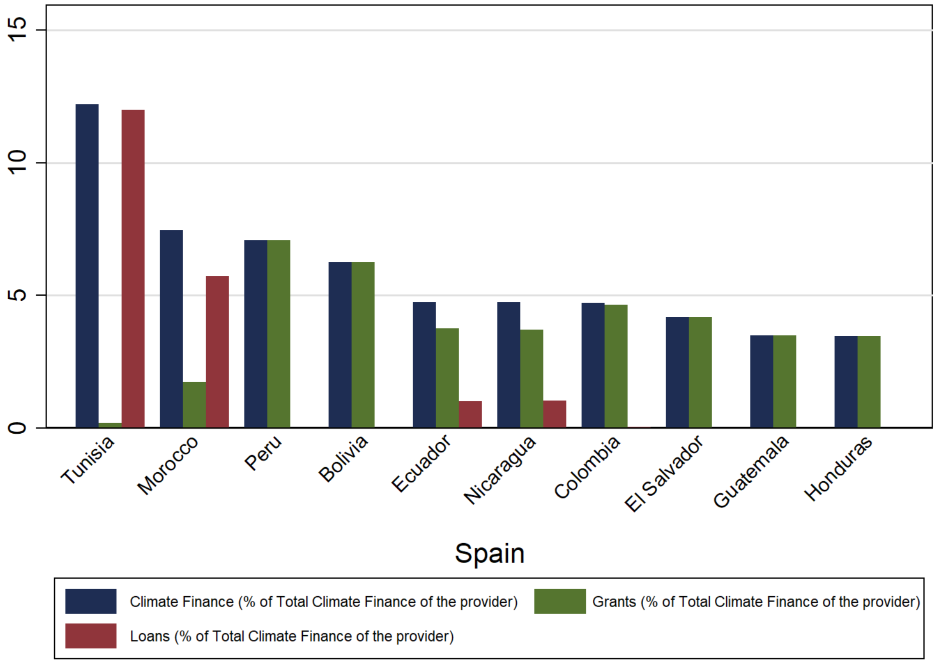

Figure 3.14: Spain and its most recipients (% of the Total Climate Finance of the provider)

Stylized facts indicate that African countries, many of which have low income levels, receive a higher proportion of grants compared to other regions. This suggest that grants are more likely to be allocated to countries with lower GDP per capita and, consequently, limited repayment capacity. Additionally, several donors countries tend to provide aid to their former colonies and countries with which they share geographical proximity. Thus, it can be inferred that both the GDP per capita of recipient countries and proximity factors may influence the flow of climate finance. The econometric analysis in the following section will test these hypotheses and identify other factors that may affect the allocation of climate aid.

3.3 Econometric Methodology

This section outlines the econometric framework regarding the potential determinants of international climate finance by estimating a gravity panel model using bilateral data, which includes information from both recipients and providers.

3.3.1 Data

The empirical analysis utilizes a sample of 140 recipient countries and 30 provider countries spanning the years 2000 to 2021. The data is sourced from various databases, including the OECD, CEPII and the World Bank′s Worldwide Development Indicators (WDI).

Dependent variable

The dependent variable is international climate finance as described in the previous section, referred to as "CFinance" and it is categorized into Grants and Loans in the econometric estimation.

Recipient variables

The model incorporates several independent variables, particularly those related to recipient characteristics, which are outlined as follows.

○ Climate change Vulnerability (CV03).Climate change vulnerability is expected to be positively associated with international climate finance flows, as vulnerable countries require financial support to aid their climate change adaptation processes. In this study, we utilize a newly constructed indicator (CV03)[3] derived from the ND-GAIN Vulnerability indicator (Refer to Chapter 2). While the ND-GAIN Vulnerability indicator has been employed in several recent studies (Fuller, 2021; Halkos et al., 2020), it may present issues of biased results when employed in econometric models due to its strong association with the economic development of countries (as mentioned in chapter 2). The new indicator addresses theses biases in results and minimizes economic considerations in measuring climate vulnerability. The values of this indicator range from 0 to 1, where a value close to 1 indicates a high level of vulnerability to climate change.

○ Gross domestic product per capita (GdpcR) at 2010 constant prices, from the World Bank. This variable allows to have an overview on the size of the economy and the level of devel-

[3] The indicator CV03 is calculated using the arithmetic mean of the sub-indicators from the ND-GAIN Vulnerability indicator that exhibit a correlation with GDP per capita (Gross Domestic Product per capita) of less than 0.3 in absolute value. This new indicator shows a lower correlation with the GDP per capita of recipients countries compared to the ND-GAIN Vulnerability indicator.

opment of the recipient countries. It is expected a negative association between high level of Gross Domestic Product per capita and climate finance assistance, as provider countries tend to prioritize less developed countries (Robertsen et al., 2015; Neumayer, 2003).

◦ Natural resource rent (Nrent). This variable is used as an indicator of natural resource wealth, encompassing oil, natural gas, and minerals, and is utilized to characterized resource-rich countries [4] within the model. Indeed, these resource-rich nations appear to be among the most vulnerable to climate change (refer to Chapter 2). Despite their abundant resources, they encounter numerous economic and social challenges, including social and political conflicts, corruption, unemployment and high poverty levels (Beck and Poelhekke, 2017; Sachs and Warner, 2001; Sala-i-Martin and Subramanian, 2003). Additionally, they face the pressing need to diversify their economies, witch could result in a reduction of natural resource production and, consequently, a decline of income. These countries require support and assistance to ensure their economic development and adaptation to climate change. The purpose of employing this variable is to investigate whether resource-rich countries are more likely to attract increased climate finance flows, given their unique circumstances. These countries also face the challenge of the implementation of climate-friendly policies aimed at reducing greenhouse gas emissions from natural resource extraction, which contribute to global warming and exacerbates local environment degradation (Afolabi, 2023; Agboola et al., 2021), thereby increasing their vulnerability to climate change (See Chapter 2). In the robustness check, we focus exclusively on a sample of resource-rich countries. Data for this variable is available for a wide range of countries and has also been used in previous studies (Bhattacharyya, 2014; Beck and Poelhekke, 2017). The data is sourced from the World Bank database.

◦ Population (Pop). This variable helps to assess the size of a country. It is expected a positive association between population and international climate finance flows (Trumbull and wall, 1994; Tezanos Vasquez, 2008). An increase in population can raise the needs of countries in terms of housing construction, food supply, and energy provision. The data is sourced from the Word Bank database.

◦ Institutional Quality (IQ). The Institutional Quality indicator assesses the level of governance and is derived from Worldwide Governance Indicators through Principal Component Analysis (PCA). These indicators include Voice and Accountability, Political Stability and Absence of Violence and Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption. As a variable related to recipient merit, institutional quality is expected to influence the allocation of development aid (Clist, 2011; Michaelowa and

[4] The WBG (World Bank Group) Fragile , Conflict and Violence Group - Investment Climate Teams defines resources-rich countries as those where the average total natural resources rent (% of GDP) over the past three years is at least ten percent.

Michaelowa, 2012), and in the same manner the allocation of climate aid. Countries with high levels of institutional quality are expected to manage financial assistance effectively in the implementation of climate policies. The indicator's value has been normalized on a scale from 0 to 1, where a value close to 1 indicates a strong institutional framework.

◦ Greenhouse Gas emissions per capita (GHGR). This variable pertains to the greenhouse gas (GHG) emissions of recipients countries. An increase in GHG emissions can lead to environmental degradation and contribute to Global warming. Therefore, climate finance is expected to be directed towards countries that generate higher levels of GHG emissions, in order to assist these nations in adopting climate-friendly policies. In this context, Halimanjaya (2015) noted that developing countries with higher CO_2 intensity tend to receive more climate mitigation finance. The data is sourced from EDGAR (Emissions database for Global Atmospheric Research).

Provider variables

In the model, we include variables related to provider countries that pertain to income levels (GdpcP) and the environmental data of donors.

◦ Gross Domestic Product per Capita (GdpcP) at 2010 constant prices. Countries with higher greater financial resources are anticipated to offer more financial assistance to developing nations. The data is sourced from the World Bank database.

◦ Greenhouse Gas emissions per capita (GHGP). This variable pertains to the GHG emissions of donor countries. The Cancun agreements of 2010 (COP 16) asserted that polluting countries should contribute to climate finance in accordance with their current and historical GHG emissions, which is based on the "Polluter pays" principle (Schalatek et al., 2012). Therefore, we can expect that donor countries with higher GHG emissions will be pressured to provide more climate finance. The data is obtained from EDGAR (Emissions database for Global Atmospheric Research).

Common variables

Other bilateral variables are also incorporated into the model, such as colonial ties (Colonial history), proximity variables (e.g., distance from capitals cities), and Bilateral Development Assistance flows (ODA). Several of these variables serve as indicators of donor interests.

◦ Exports from provider to recipient countries (Exports). This variable can be regarded as a measure of the economic interests of provider nations. Indeed, countries with significant trade flows to recipient countries are expected to offer more financial assistance to their partners in order to strengthen their trade relationships. Therefore, a positive association between climate finance and exports is expected, as suggested by previous studies (Bayramoglu et al., 2023, Weiler et al., 2018). The data is sourced from the CEPII database. Since the data is in current US dollars, we adjusted the export values for inflation using the US Consumer Price Index (CPI) (base 2010) from the World Bank Development Indicators (WDI), following Bayramoglu et al. (2023).

◦ Colonial history (Col). Colonial history is anticipated to impact the allocation of international climate finance. Betlozt and Weiler (2016) assert that donor-recipient relationships matter and past colonial ties can influence the distribution of development aid to recipient countries. A positive association is expected between climate finance flows and an existing colonial history between provider and recipient countries. The data is also obtained from the CEPII database.

◦ Diplomatic Disagreement (DiploD). This variable pertains to the political distance between the provider country and the recipient country, derived from UN Assembly votes. A high value indicates a significant political divergence in voting patterns at the UN Assembly between the two countries. A positive coefficient for this variable suggests that the provider country may be seeking to gain political support from the recipient country in UN Assembly votes. Conversely, a negative coefficient implies that provider countries tend to allocate less climate finance to countries that do not align with their political stance. The data is sourced from CEPII.

◦ Trade Agreements (RTA). This is a dummy variable that indicates whether the provider and recipient countries have ratified treaties concerning bilateral trade. The data is also sourced from CEPII.

◦ Distance (Distcap). Countries that are geographically close are more likely to engage in bilateral relations, such as trade exchanges, political ties, agreements (e.g., countries in European Union), or financial assistance. In this work, we measure the distance in kilometers between the capitals of the provider and recipient countries. Data is obtained from CEPII.

◦ Official Development Assistance (ODA). Countries that already receive development assistance from a provider country are likely to obtain additional climate finance from that same provider. This can be viewed as an established aid network that reduces transaction costs for providers. Hoeffler and Outram (2011) argue that an existing aid relationship can attract new aid. The data comes from the World Bank database. Since the data is available separately for each provider country, we combined data from each provider to obtain a new dataset, and as it is presented in current US dollars, we have adjusted the ODA values for inflation using the US Consumer Price Index (CPI) (base 2010), following Bayramoglu et al. (2023).

◦ Bilateral Investment treaties (BIT). This variable relates to investment treaties between the provider and recipient countries during the specified period. The data is sourced from the Electronic Database of Investment Treaties (EDIT) provided by the World Trade Institute - University of Bern. The initial database involved a textual analysis of bilateral investment treaties among various countries, noting the year of signature, termination date, and partner countries. We created a new database with a dummy variable that takes the value of 1 if an investment treaty exists during the specified period and 0 if it does not or if the treaty has ended. This variable is expected to positively influence climate finance flows, as the provider country may use climate finance to foster investment relationships with the recipient country.

Variables	Mean	St.Dev	Min	Max	N
CFinance (millions USD)	3.0616	45.7894	0.0000	5568.024	92400
Grants (millions USD)	0.9505	6.6095	0.0000	448.645	92400
Loans (millions USD)	2.0774	44.3879	0.0000	5563.981	92400
CV03	0.3988	0.0718	0.2739	0.6142	92400
Exports (millions USD)	0.4167	4.3808	0.0000	265.0104	92400
GdpcP (USD)	40594.82	20822.97	6423.421	112417.9	92400
GdpcR (USD)	4451.767	4393.807	255.1003	22879.51	89370
Nrent (% of GDP)	8.4785	11.4991	0.0000	88.5923	89700
Pop (millions)	40.9901	156.4382	0.0102	1412.36	92400
IQ	0.4439	0.1481	0.0000	0.8568	90780
GHGP (tons CO2-eq)	13.3378	6.3637	5.2128	42.7517	92400
GHGR (tons CO2-eq)	5.2250	9.2188	0.4896	179.3064	89100
ODA (millions USD)	12.1436	82.7421	-1206.34	11227.79	92400
Col (dummy)	0.0302	0.1712	0	1	92400
DiploD	1.5223	0.6950	0.0001	4.8269	85848
RTA (dummy)	0.1751	0.3801	0	1	90930
Distcap (km)	7725.624	3877.382	117	19599	90930
BIT (dummy)	0.2179	0.4128	0	1	92400

Table 3.1: Summary Statistics

3.3.2 Model

Since, our focus is on bilateral data (i.e., financial flows from one country to another), the most suitable model is a Gravity Panel model. This model effectively incorporates both bilateral data and individual data from both donor and recipient countries. Gravity Models, inspired by Newton's theory of gravity are commonly used in international trade analysis.

Traditional framework of gravity model

The Gravity Model originates from Newton's Law of Universal Gravitation, proposed in 1687. According to Newton, any object in the globe attracts another object with a force proportional to the product of their masses and inversely proportional to the distance between them. Beyond the field of physics, gravity models were adapted to analyze trade between countries. The idea is that trade between countries is positively correlated with their economic size (level of development) and negatively correlated with the distance between them. Tinbergen (1962) is recognized as one of the pioneers in formulating an econometric version of the gravity model for empirical analysis. As a result, Tinbergen's gravity equation has become a foundational model in the study of international trade flows. The Gravity Model is advantageous because it incorporates both bilateral data and individual data from the countries involved, offering insights each country's characteristics and their mutual relationships. The basic equation of the traditional gravity model, which posits that trade between two countries (i and j) is positively related to their incomes and negatively related to the distance between them, is represented as follows:

$$X_{ij} = \alpha \frac{Y_i Y_j}{Dist_{ij}} \tag{3.1}$$

With α a constant, X_{ij} is related to the value of bilateral trade between country i and j, Y_i and Y_j are related to respective gross domestic product (GDP) of country i and country j and $Dist_{ij}$ is related to the bilateral distance between the two countries. The linear form of this equation is specified as follows:

$$lnX_{ij} = \beta_0 + \beta_1 lnY_i + \beta_2 lnY_j + \beta_3 lnDist_{ij} + \epsilon_{ij} \tag{3.2}$$

With ϵ_{ij} an error term.
Today, gravity models are used in various fields of studies, from international trade (Linnemann, 1996; Egger, 2002; Helpmann et al. 2008; Melitz, 2008; Milner and McGowan, 2013; Baltagi et al. (2015); Santana-Gallego et al. 2016) to migration (Docquier et al.2010), bilateral foreign investments (Chang, 2014; Pericoli et al. 2014; Egger, 2010) or foreign aid (Berthelemy and Tichit, 2004; Younas, 2008).

Estimation of gravity model

The econometric methods used to estimate gravity model are diverse. However, a common view is that the accuracy of regression estimates is significantly higher in panel data, primarily because of the larger sample size compared to cross-sectional or times-series studies. Cross-sectional investigations may encounter biased results and misleading conclusions due to potential issues with omitted variables and heterogeneity (Pesaran, 2015; Wooldridge, 2002). Gravity Model is estimated either in linear form or non-linear form. In the early days of gravity models, the linear form was used and models were estimated by considering the log-linear specification. The methods of estimation in this context was Ordinary Least Squared (OLS) or traditional Panel estimations (e.g., Panel fixed effects). As log linear OLS techniques was unable to include observations with zero values because the log of zero is undefined, most studies dropped observations with zero values, using only positive values for estimation. However, several issues can arise with these methods such as loss of information due to the removal of zero observation flows, sample selection bias, biased coefficients and heteroskedasticity issue by using logged values [5] (Santos Silva and Tenreyro, 2006). Zero values flows are a problematic issue in gravity model in log-linear specification since the logarithm of zero is not defined. Alternative methods without suppressing all zero values in the dataset, such as Truncated and censoring methods (e.g., Panel Mean-Group) can also lead to biased estimation for the omission of data (Baldwing and Harrigan, 2011; Burger et al. 2009; Martin and Pham, 2015). Linders and de Groot, 2006 and Burger et al., 2009 agued that these methods, where the zero values are substituted by a small positive constant, are arbitrary without any strong theoretical or empirical justification and can distort significantly the results, leading to inconsistent estimates. To deal with theses issues, non linear methods are proposed in the literature of gravity model. Amongs them, we can notice the Non linear Least Square (NLS) (Frankel and Wei, 1997), the Gamma Pseudo Maximum Likelihood (GPML) (Manny and Mullay, 2001), the Heckman Sample Selection Model (Heckman, 1979; Linder and de Groot, 2006) or the Poisson Pseudo Maximum Likelihood (PPML) (Santos Silva and Tenreyro, 2006). Santos Silva and Tenreyro (2006) show that the PPML estimator is an efficient estimator allowing to deal with zero values issue and mitigates the heteroskedasticity issue. According to them, in the presence of zero-valued observations and because the logarithmic transformation of the gravity equation, OLS(both truncated and censored OLS) is inconsistent and exhibits a significant bias that does not diminish as the sample size grows, thus confirming its inconsistency (Santos Silva and Tenreyro, 2011). On the other hand, the PPML approach estimates the gravity equation in levels rather than using logarithms, which is said to avoid the issues encountered with OLS under logarithmic transformation. They argue that the PPML estimation is suitable for several reasons: first, the Poisson estimation accounts for heterogeneity in units. Second, the PPML estimation method provides a natural solution for zero-valued observations due to its multiplicative forms. Third, the method prevents the underestimation of large observations flows (in the case of trade data for example) by producing estimates of these observations in levels rather than their logarithms. While

[5] Heteroskedasticity arises when the variance of the error terms is correlated with the dependent variable. Hence, bigger values of the dependent variable tend to have higher variance errors.

Burger et al. 2009, noted that the PPML estimator can be vulnerable to the problem of overdispersion in the dependent variable and excessive zero flows, Santos Silva and Tenreyro (2011) replicated that PPML is consistent and generally performs well even where there is overdispersion in the dependent variable (i.e., when the conditional variance is not equal to the conditional mean), and a high proportion of zeros does not impacts its performance. Additionally, Soren and Bruemmer (2012) argued that PPML performs well under overdispersion and is behaves well bimodal distributed trade data. Similarly, Staub and Winkelmann (2013) found that the PPML estimator is consistent even with an excessive number of zeros. Moreover, the PPML estimator is posited to be less affected by heteroskedasticity compared to other estimators such as GPML or NLS (Martinez-Zarzosso, 2013; Martin and Pham, 2008). Regarding the other estimation techniques, Santos Silva and Tenreyro (2011) found that the GPML is consistent and performs well in Monte Carlo Simulations, even when there are many zero values generated by a constant elasticity model, however, it exhibits a larger bias compared to PPML, suggesting that PPML is the superior estimator. Additionally, Martinez-Zarzoso (2013) observed that GPML can suffer from a significant loss of precision, especially if the variance function is mis-specified or the log-scale residuals exhibit high kurtosis[6]. Furthermore, Santos Silva and Tenreyro (2006) show that while GPML and NLS can address zero values issue, NLS technique assigns greater weight to noisier observations, decreasing the estimator's efficiency. PPML, on the other hand, assigns equal weight to all observations and assumes the conditional variance is proportional to the conditional mean. In contrast, both GPML and NLS give more weight to observations with larger means, due to the more pronounced curvature of the conditional mean for these observations, which typically have larger variances and are therefore noisier. Additionally, they noted that NLS can be very inefficient as it generally ignores the heteroskedasticity in the data. The Heckman selection model, frequently used in literature shows also some limits. Indeed, transforming the model into logarithmic form before estimation can lead to biased coefficients (Haworth and Vincent, 1979; Santos Silva and Tenreyro, 2006). Additionally, Flam and Nordstrom (2011) and Santos Silva and Tenreyro (2009) argued that this model do not account for heteroskedasticity.

Regarding the advantages offered by the PPML estimation, our estimation technique will rely on this estimation. The model with bilateral climate finance flows and control variables is described as follows:

$$lnCFinance_{ijt} = lnX_{it}\beta + lnY_{jt}\theta + lnZ_{ijt}\delta + u_i + u_j + \epsilon_{ijt} \tag{3.3}$$

[6]Kurtosis measures the concentration of data in the tails of the distribution compared to a normal distribution. In other words, it indicates whether the data has more or fewer extreme values than expected in a normal distribution. Kurtosis is important for evaluating the normality of residuals in regression models. High kurtosis values can indicate that the residuals have heavier tails, which can affect statistical tests and predictions.

$Cfin_{ijt}$ is related to climate finance flows from country i to country j at time t; $i = 1, ..., N$ is related to the numbers of provider countries; $j = 1, ..., N$, the number of recipient countries and $t = 1, ..., T$, the number of time periods. X_{it} is related to variables of provider countries such as Gross domestic product per Capita (GdpcP). Y_{jt} is related to recipient countries variables such as Gross domestic product (GdpcR), Climate Vulnerability (CV03) or Population (Pop). Z_{ijt} is related to common variables between country i and country j. We include to the model common dummy variables such as colonial ties in order to take into account political links, Trade agreement or Bilateral investment treaties. u_i is related to provider country's fixed effects, u_j is related to recipient country's fixed effects and ϵ_{ijt} is related to the error term.
Following the Poisson Pseudo Maximum Likelihood (PPML) estimation, allowing to deal with problem of heteroskedasticity and zero values (Silva and Tenreyro, 2006), the model is transformed to have the dependent variable in level and is specified as follows:

$$CFinance_{ijt} = exp\{lnX_{it}\beta + lnY_{jt}\theta + lnZ_{ijt}\delta + u_i + u_j + \epsilon_{ijt}\} \tag{3.4}$$

The model is estimated separately with three dependent variables that are total climate finance (CFinance), Grants and Loans. It's estimated through an augmented estimation technique known as PPMLHDFE (Poisson Pseudo Maximum Likelihood with High Dimension Fixed Effects) from Correia et al. 2020 allowing to control for multiple fixed effects. This estimator has the advantage to take into account the advantage of the PPML estimator and allows for controlling multiple levels of fixed effects and multiple sources of heterogeneity.

3.3.3 Baseline Results

Table 3.2 outlines the determinants of international climate finance, including total climate finance (CFinance), Grants and Loans. The coefficient for the climate vulnerability variable (CV03) is not significant across all categories, suggesting that vulnerable countries are not more likely to receive climate finance. The coefficient for the income level of recipient countries (GdpcR) is negative but not significant for total climate finance flows and loans, indicating that climate finance is generally not directed towards countries with lower GDP per capita. However, grants are more likely to be allocated to these lower income countries, confirming the hypothesis from the stylized facts in section 2. Exports from donor to recipient countries play a significant role in the allocation of climate finance, as supported by previous studies (Bayramoglu et al., 2023; Weiler et al., 2018). Similarly, the positive coefficient for trade agreements (RTA) in the context of total climate finance and loans suggests that donor countries tend to allocate climate aid, especially loans, to countries with which they share trade relationships. Additionally, the positive and significant coefficient for Bilateral investment treaties (BIT) across all climate finance flows indicates that investment interests of donor countries contribute significantly influence the provision of climate finance. These findings imply that economic interests of donor countries play a substantial role in the allocation of climate finance. The results also indicate that donor countries contributing more to global warming through higher greenhouse gas emissions are not more likely to provide climate finance, as shown by the negative but not significant coefficient for the GHGP variable in total climate finance and grants. Similarly, recipient countries that contribute more to global warming tend to receive less climate finance overall, particularly in the form of loans. The positive coefficients for colonial ties (Col) in total climate finance and grants suggest that donor countries are inclined to support their former colonies. The negative and significant coefficient for the Diplomatic Disagreement variable (DiploD) across all climate finance flows indicates that donor countries are more likely to assist politically aligned nations. Geographical proximity (Distcap) also plays a significant role in climate finance distribution; recipients geographically closer to donor countries are likely to receive more climate finance, particularly in the form of grants. For example, and as mentioned from stylized facts in section 2, several donor countries, such as Australia, Japan or New Zealand, frequently assist countries within their own region (see Figures 3.9, 3.10 and 3.11). However, loans appear to be distributed independently of geographical proximity. The coefficient for natural resources rent (Nrent) is significant at 5% level for grants but not significant for total climate finance and loans, suggesting that resource-rich countries are primarily likely to receive grants which constitute a small portion of total climate finance (see Figure 3.1). An other finding is that recipient countries with large populations (Pop) and those that receive development aid (ODA) are more likely to receive climate aid. Regarding recipient merits, the level of institutional quality (IQ) appears to play a key role in the provision of total climate aid, particularly grants. A strong institutional framework can provide assurance to donor countries regarding the effective management of climate aid.

Variables	CFinance	Grants	Loans
CV03 (lagged)	-9.3616	-5.3363	-18.1782
	(7.3136)	(6.1619)	(12.0398)
Exports (lagged)	0.2429***	0.2443***	0.3927***
	(0.0523)	(0.0379)	(0.1025)
GdpcR	-0.0403	-0.5209*	0.2822
	(0.5224)	(0.2811)	(0.9052)
GdpcP	2.4427**	0.3478	6.6059***
	(1.1032)	(0.4722)	(2.2935)
Pop	2.8551***	2.7259***	3.5721***
	(0.4771)	(0.4928)	(0.0105)
Nrent	0.1405	0.2086**	0.1474
	(0.0992)	(0.0747)	(0.1576)
RTA	0.4908***	0.0922	0.5476***
	(0.1282)	(0.0985)	(0.2105)
BIT	0.2165**	0.2468***	0.2413*
	(0.0901)	(0.0859)	(0.1252)
ODA (lagged)	1.3331***	2.1086***	1.0183***
	(0.3989)	(0.4131)	(0.2769)
GHGP (lagged)	-0.9116	-0.4931	-2.3489
	(0.8225)	(0.5124)	(1.5275)
GHGR (lagged)	-1.0591**	-0.0921	-1.8964**
	(0.4239)	(0.3381)	(0.7265)
IQ	4.4039**	4.6234***	3.6434
	(2.0439)	(1.1568)	(3.0046)
Col	0.3296**	1.0115***	-0.0103
	(0.1781)	(0.1847)	(0.3782)
DiploD (lagged)	-0.7012**	-0.6538***	-0.7181*
	(0.3243)	(0.2332)	(0.4576)
Distcap	-0.4727***	-0.4681***	-0.1351
	(0.1479)	(0.1002)	(0.2673)
Observations	79246	79246	79246
Pseudo R-squared	0.7443	0.6138	0.7609
Log pseudolikelihood	-288186737.9	-100988589	-185730074.5
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.2: Baseline result of potential determinants of international climate finance

3.3.4 Robustness Checks

In this section, we subject our baseline results to a series of robustness tests. First, we re-evaluate the baseline results without including lags, without GHG emissions and with the inclusion of recipient imports instead of donors exports. Second, apply a dynamic probit model. Third, we use alternative vulnerability indicators. Fourth, we focus specifically on resource-rich countries, defined as those with natural resource rents exceeding 10% of GDP, a criterion suggested by the World Bank Group. Fifth, we estimate the baseline model using data from the ten largest donor countries. Sixth, we estimate the baseline model for the most recipient regions. Seventh, we test the baseline results using data from Small Islands Countries. Finally, we consider allocations based on targeted objectives by distinguishing between climate adaptation finance and climate mitigation finance.

Estimations without lags, without GHG emissions and with recipient's imports

We estimate the baseline model without including lags, without considering GHG emissions and using recipient imports instead of provider exports. The estimation without lags yields results similar to the baseline. For the estimation without GHG emissions, we conducted this test because we suspected a correlation between GHG emissions and GDP per capita (as GDP per capita increases, GHG emissions may rise due to industrialization, transportation, or urbanization), which could influence the baseline results. However, the findings remain consistent with the baseline, showing that the most vulnerable countries are not likely to receive climate aid. Additionally, the signs and significance of the coefficients for other variables are very similar to the baseline results. Regarding the estimation using recipient imports, we performed this test to compare trade flows reported by providers and recipients. Each reporting country specifies the trade volume it has with each of its partner countries, both in terms of exports and imports. The key difference is that exports are reported by the providers as FOB (Free on Board), while imports are reported by the recipients as CIF (Cost, Insurance, and Freight). The results align with the baseline, suggesting that vulnerable countries are not likely to receive climate aid. Similar to provider exports in the baseline results, recipient imports tend to positively influence the provision of climate aid. Therefore, countries that import more from the provider are likely to receive more climate aid. Trade agreements (RTA), investment treaties (BIT), development aid (ODA), institutional quality (IQ), colonial ties (Col), political alignment (DiploD) and geographical distance (Distcap) all play key roles in the provision of climate aid. Compared to loans, grants are more likely to be provided to countries with strong institutional quality and those that share colonial ties, political alignment, and geographical proximity with the provider.

Variables	CFinance	Grants	Loans
CV03	-3.9299	-3.9576	-8.1307
	(7.0312)	(6.6923)	(11.0607)
Exports	0.2228***	0.2425***	0.3107***
	(0.0533)	(0.0404)	(0.1111)
GdpcR	-0.2448	-0.4048	-0.0515
	(0.5008)	(0.3371)	(0.8041)
GdpcP	1.5132	0.9552**	3.5508
	(1.0452)	(0.5257)	(2.2271)
Pop	2.4406***	2.9561***	2.7058***
	(0.4720)	(0.4889)	(0.9921)
Nrent	0.1454	0.1478*	0.1877
	(0.1075)	(0.0854)	(0.1722)
RTA	0.4758***	0.0793	0.4929**
	(0.1282)	(0.1066)	(0.1931)
BIT	0.1920**	0.2441***	0.2182*
	(0.0892)	(0.0889)	(0.1271)
ODA	1.7259***	2.0885***	1.4567***
	(0.4721)	(0.3846)	(0.3732)
GHGP	-1.7136**	-1.6441***	-2.3842
	(0.8225)	(0.5641)	(1.5946)
GHGR	-0.7099*	-0.2391	-1.2545*
	(0.4339)	(0.3456)	(0.7328)
IQ	6.0309***	4.6851***	6.7258**
	(1.8880)	(1.2538)	(2.8902)
Col	0.3366**	1.0104***	0.0464
	(0.1833)	(0.1889)	(0.3995)
DiploD	0.6206	-0.6851**	1.4873***
	(0.4311)	(0.2756)	(0.5329)
Distcap	-0.5176***	-0.4306***	-0.3444
	(0.1471)	(0.1034)	(0.2709)
Observations	79068	79068	79068
Pseudo R-squared	0.7504	0.6108	0.7706
Log pseudolikelihood	-262720385.4	-94948504.49	-166413387.8
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.3: baseline results without lags

Variables	CFinance	Grants	Loans
CV03 (lagged)	-10.0106	-4.9901	-20.2333
	(7.6346)	(6.1081)	(12.6455)
Exports (lagged)	0.2421***	0.2342***	0.4047***
	(0.0512)	(0.0372)	(0.1015)
GdpcR	-0.6514	-0.5551*	-0.9309
	(0.5215)	(0.2901)	(0.8852)
GdpcP	1.9258**	0.1119	4.7769***
	(0.8932)	(0.4639)	(1.7297)
Pop	2.7966***	2.7179***	3.3108***
	(0.4725)	(0.4773)	(0.9789)
Nrent	0.1163	0.2054**	0.1177
	(0.0994)	(0.0731)	(0.1588)
RTA	0.4532***	0.0811	0.4717**
	(0.1297)	(0.0981)	(0.2095)
BIT	0.1965**	0.2351***	0.2088*
	(0.0902)	(0.0852)	(0.1282)
ODA (lagged)	1.3642***	2.1072***	1.0754***
	(0.4031)	(0.4075)	(0.2919)
IQ	4.7062**	4.6051***	4.1611
	(2.1502)	(1.1762)	(3.3262)
Col	0.3356*	1.0223***	-0.0211
	(0.1777)	(0.1846)	(0.3815)
DiploD (lagged)	-0.6627**	-0.6216***	-0.6911
	(0.3317)	(0.2288)	(0.4766)
Distcap	-0.5099***	-0.5032***	-0.1945
	(0.1449)	(0.0992)	(0.2576)
Observations	81466	81466	81466
Pseudo R-squared	0.7434	0.6142	0.7572
Log pseudolikelihood	-292588229	-102000610.5	-190103261
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.4: Baseline estimation without Greenhouse gas emission variables

Variables	CFinance	Grants	Loans
CV03 (lagged)	-8.8445	-5.4067	-17.2433
	(7.2337)	(6.1923)	(11.9098)
Imports (lagged)	0.1503***	0.1967***	0.2772**
	(0.0517)	(0.0368)	(0.1201)
GdpcR	0.1002	-0.4151	0.5157
	(0.5328)	(0.2835)	(0.9108)
GdpcP	2.4218**	0.3421	6.3855***
	(1.0925)	(0.4702)	(2.2758)
Pop	2.8184***	2.6969***	3.4978***
	(0.4725)	(0.4912)	(0.9887)
Nrent	0.1395	0.2086**	0.1588
	(0.0987)	(0.0734)	(0.1551)
RTA	0.4796***	0.0852	0.5129**
	(0.1334)	(0.0991)	(0.2149)
BIT	0.8126**	0.2365***	0.2319*
	(0.0912)	(0.0867)	(0.1302)
ODA (lagged)	1.3285***	2.1418***	1.0179***
	(0.4061)	(0.4031)	(0.2752)
GHGP (lagged)	-0.9397	-0.4936	-2.4213
	(0.8228)	(0.5111)	(1.5257)
GHGR (lagged)	-1.0969**	-0.1622	-1.9839***
	(0.4266)	(0.3349)	(0.7161)
IQ	4.3318**	4.4319***	3.7211
	(2.1319)	(1.1374)	(3.2028)
Col	0.4332**	1.0504***	0.1611
	(0.1737)	(0.1853)	(0.3571)
DiploD (lagged)	-0.7081**	-0.6821***	-0.6993
	(0.3168)	(0.2292)	(0.4438)
Distcap	-0.6337***	-0.5658***	-0.3613
	(0.1504)	(0.0984)	(0.2795)
Observations	79246	79246	79246
Pseudo R-squared	0.7429	0.6124	0.7593
Log pseudolikelihood	-289676161.4	-101349587.5	-187013632.6
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.5: Baseline estimation with recipient's imports

Use of alternative estimation: Dynamic Probit Model

We employ a dynamic probit model to assess the likelihood of recipient countries receiving climate aid based on the determinants used in the baseline results. Unlike a standard probit model, the dynamic probit model includes the lag of the dependent variable among the explanatory variables. This model is particularly valuable when analyzing data with temporal dependencies or persistence effects, which may be the case in climate finance flows. The inclusion of past values of the dependent variable allows to capture the effect of historical events on current outcomes, offering a clearer understanding of how past experiences influence present probabilities. By incorporating lagged values, the model can control for unobserved effects that vary over time and mitigate omitted variable bias (Arrelano and Bond, 1991; Roodman, 2009b; Cameron and Trivedi, 2021). Compared to static model, dynamic probit model is supported to handle complex panel data structures and enhance forecasting accuracy by considering the temporal dimension of data (Wooldridge, 2002; Bun and Makridis, 2022). Here, the dependent variables - CFinance, Grants, and Loans - are treated as binary, taking a value of 1 if the recipient country receives climate finance and 0 otherwise. The model used and its estimation follow the approach outlined by Albarran et al. (2019) and Albarran et al. (2020). Albarran et al. 2019 implement the model by addressing challenges associated with unbalanced panels and the correlation between random effects and explanatory variables, which can complicate estimation. They opt for random effects rather than fixed effects due to their ability to efficiently use both between- and within-unit variations, their robustness to unbalanced data, and the flexibility their offer for modeling temporal dynamics. This choice helps overcome some limitations of fixed effects, particularly regarding missing data and computational complexity (Cameron and Trivedi, 2005; Baltagi, 2008; Wooldridge, 2010; Greene, 2012). Estimation is conducted for each sub-panel, with the common parameters being obtained via the minimum distance method. This approach is asymptotically equivalent to the maximum likelihood estimator, but reduces computational complexity. The model is structured as follows:

$$CFin_{ijt} = \phi CFin_{ijt-1} + X_{it}\gamma + Y_{jt}\lambda + Z_{ijt}\varphi + \epsilon_{ijt} \tag{3.5}$$

Where $CFin$ represents the binary dependent variables: CFinance, Grants, and Loans. X_{it} refers to the variables specific to provider countries, Y_{jt} relates to the recipient countries' specific variables, Z_{ijt} encompasses the shared variables between countries i and j and ϵ_{ijt} represents to the error term. We estimated the model both with and without lags of other explanatory variables (Tables 3.6 and 3.7, respectively). The results align with the baseline findings, indicating that countries vulnerable to climate change unlikely to receive climate aid. Consistent with the benchmark results, the probability of receiving climate aid is positively associated with factors such as the provider's exports, trade agreements (RTA), investment treaties (BIT), development aid, institutional quality and colonial ties, as shown by the positive and significant coefficients for theses variables when considered for the "CFinance" dummy variable. When comparing grants and loans, having a colonial link with the provider country increases the likelihood of receiving grants, while having political proximity (DiploD) with the provider countries increases the likelihood of receiving loans. A new insight from this model is that countries that have previously received climate aid are more likely to receive it again in the future.

Variables	CFinance	Grants	Loans
CFinance (lagged)	1.1457***		
	(0.0185)		
Grants (lagged)		1.1551***	
		(0.0186)	
Loans (lagged)			0.5853***
			(0.0646)
CV03 (lagged)	0.2388	0.1912	0.6798
	(0.3379)	(0.3383)	(0.8855)
Exports (lagged)	0.1448***	0.1445***	0.3884***
	(0.0057)	(0.0057)	(0.0248)
GdpcR	-0.1581***	-0.1632***	-0.3425***
	(0.0289)	(0.0289)	(0.0775)
GdpcP	0.6817***	0.6802***	-0.1423
	(0.0343)	(0.0344)	(0.0964)
Pop	2.4531***	2.4478***	1.9608***
	(0.0769)	(0.0771)	(0.2271)
Nrent	-0.0119	-0.0131	-0.0149
	(0.0145)	(0.0145)	(0.0384)
RTA	0.0459*	0.0514*	0.1956***
	(0.0284)	(0.0285)	(0.0696)
BIT	0.2319***	0.2215***	0.3196***
	(0.0321)	(0.0321)	(0.0682)
ODA (lagged)	0.1582***	0.1581***	1.9015***
	(0.0521)	(0.0521)	(0.1981)
GHGP (lagged)	-0.3365***	-0.3401***	-0.6319***
	(0.0375)	(0.0376)	(0.0972)
GHGR (lagged)	-0.2064***	-0.2008***	-0.1751**
	(0.0304)	(0.0304)	(0.0848)
IQ	0.7011***	0.6581***	1.7606***
	(0.1905)	(0.1907)	(0.5464)
Col	0.5021***	0.5001***	0.1303
	(0.0825)	(0.0825)	(0.1346)
DiploD (lagged)	0.0553	0.0683	-0.3809***
	(0.0471)	(0.0472)	(0.1164)
Distcap	0.1549***	0.1573***	0.3271***
	(0.0272)	(0.0273)	(0.0644)
Observations	79246	79246	79246
Log likelihood	-21552.52	-21428.46	-2660.98
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.6: Dynamic Probit Model

Variables	CFinance	Grants	Loans
CFinance (lagged)	1.1401***		
	(0.0191)		
Grants (lagged)		1.1503***	
		(0.0192)	
Loans (lagged)			0.4652***
			(0.0635)
CV03	0.2506	0.2169	0.6677
	(0.3378)	(0.3381)	(1.0981)
Exports	0.1528***	0.1515***	0.4732***
	(0.0058)	(0.0058)	(0.0291)
GdpcR	-0.2058***	-0.2085***	-0.4385***
	(0.0292)	(0.0292)	(0.0953)
GdpcP	0.6531***	0.6511***	-0.1966
	(0.0344)	(0.0344)	(0.1202)
Pop	2.6179***	2.6116***	2.5086***
	(0.0818)	(0.0819)	(0.2635)
Nrent	-0.0157	-0.0163	-0.0284
	(0.0148)	(0.0149)	(0.0464)
RTA	0.0566*	0.0611**	0.2089**
	(0.0293)	(0.0294)	(0.0822)
BIT	0.2226***	0.2136***	0.3634***
	(0.0323)	(0.0323)	(0.0833)
ODA	0.1037**	0.0979*	1.2932***
	(0.0521)	(0.0523)	(0.2094)
GHGP	-0.3273***	-0.3291***	-0.7339***
	(0.0376)	(0.0377)	(0.1227)
GHGR	-0.1705***	-0.1662***	-0.1678
	(0.0308)	(0.0308)	(0.1033)
IQ	0.8362**	0.7881***	2.2309***
	(0.1921)	(0.1921)	(0.6606)
Col	0.4668***	0.4681***	0.1188
	(0.0817)	(0.0815)	(0.1893)
DiploD	0.1113**	0.1121**	-0.2813**
	(0.0476)	(0.0477)	(0.1423)
Distcap	0.1642***	0.1666***	0.3932***
	(0.1479)	(0.0274)	(0.0824)
Observations	75791	75791	75791
Log likelihood	-20478.52	-20361.09	-2456.78
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.7: Dynamic Probit Model without lags of other explanatory variables

Use of alternative climate Vulnerability indicators: ND-GAIN Vulnerability indicator (NDG) and World Risk Index (WRI)

We assess the baseline results using alternative vulnerability indicators: the NDG-GAIN Vulnerability indicator (NDG) and the World Risk Index (WRI). The NDG indicator ranges from 0 to 1, with higher values indicating greater vulnerability. The WRI is not confined to a specific range, but higher values similarly reflect increased climate vulnerability (See Chapter 2 for more details on these indicators). In the estimation using the NDG indicator (Table 3.8), the coefficient for NDG indicator is negative and significant for total climate finance and loans, suggesting that more vulnerable countries generally receive less climate finance, particularly in the form of loans. As in the baseline result, provider exports, trade agreements (RTA), investment treaties (BIT), development aid, institutional quality (IQ), colonial ties (Col), political alignment (DiploD) and geographical proximity (Distcap) all play a role in the allocation of climate aid. Grants are specially likely to go to countries with strong institutional frameworks and those that share colonial, political and geographical proximity with the provider. Compared to grants, loans are more likely to be directed towards countries that have a trade agreement with the provider. Similarly, the estimation using the WRI indicator (Table 3.9) aligns with the baseline results. The most vulnerable countries are still unlikely to receive climate aid. Provider exports, trade agreements, investment treaties, development aid, institutional quality, colonial ties, political proximity, and geographical proximity continue to significantly influence the distribution of climate aid. Grants, in particular, are more often given to countries with good institutional quality and those that share colonial, political and geographical ties with the provider. As with NDG estimation, loans are more likely to be allocated to countries that share a trade agreement with the provider.

Variables	CFinance	Grants	Loans
NDG (lagged)	-14.6488*	3.3155	-31.4223**
	(8.7042)	(6.1797)	(13.3449)
Exports (lagged)	0.2393***	0.2443***	0.3792***
	(0.0521)	(0.0381)	(0.1007)
GdpcR	-0.2457	-0.4921	-0.1556
	(0.5032)	(0.3101)	(0.8579)
GdpcP	2.4868**	0.3537	6.7017***
	(1.1001)	(0.4719)	(2.2554)
Pop	2.7018***	2.7062***	2.9591***
	(0.4771)	(0.4923)	(1.0156)
Nrent	0.1376	0.2198**	0.1487
	(0.0981)	(0.0761)	(0.1571)
RTA	0.4947***	0.0977	0.5544***
	(0.1275)	(0.0982)	(0.2067)
BIT	0.2194**	0.2462***	0.2518**
	(0.0906)	(0.0859)	(0.1268)
ODA (lagged)	1.3111***	2.1121***	0.9751***
	(0.3888)	(0.4097)	(0.2544)
GHGP (lagged)	-0.9307	-0.4935	-2.4109
	(0.8213)	(0.5128)	(1.5058)
GHGR (lagged)	-1.0653**	-0.0848	-1.9215***
	(0.4118)	(0.3385)	(0.6657)
IQ	4.7686**	4.6997***	4.5208
	(1.9663)	(1.1706)	(2.8679)
Col	0.3341**	1.0114***	0.0086
	(0.1775)	(0.1847)	(0.3704)
DiploD (lagged)	-0.7251**	-0.6575***	-0.7271
	(0.3318)	(0.2339)	(0.4725)
Distcap	-0.4744***	-0.4676***	-0.1431
	(0.1486)	(0.1002)	(0.2697)
Observations	79246	79246	79246
Pseudo R-squared	0.7444	0.6138	0.7617
Log pseudolikelihood	-287978714.4	-100994438.9	-185140815.8
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.8: Estimation with ND-GAIN vulnerability indicator

Variables	CFinance	Grants	Loans
WRI (lagged)	-0.2371	-0.3028	-0.4858
	(0.2699)	(0.2376)	(0.4295)
Exports (lagged)	0.2418***	0.2441***	0.3863***
	(0.0521)	(0.0379)	(0.1012)
GdpcR	-0.0951	-0.5195*	0.2001
	(0.5339)	(0.2836)	(0.9315)
GdpcP	2.4651**	0.3581	6.6251***
	(1.1089)	(0.4719)	(2.3055)
Pop	2.9036***	2.6912***	3.7349***
	(0.4817)	(0.4888)	(0.9793)
Nrent	0.1528	0.2183**	0.1691
	(0.0994)	(0.0794)	(0.1587)
RTA	0.4951***	0.0961	0.5537***
	(0.1298)	(0.0981)	(0.2101)
BIT	0.2174**	0.2481***	0.2461**
	(0.0899)	(0.0859)	(0.1251)
ODA (lagged)	1.3424***	2.0958***	1.0379***
	(0.4037)	(0.4094)	(0.2831)
GHGP (lagged)	-0.9074**	-0.4961	-2.2896
	(0.8295)	(0.5128)	(1.5468)
GHGR (lagged)	-1.1044***	-0.0634	-2.0627***
	(0.4187)	(0.3349)	(0.7085)
IQ	4.5244**	5.0278***	4.0306
	(1.9516)	(1.2306)	(2.8461)
Col	0.3304*	1.0121***	-0.0041
	(0.1779)	(0.1848)	(0.3766)
DiploD (lagged)	-0.6988**	-0.6594***	-0.6911
	(0.3283)	(0.2317)	(0.4757)
Distcap	-0.4735***	-0.4679***	-0.1433
	(0.1475)	(0.1003)	(0.2649)
Observations	79246	79246	79246
Pseudo R-squared	0.7442	0.6139	0.7609
Log pseudolikelihood	-288221277.4	-100971998.4	-185768840.5
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.9: Estimation with World Risk Index (WRI)

Estimation regarding resource-rich countries

We evaluate now the potential determinants of international climate finance by focusing specifically on resource-rich countries, defined by the World Bank Group as nations where natural resource rents exceed 10% of GDP on average over the last three years. These countries face multiple challenges. In addition to their susceptibility to climate change events such as droughts, floods or extreme temperatures (see Chapter 2) and therefore need financial assistance for adaptation actions, many are major producers of natural resources like oil, gas, and minerals. The extraction and utilization of these resources are often designed as significant drivers of greenhouse gas emissions (Mason and William, 2020; Bardoux et al., 2016), contributing to global warming and exacerbating their vulnerability to climate change through environmental degradation (Afolabi, 2023; Agboola et al., 2021). Providing financial assistance to these countries for economic diversification and climate-friendly projects could yield substantial benefits by contributing to climate mitigation efforts. However, our results indicate that vulnerable countries within this group are not prioritized in the allocation of climate finance. Generally, climate finance tends to be directed towards countries that receive more exports from provider nations, have established investment treaties, share colonial ties, already received development aid, possess strong institutional frameworks, and are geographically proximate to the providers. Moreover, the coefficient associated with the natural resources variable (Nrent) is not significant for total climate finance, suggesting that resource-rich countries are not more likely to receive increased climate aid. Grants are predominantly allocated to countries that are politically aligned with the providers and resource-rich countries are only likely to receive grants (as indicated by the positive and significant coefficient for the "Nrent" variable in the case of Grants) even though grants constitute a small portion of total climate finance (see Figure 1). In contrast, loans are mainly provided to countries that have investment treaties with the providers. Considering that climate finance is often directed towards countries with high institutional quality, it is imperative for resource-rich nations to enhance their institutional frameworks by promoting transparency, combating corruption, and ensuring effective governance. Such improvements could serve as assurances for provider countries regarding the efficient and responsible management of climate aid.

Variables	CFinance	Grants	Loans
CV03 (lagged)	-5.7222	-13.2983	9.0535
	(9.1213)	(10.2531)	(19.6748)
Exports (lagged)	0.1556***	0.2118***	0.0281**
	(0.0589)	(0.0484)	(0.0136)
GdpcR	0.2161	0.4435	-0.2886
	(0.4971)	(0.3859)	(1.7336)
GdpcP	0.0742	-0.6855	7.0076*
	(1.1249)	(0.7799)	(4.3521)
Pop	4.0081**	4.7365***	8.4219*
	(1.6318)	(0.9041)	(5.1237)
Nrent	0.0056	0.3404**	-1.1029**
	(0.1774)	(0.1426)	(0.4346)
RTA	0.1526	-0.1398	0.1746
	(0.2521)	(0.2107)	(0.6199)
BIT	0.4973**	0.1029	0.5947*
	(0.1981)	(0.1584)	(0.3552)
ODA (lagged)	2.1796***	2.6054***	1.3461
	(0.5181)	(0.4423)	(0.9113)
GHGP (lagged)	-0.3841	-1.2634	-1.9997
	(0.9545)	(0.8193)	(3.0927)
GHGR (lagged)	0.0162	-0.5524	-1.6837
	(0.4781)	(0.4262)	(1.6044)
IQ	10.7119***	4.3538**	25.1971***
	(2.2183)	(1.8811)	(6.9197)
Col	1.0542***	1.0006***	3.4955***
	(0.3228)	(0.3465)	(0.7328)
DiploD (lagged)	-0.4619	-0.8216**	-0.2221
	(0.5408)	(0.4132)	(1.2858)
Distcap	-0.8989***	-0.8977***	-1.5691**
	(0.2801)	(0.2019)	(0.6414)
Observations	24834	24834	24834
Pseudo R-squared	0.6270	0.6425	0.6594
Log pseudolikelihood	-57465044.02	-27845888.13	-25042064.94
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table 3.10: Estimation with Resource-rich countries

Estimation With the 10 Largest Provider Countries

We estimate the baseline model for the ten largest provider countries: Japan, Germany, France, the United States, Norway, the United Kingdom, South Korea, the Netherlands, Australia and Sweden. These countries contribute significantly, accounting for approximately 90% of total climate finance. The results are consistent with the baseline findings, indicating that vulnerable countries are not prioritized in the allocation of climate aid, as evidenced by the negative and insignificant coefficient associated with the vulnerability indicator (CV03). Factors such as exports from provider countries, trade agreements (RTA), investment treaties (BIT), development aid (ODA), institutional quality (IQ), political proximity (DiploD) and colonial ties generally influence the allocation of climate aid. In the specific case of grants and loans, grants tend to be particularly directed towards countries with lower GDP per capita, those with strong institutional quality, countries with colonial ties to the provider and those geographically closer to the provider, similar to the benchmark results.

Variables	CFinance	Grants	Loans
CV03 (lagged)	-7.2975	-0.2781	-15.3726
	(7.9602)	(7.5461)	(11.9102)
Exports (lagged)	0.2629***	0.2668***	0.3951***
	(0.0613)	(0.0496)	(0.1057)
GdpcR	-0.0476	-0.6185**	0.1972
	(0.5746)	(0.3106)	(0.9184)
GdpcP	5.1423***	2.0875*	7.5522***
	(1.8336)	(1.0821)	(2.8862)
Pop	3.1986***	2.9971***	3.5217***
	(0.5406)	(0.5489)	(1.0522)
Nrent	0.1285	0.1748*	0.1379
	(0.1114)	(0.0909)	(0.1597)
RTA	0.5495***	0.178*	0.5653***
	(0.1401)	(0.1084)	(0.2163)
BIT	0.2205**	0.1837*	0.2532**
	(0.0958)	(0.0995)	(0.1276)
ODA (lagged)	1.2378***	1.8973***	1.0033***
	(0.3622)	(0.4346)	(0.2733)
GHGP (lagged)	-2.4113**	-2.7013***	-2.6318*
	(0.9626)	(0.5173)	(1.5774)
GHGR (lagged)	-1.1525**	-0.0032	-1.8961**
	(0.4711)	(0.4076)	(0.7367)
IQ	4.4788**	5.0348***	3.6077
	(2.1624)	(1.3071)	(3.0224)
Col	0.2418	0.7436***	0.0171
	(0.1939)	(0.2045)	(0.4003)
DiploD (lagged)	-0.7696**	-0.5186*	-0.8574*
	(0.3571)	(0.2827)	(0.4471)
Distcap	-0.3734**	-0.3775***	-0.1132
	(0.1681)	(0.1185)	(0.2748)
Observations	26490	26490	26490
Pseudo R-squared	0.7164	0.5931	0.6844
Log pseudolikelihood	-237564232.3	-65364213.94	-175651188.2
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.11: Estimation for the 10 most provider countries

Estimation for the Most Recipient Regions: Asia, Africa and America

We focus on the most recipient regions: Asia (Table 3.12), Africa (Table 3.13) and the Americas (Table 3.14). The findings suggest that vulnerable countries in Asia are not prioritized in the allocation of climate finance, as indicated by insignificance of the vulnerability indicator (CV03) across all climate finance flows. Similar to the benchmark results, factors such as exports from provider countries, trade agreements (RTA), investment treaties (BIT), development aid (ODA) and colonial ties tend to positively influence climate aid allocation to this region. Political proximity (DiploD) also appears to contribute to the provision of climate aid, particularly in the form of loans. Additionally, provider countries tend to grant aid to nations geographically closer to them, as suggested by the negative and significant coefficient associated with the distance between countries (Distcap). In Africa, vulnerable countries similarly do not appear to be prioritized in the provision of climate aid. Factors such as provider exports, development aid, and institutional quality play key roles in the allocation of all type of climate finance in this region. Investment treaties (BIT), colonial ties (Col) and Political proximity (DiploD) particularly influence the distribution of grants. For the Americas, the trend continues: vulnerable countries in this region are also not prioritized in receiving climate aid. As in Asia and Africa, exports from provider countries, development aid, and colonial ties generally influence the allocation of climate aid. Grants are particularly allocated to countries with low GDP per capita, strong institutional quality, and geographical proximity to the provider countries. Loans, on the other hand, are particularly provided to countries that share investment treaties and political alignment with the provider country.

Variables	CFinance	Grants	Loans
CV03 (lagged)	-16.6947	-1.2236	-27.1106
	(16.1462)	(11.6916)	(24.2386)
Exports (lagged)	0.1611*	0.0243*	0.3848**
	(0.0984)	(0.0101)	(0.1588)
GdpcR	0.6905	-1.2642***	1.1462
	(0.8622)	(0.4449)	(1.2183)
GdpcP	4.2346**	0.3098	8.1681**
	(2.0106)	(1.1724)	(3.3847)
Pop	3.0697***	1.5428	3.5319*
	(1.1234)	(1.1377)	(2.0635)
Nrent	0.3009	0.2607**	0.3244
	(0.2851)	(0.1258)	(0.2642)
RTA	0.5691**	0.4155**	0.5255*
	(0.2544)	(0.1915)	(0.3255)
BIT	0.1967*	0.2851**	0.2719*
	(0.1236)	(0.1248)	(0.1701)
ODA (lagged)	0.9867***	1.1518***	0.8694***
	(0.2678)	(0.4114)	(0.2391)
GHGP (lagged)	-1.9109	-0.3756	-3.8982*
	(1.3393)	(0.8852)	(2.1307)
GHGR (lagged)	-1.5153**	0.4801	-2.5841**
	(0.7019)	(0.5714)	(1.0127)
IQ	3.4172	7.8149***	1.8233
	(3.1358)	(1.9099)	(3.5598)
Col	0.5099*	0.9418***	0.9699**
	(0.2621)	(0.3057)	(0.3913)
DiploD (lagged)	-1.1847**	-0.7231	-1.2318**
	(0.4825)	(0.5017)	(0.5741)
Distcap	-0.3205	-0.6215***	-0.0864
	(0.3039)	(0.2055)	(0.4182)
Observations	21508	21508	21508
Pseudo R-squared	0.8109	0.6463	0.7926
Log pseudolikelihood	-122506130.8	-30103569.24	-93698499.81
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.12: Estimation for Asia

Variables	CFinance	Grants	Loans
CV03 (lagged)	5.1146	-3.8699	18.9301
	(10.1297)	(9.4862)	(15.5385)
Exports (lagged)	0.2934***	0.1693***	0.9153***
	(0.0701)	(0.0443)	(0.1245)
GdpcR	0.2269	0.1989	0.9614
	(0.4194)	(0.3681)	(1.6756)
GdpcP	0.1054	-0.0694	1.7934
	(0.7992)	(0.5347)	(4.2251)
Pop	3.0264***	3.3625***	6.1825***
	(0.7784)	(1.0782)	(2.2118)
Nrent	0.2323	0.1671	0.1959
	(0.1576)	(0.1196)	(0.2759)
RTA	0.2413	0.0653	0.8723**
	(0.2112)	(0.1332)	(0.3689)
BIT	0.3221**	0.2123*	-0.3844
	(0.1352)	(0.1205	(0.2596)
ODA (lagged)	2.6016***	3.6976***	-1.4355**
	(0.6169)	(0.5207)	(0.7046)
GHGP (lagged)	0.4261	-0.6687	4.7833
	(0.9737)	(0.7347)	(4.3561)
GHGR (lagged)	0.1817	-0.3334	0.6389
	(0.5321)	(0.4775)	(1.5531)
IQ	6.5849***	2.8628*	14.0937***
	(2.4641)	(1.7107)	(5.2936)
Col	0.3468	0.7977***	-0.7544**
	(0.2176)	(0.2611)	(0.3751)
DiploD (lagged)	-1.0653**	-1.1167***	-1.8012
	(0.4467)	(0.3551)	(1.1564)
Distcap	0.5123	-0.3437	1.7694
	(0.3281)	(0.3951)	(0.4667)
Observations	30456	30456	30456
Pseudo R-squared	0.6510	0.6280	0.6591
Log pseudolikelihood	-77689688.86	-41515125.18	-35075278.11
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.13: Estimation for Africa

Variables	CFinance	Grants	Loans
CV03 (lagged)	5.0221	-3.5964	21.6038
	(19.0783)	(15.2153)	(37.7793)
Exports (lagged)	0.5151***	0.4356***	0.7881***
	(0.1127)	(0.1229)	(0.2194)
GdpcR	0.1621	-1.7782***	2.9176
	(1.0149)	(0.5431)	(2.3717)
GdpcP	0.9791	1.2292	3.8966
	(2.4791)	(1.2957)	(7.8031)
Pop	1.2611	1.0756	3.2471
	(2.9094)	(1.7283)	(6.3571)
Nrent	-0.3885**	-0.0025	-0.6465**
	(0.1635)	(0.1589)	(0.3116)
RTA	0.0446	0.0397	0.2765
	(0.2291)	(0.1741)	(0.3728)
BIT	0.2732*	0.0659	0.2052*
	(0.1786)	(0.2416)	(0.1999)
ODA (lagged)	3.3245***	3.0682***	2.6036**
	(0.8141)	(0.5793)	(1.1931)
GHGP (lagged)	2.9719**	0.3647	5.7257
	(1.4826)	(1.1145)	(4.6139)
GHGR (lagged)	-2.8965**	-0.7451	-3.1774
	(1.2111)	(0.9892)	(2.5271)
IQ	8.2653**	6.2671**	7.8083
	(3.6197)	(2.7426)	(6.6725)
Col	1.1375***	0.6296*	1.2239*
	(0.3684)	(0.5197)	(0.6989)
DiploD (lagged)	-0.8746	-0.3012	-1.8495*
	(0.7767)	(0.4271)	(1.4271)
Distcap	0.2138	-0.9247*	3.7228***
	(0.7811)	(0.5927)	(1.4341)
Observations	18094	18094	18094
Pseudo R-squared	0.7184	0.6688	0.6813
Log pseudolikelihood	-38367992.3	-13929166.56	-23830171.95
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.14: Estimation for America

Estimation for Small Islands Countries

We focus on Small Island countries which appear to be among most vulnerable nations (See chapter 2) and are particularly susceptible to sea-level rise and flooding. Despite their critical geographic situation, these countries are also not prioritized in the provision of climate finance. The coefficient associated with the vulnerability indicator (CV03) is not significant across all climate finance flows. Factors such as donor exports, investment treaties (BIT) and institutional quality seem to positively influence the allocation of climate finance, especially in the form of loans to these countries. Additionally, colonial ties (Col) and geographical proximity also play a significant role in the provision of climate finance, particularly in the distribution of grants.

Variables	CFinance	Grants	Loans
CV03 (lagged)	4.4866	-2.2377	9.9771
	(11.9613)	(12.3814)	(14.5956)
Exports (lagged)	0.3397***	0.1706***	0.7605***
	(0.1002)	(0.0549)	(0.1957)
GdpcR	-0.7739	-1.1128	0.8133
	(0.9152)	(0.9331)	(3.5853)
GdpcP	0.7328	0.4718	-1.1055
	(3.0473)	(1.9415)	(7.8907)
Pop	4.5041	2.9561***	-3.8469
	(3.0629)	(2.8891)	(3.8054)
Nrent	0.3582	0.1584	0.3824
	(0.2612)	(0.2527)	(0.7209)
RTA	0.5043**	-0.2152	0.6597
	(0.2366)	(0.3211)	(0.4741)
BIT	1.6636***	0.1827	2.6188***
	(0.2196)	(0.3346)	(0.8081)
ODA (lagged)	-0.7329	0.0355	-0.8567
	(1.6744)	(1.0425)	(1.0202)
GHGP (lagged)	4.0808**	1.4511	13.9008**
	(1.8967)	(1.4682)	(6.5098)
GHGR (lagged)	-0.4702	-0.5996	0.0111
	(0.6669)	(0.6393)	(1.7426)
IQ	7.2855**	4.7431	26.0975*
	(3.1212)	(3.3389)	(14.6051)
Col	1.0051***	1.3194***	0.1782
	(0.2444)	(0.3341)	(0.6232)
DiploD (lagged)	1.4766*	1.0803**	4.4772**
	(0.7624)	(0.5521)	(1.7364)
Distcap	-0.9202***	-1.6174***	0.5862
	(0.3512)	(0.2557)	(0.5888)
Observations	16461	16461	16461
Pseudo R-squared	0.6741	0.6867	0.6556
Log pseudolikelihood	-11382283.31	-6600116.48	-3919632.089
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.15: Estimation for Small Islands countries

Estimation by Considering Climate Finance Through Targeted Objective: Climate Adaptation Finance and Climate Mitigation Finance

We assess our results by examining climate finance through targeted objectives: Climate Adaptation and climate Mtigation. Climate Adaptation Finance (CAF) aims to enhance a country's capacity to cope with the impacts of climate change, while Climate Mitigation Finance (CMF) provides financial support to reduce carbon emissions and foster greener economic growth. The findings for both adaptation finance (Table 3.16) and mitigation finance (Table 3.17) are consistent with the benchmark results. Vulnerable countries are not prioritized in the distribution of climate aid. Specifically, the coefficient for the vulnerability indicator (CV03) is negative and significant for total climate adaptation finance and loans-CAF, indicating that more vulnerable countries tend to receive less climate adaptation finance, particularly in the form of loans. Provider exports and trade agreements also seem to influence climate adaptation finance in a manner similar to the baseline results. Additionally, investment treaties (BIT), development aid (ODA), colonial relationships and institutional quality are positively associated with climate adaptation finance, particularly in the provision of grants. As with the baseline results, donor countries tend to allocate climate adaptation finance, especially grants, to countries that are geographically closer to them. Regarding climate mitigation finance, the vulnerability indicator is negative and not significant across all climate finance flows, suggesting that vulnerable countries are less likely to receive climate mitigation finance. Donor exports, trade agreements, investment treaties, and development aid positively influence the allocation of climate mitigation finance. Political proximity (DiploD) and geographical proximity (Distcap) also seem to contribute to the provision of climate mitigation finance. Another notable finding is that recipient countries with higher greenhouse gas emissions are not prioritized in the allocation of climate mitigation finance, which contrast with Halimanjaya (2015), who argued that climate mitigation finance tends to be allocated to countries with higher carbon emission intensity.

Variables	Total CAF	Grants-CAF	Loans-CAF
CV03 (lagged)	-28.8973**	-5.8208	-59.1561**
	(12.8292)	(6.9184)	(24.6363)
Exports (lagged)	0.2192***	0.2606***	0.2793**
	(0.0494)	(0.0366)	(0.1137)
GdpcR	0.0106	-0.4894	1.4582
	(0.5541)	(0.3473)	(1.2745)
GdpcP	-0.9921	-0.8053	5.7178*
	(0.8488)	(0.5453)	(3.4858)
Pop	0.3565	1.3525*	2.5987
	(0.9299)	(0.7818)	(2.0008)
Nrent	0.0582	0.3489***	-0.1463
	(0.1505)	(0.0941)	(0.2894)
RTA	0.6532***	0.0226	1.2051***
	(0.1718)	(0.1077)	(0.2575)
BIT	0.2354**	0.2801***	0.2011*
	(0.1049)	(0.0951)	(0.1582)
ODA (lagged)	1.0901*	1.5598***	0.6892*
	(0.6666)	(0.3898)	(0.3751)
GHGP (lagged)	1.0293	1.1172*	-3.3337
	(0.7782)	(0.6611)	(2.1194)
GHGR (lagged)	0.0034	0.1382	-0.3065
	(0.5926)	(0.2696)	(1.5981)
IQ	3.2652*	3.1493**	0.6694
	(2.1939)	(1.3837)	(4.6837)
Col	0.4652**	0.9989***	0.0435
	(0.1838)	(0.2085)	(0.3444)
DiploD (lagged)	-0.4318	-0.3581	-0.4195
	(0.4264)	(0.2764)	(0.8292)
Distcap	-0.4523***	-0.6611***	0.2514
	(0.1521)	(0.1079)	(0.2863)
Observations	79246	79246	79246
Pseudo R-squared	0.6518	0.6123	0.6481
Log pseudolikelihood	-140167667.6	-61153503.83	-76153701.48
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.16: Baseline estimation with Climate Adaptation Finance (CAF)

Variables	Total CMF	Grants-CMF	Loans-CMF
CV03 (lagged)	-5.4835	-6.6421	-12.9901
	(6.9864)	(6.72633)	(11.7507)
Exports (lagged)	0.2596***	0.2318***	0.4548***
	(0.0611)	(0.0473)	(0.1157)
GdpcR	-0.0301	-1.0387***	0.5211
	(0.6597)	(0.3657)	(1.0308)
GdpcP	2.7341*	0.8225	7.1301**
	(1.4491)	(0.5982)	(3.1061)
Pop	2.3117***	1.8947***	3.4344***
	(0.5424)	(0.4967)	(1.1777)
Nrent	0.1307	0.1301	0.1699
	(0.1199)	(0.0953)	(0.1741)
RTA	0.4783***	0.2078*	0.4908**
	(0.1638)	(0.1121)	(0.2326)
BIT	0.2257**	0.2502**	0.2519*
	(0.1112)	(0.0997)	(0.1467)
ODA (lagged)	1.5384***	2.5182***	1.2075***
	(0.3612)	(0.4473)	(0.2771)
GHGP (lagged)	-1.1142	-1.2625**	-2.5781
	(1.0361)	(0.6331)	(1.8502)
GHGR (lagged)	-1.4936***	-0.0633	-2.7177***
	(0.5748)	(0.4296)	(0.9043)
IQ	4.6158*	6.0445***	3.6805
	(2.6748)	(1.4545)	(3.6982)
Col	0.2196	0.9015***	-0.1042
	(0.2127)	(0.1696)	(0.4599)
DiploD (lagged)	-0.7572**	-0.7891***	-0.7397*
	(0.3832)	(0.2901)	(0.5459)
Distcap	-0.4569***	-0.3711***	-0.1619
	(0.1717)	(0.1227)	(0.3079)
Observations	79246	79246	79246
Pseudo R-squared	0.7269	0.5564	0.7348
Log pseudolikelihood	-238797339.3	-75463285.28	-157902134
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3.17: Baseline estimation with Climate Mitigation Finance (CMF)

3.4 Conclusion and Policy Implications

This chapter examined the challenge of climate change in relation to the determinants of international climate finance. Analyzing a sample of 140 recipient countries and 30 donor countries from 2000-2021 using a Gravity Panel Model, our findings indicate that countries highly vulnerable to climate change are less likely to receive climate finance, both in form of grants and loans. This suggests that vulnerable countries are not prioritized in international climate finance allocations. Additionally, self-interest factors such as economic and geopolitical considerations significantly influence bilateral climate finance, mirroring trends seen in development aid. Our results remain robust across various checks, including alternative model specifications and subsample analyses. Resource-rich countries, despite their vulnerability, also tend to receive less climate finance. This is noteworthy given their dual challenge of transitioning to sustainable energy and diversifying their economies, which could contribute to climate mitigation by reducing greenhouse gas emissions from resource extraction. For policy recommendations, we advise developed countries to focus more on vulnerable nations, particularly resource-rich ones. Since climate finance often favors countries with better institutional quality, we recommend that recipient countries work to enhance their institutional frameworks. Furthermore, given that bilateral climate aid is less likely to target the most vulnerable countries, we suggest that international institutions increase multilateral climate finance, with a focus on the most vulnerable nations. Additionally, we propose the establishment of an impartial international institution similar to the International Monetary Fund (IMF) or the World Bank, dedicated specifically to providing financial assistance to the countries most at risk from climate change.

Appendix

A List of Recipient and Provider Countries

Table A1: Recipient countries

Afghanistan	Georgia	Pakistan
Albania	Ghana	Palau
Algeria	Grenada	Panama
Angola	Guatemala	Papua New Guinea
Antigua and Barbuda	Guinea	Paraguay
Argentina	Guinea-Bissau	Peru
Armenia	Guyana	Philippines
Azerbaijan	Haiti	Rwanda
Bangladesh	Honduras	Samoa
Barbados	India	Sao Tome and Principe
Belarus	Indonesia	Saudi Arabia
Belize	Iran, Islamic Rep.	Senegal
Benin	Iraq	Serbia
Bhutan	Jamaica	Seychelles
Bolivia	Jordan	Sierra Leone
Bosnia and Herzegovina	Kazakhstan	Solomon Islands
Botswana	Kenya	Somalia
Brazil	Korea, Dem. People's Rep.	South Africa
Burkina Faso	Kyrgyz Republic	Sri Lanka
Burundi	Lao PDR	St. Kitts and Nevis
Cabo Verde	Lebanon	St. Lucia
Cambodia	Lesotho	Sudan
Cameroon	Liberia	Suriname
Central African Republic	Libya	Syrian Arab Republic
Chad	Madagascar	Tajikistan
Chile	Malawi	Tanzania
China	Malaysia	Thailand
Colombia	Maldives	Timor-Leste
Comoros	Mali	Togo

Continued on next page

Table A1 – *Continued from previous page*

Congo, Dem. Rep.	Marshall Islands	Tonga
Congo, Rep.	Mauritania	Trinidad and Tobago
Costa Rica	Mauritius	Tunisia
Cote d'Ivoire	Mexico	Turkiye
Croatia	Micronesia, Fed. Sts.	Turkmenistan
Cuba	Moldova	Uganda
Djibouti	Mongolia	Ukraine
Dominica	Montenegro	Uruguay
Dominican Republic	Morocco	Uzbekistan
Ecuador	Mozambique	Vanuatu
Egypt, Arab Rep.	Myanmar	Venezuela, RB
El Salvador	Namibia	Vietnam
Equatorial Guinea	Nauru	Yemen, Rep.
Eritrea	Nepal	Zambia
Eswatini	Nicaragua	Zimbabwe
Ethiopia	Niger	
Fiji	Nigeria	
Gabon	North Macedonia	
Gambia, The	Oman	

Table A2: Provider countries by region

Europe	Asia	America	Oceania
Austria	Japan	Canada	Australia
Belgium	Korea, Rep.	United States	New Zealand
Czech Republic	United Arab Emirates		
Denmark			
Finland			
France			
Germany			
Greece			
Iceland			
Ireland			
Italy			
Lithuania			
Luxembourg			
Netherlands			
Norway			
Poland			
Portugal			
Slovak Republic			
Slovenia			
Spain			
Sweden			
Switzerland			
United Kingdom			

B Provider Countries and their Most Recipient countries

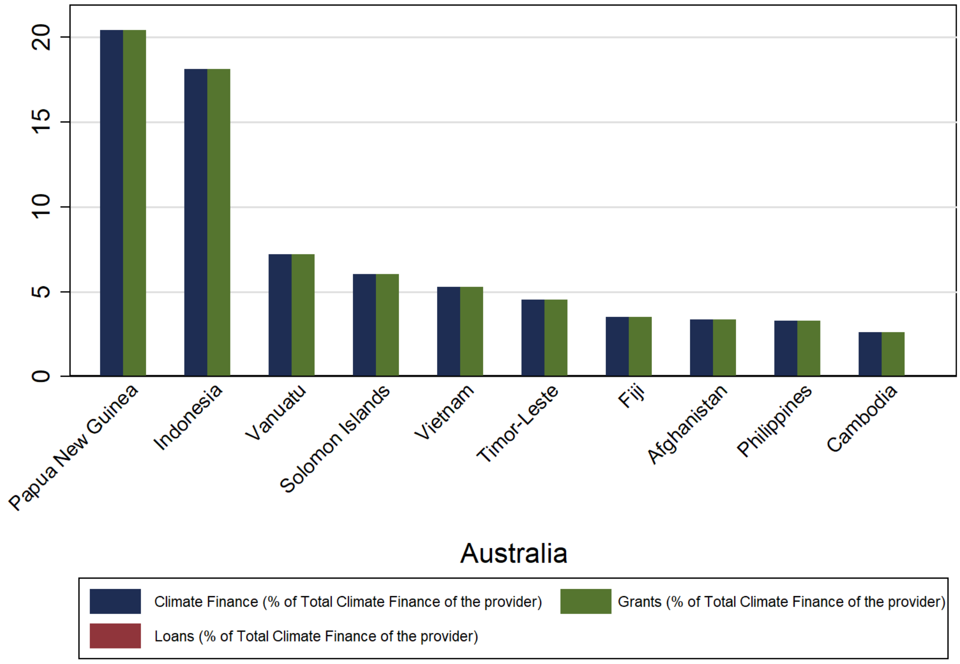

Figure B1: Australia and its 10 most recipients

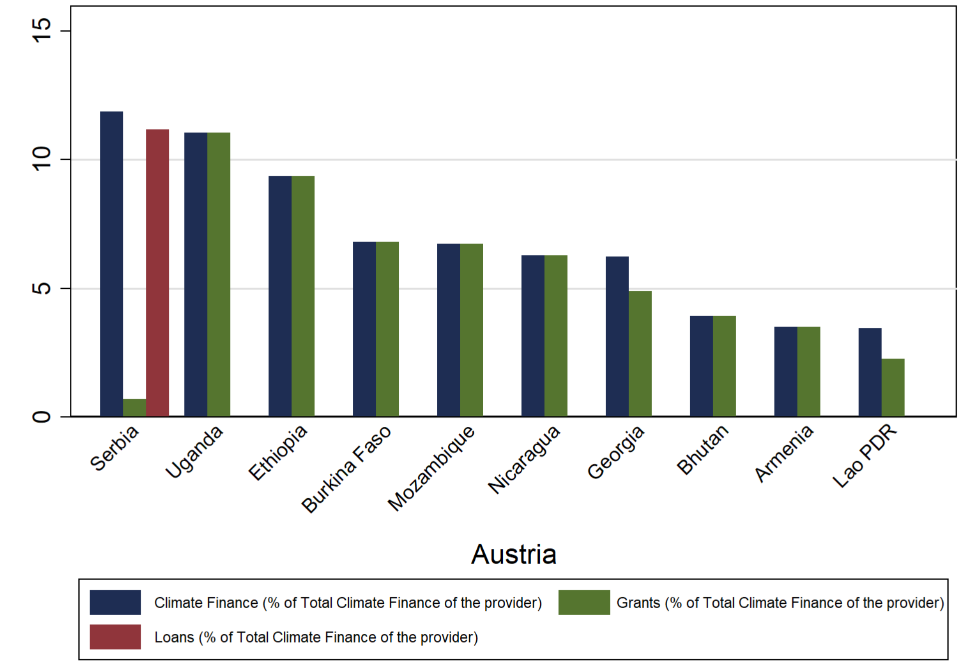

Figure B2: Austria and its 10 most recipients

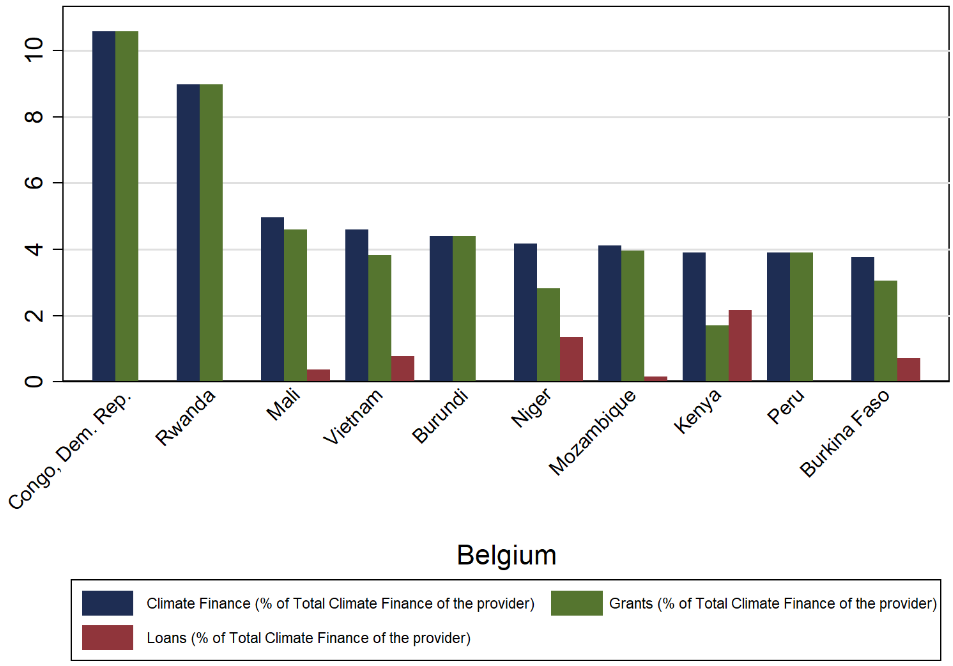

Figure B3: Belgium and its 10 most recipients

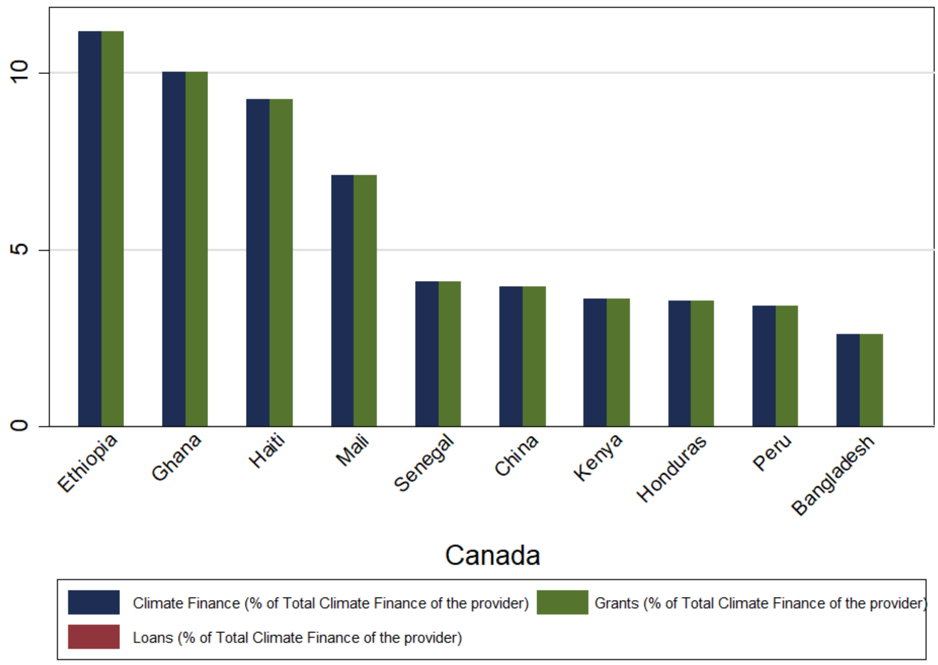

Figure B4: Canada and its 10 most recipients

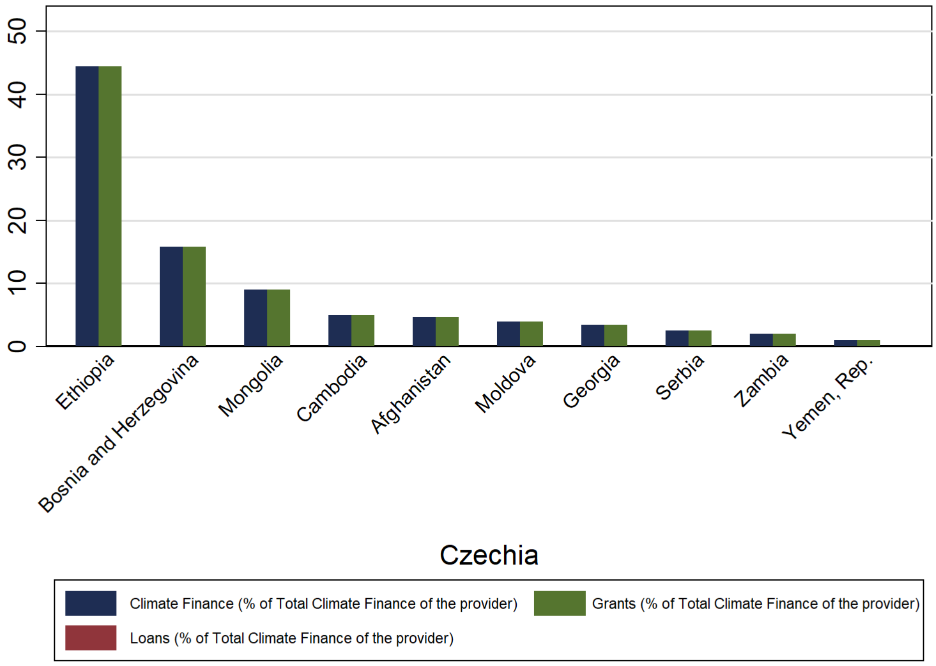

Figure B5: Czech Republic and its 10 most recipients

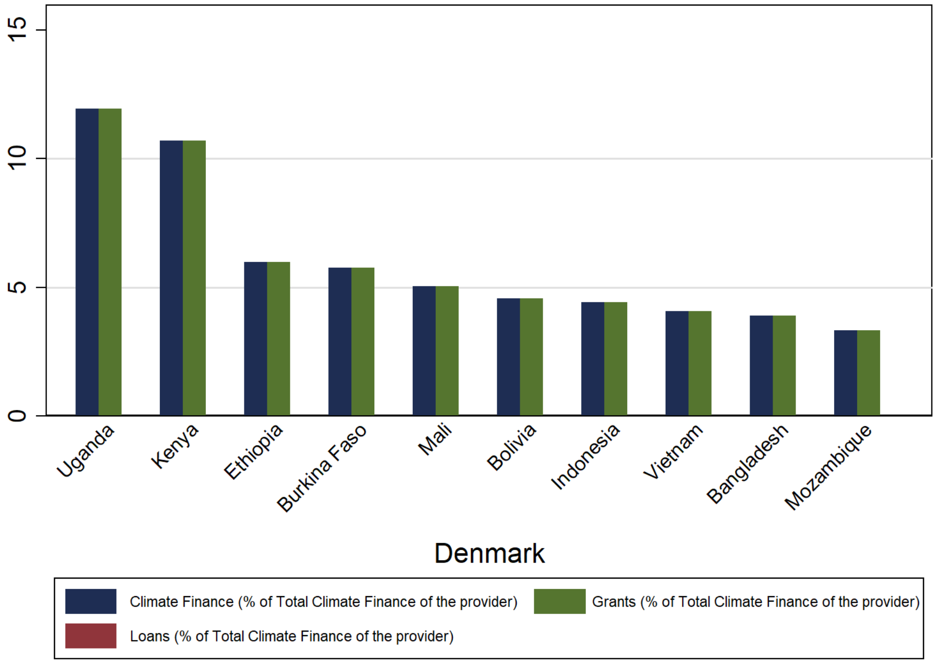

Figure B6: Denmark and its 10 most recipients)

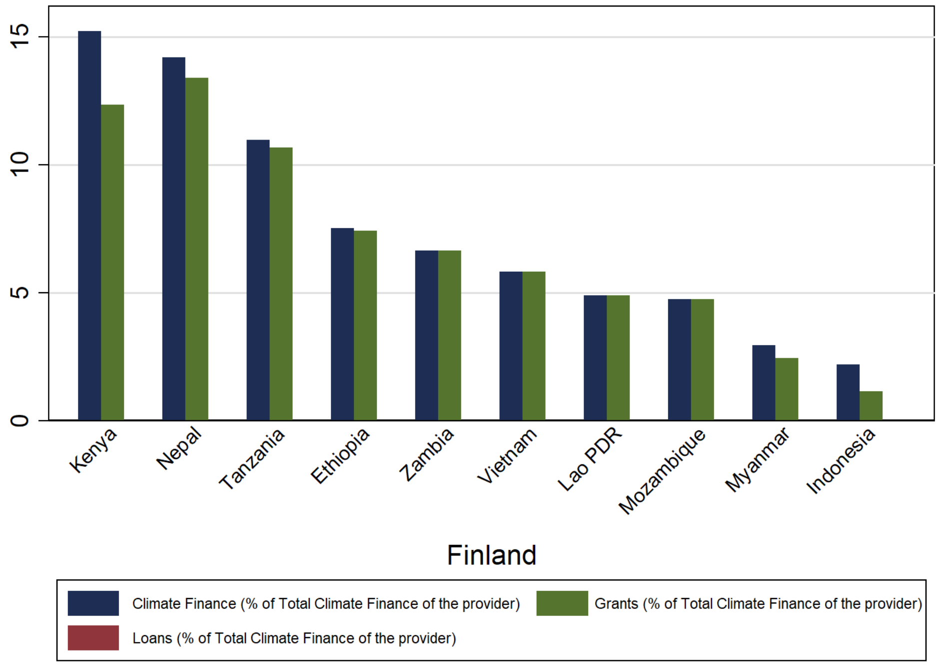

Figure B7: Finland and its 10 most Recipients

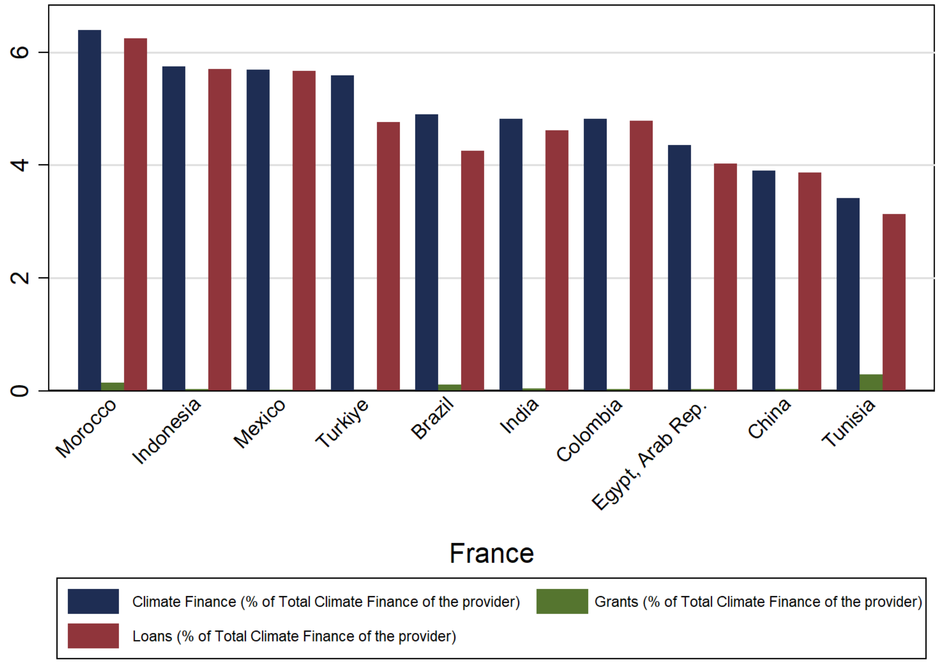

Figure B8: France and its 10 most recipients

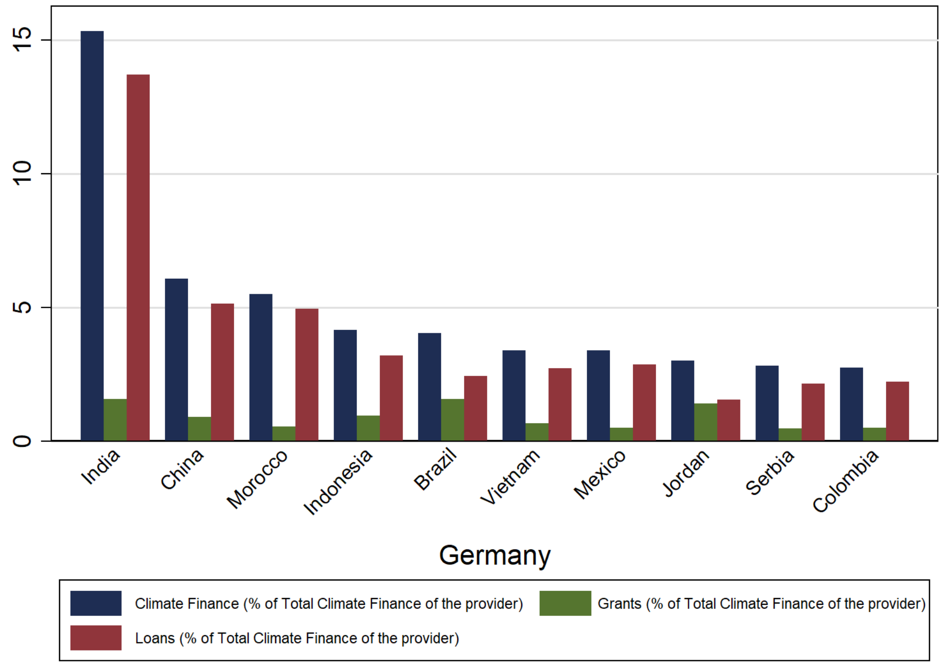

Figure B9: Germany and its 10 most recipients)

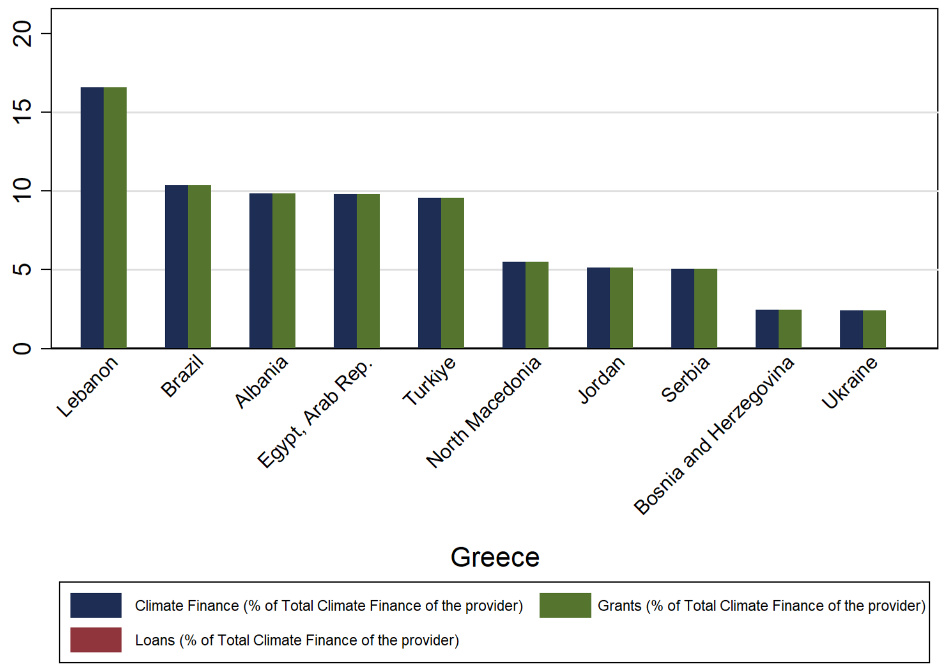

Figure B10: Greece and its 10 most recipients

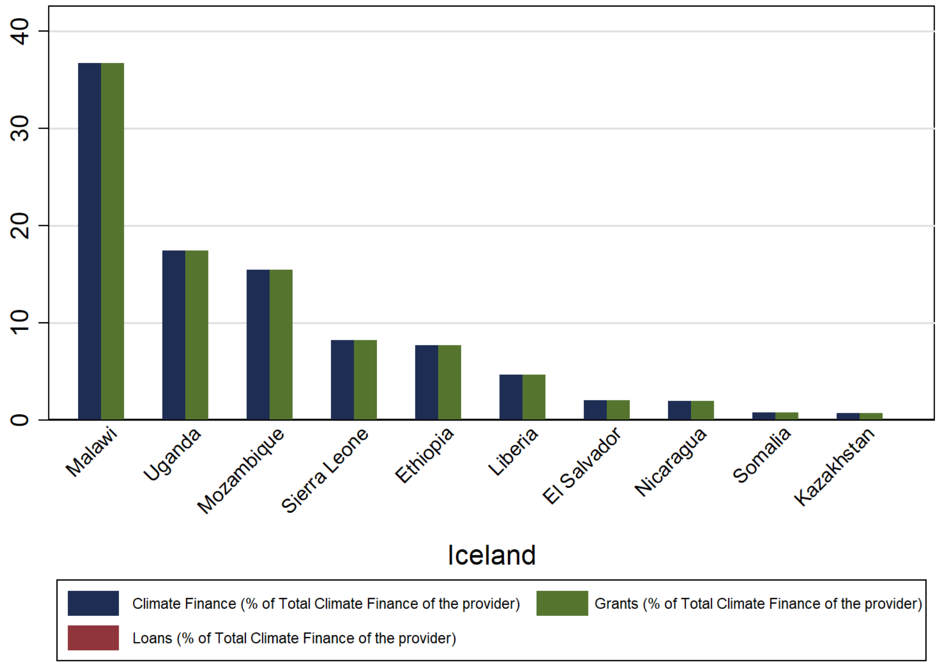

Figure B11: Iceland and its 10 most recipients

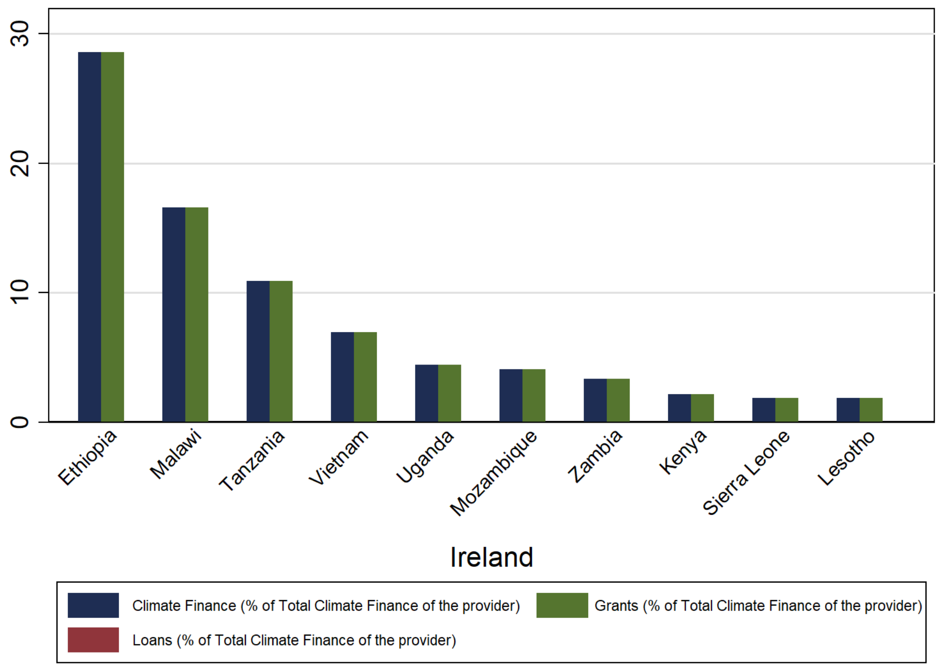

Figure B12: Ireland and its 10 most recipients

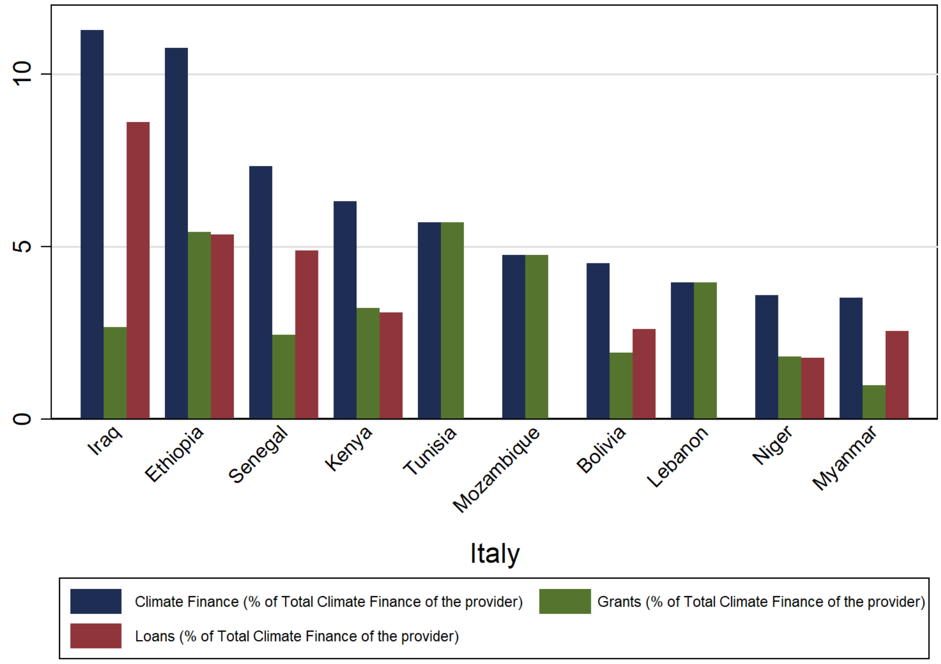

Figure B13: Italy and its 10 most recipients

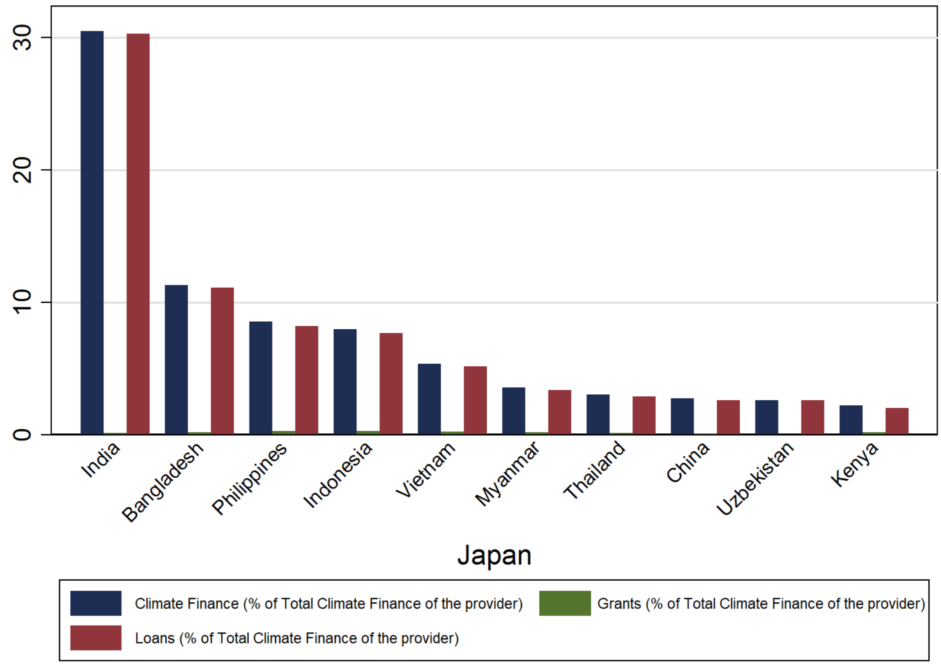

Figure B14: Japan and its 10 most recipients

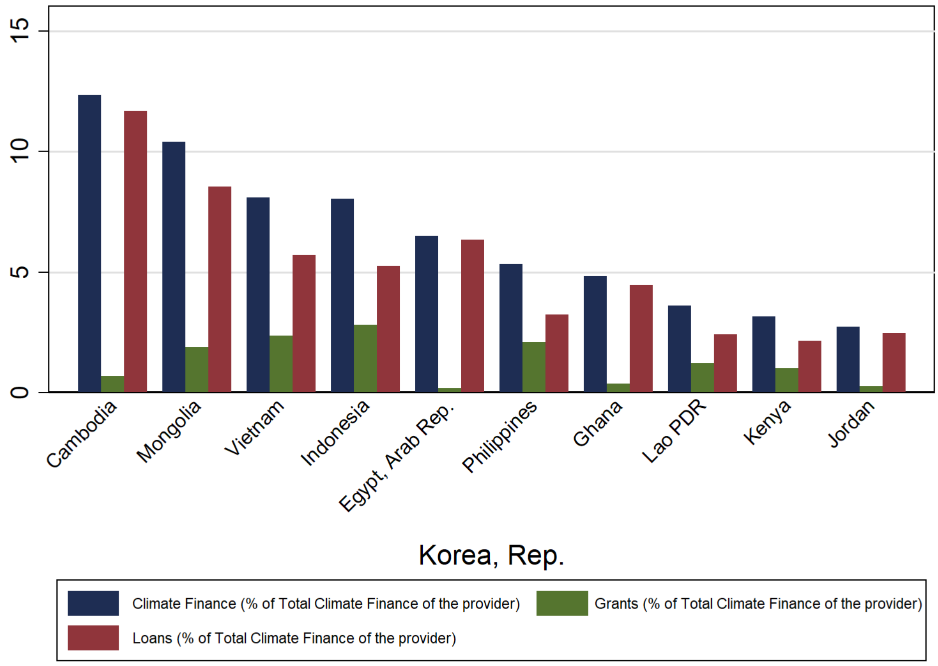

Figure B15: Korea Republic and its 10 most recipients

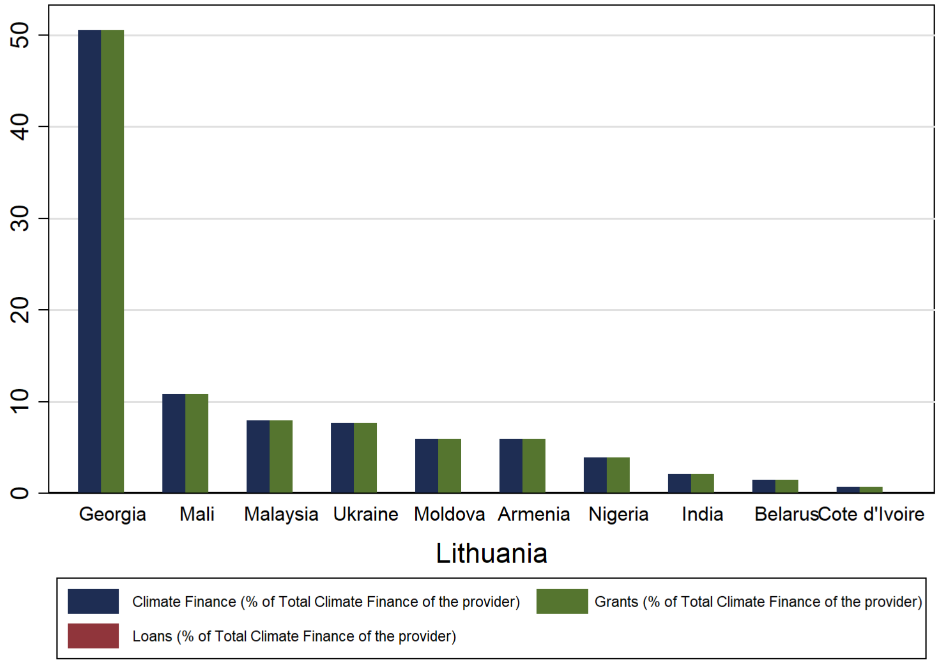

Figure B16: Lithuania and its 10 most recipients

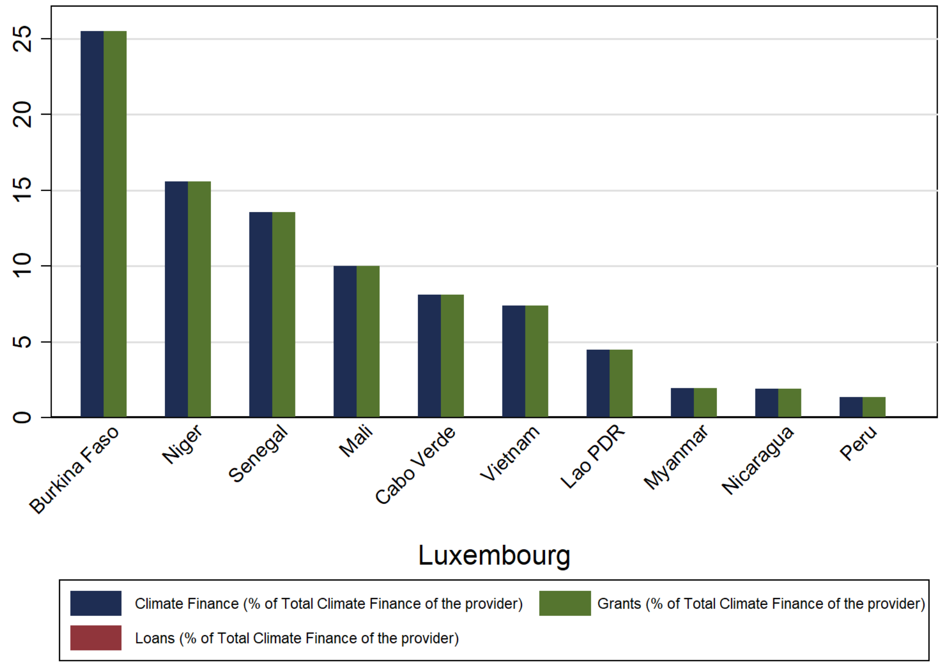

Figure B17: Luxembourg and its 10 most recipients

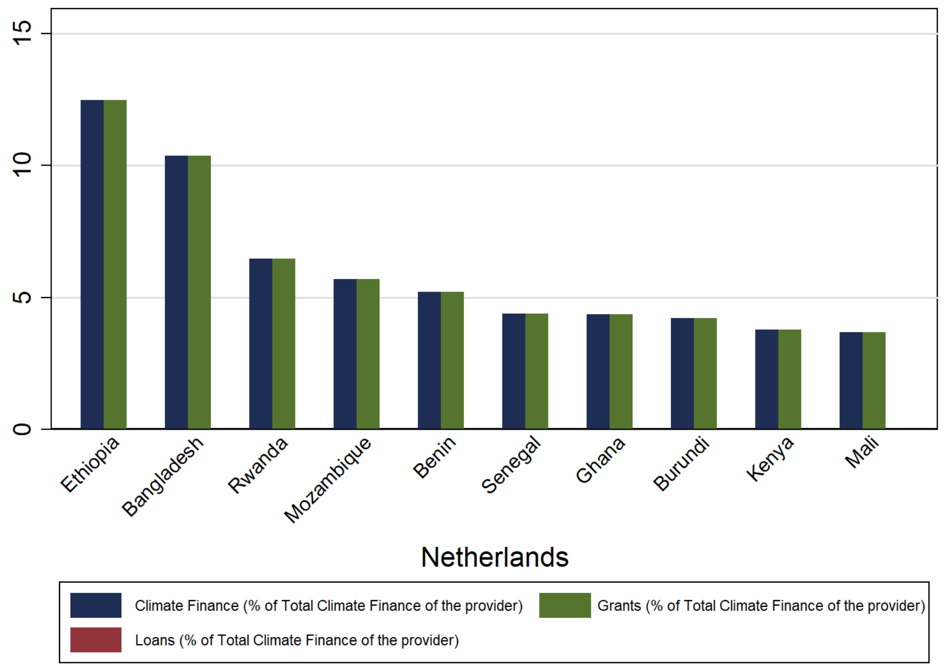

Figure B18: Netherlands and its 10 most recipients

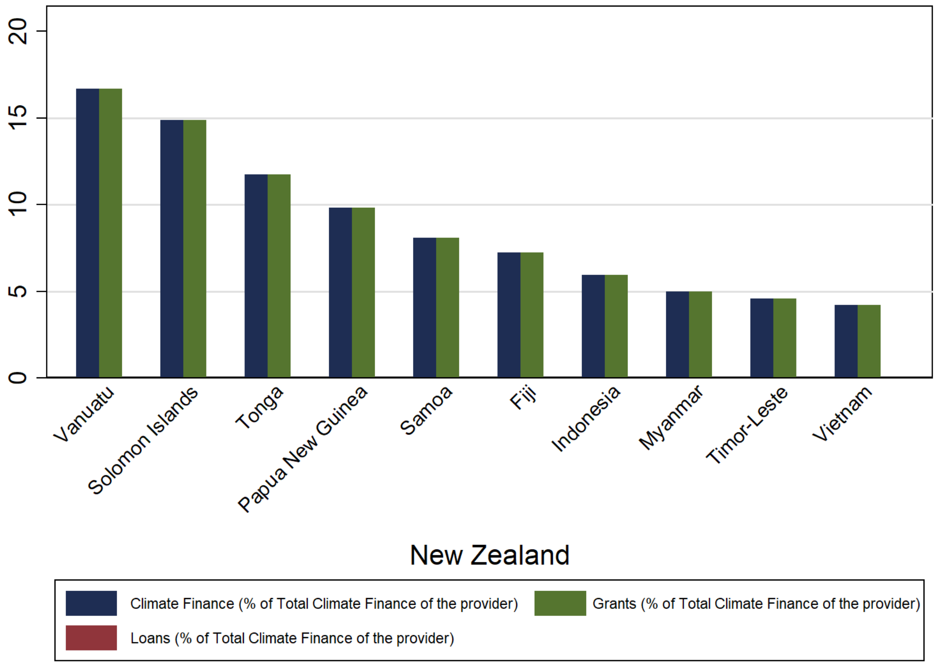

Figure B19: Newzealand and its 10 most recipients

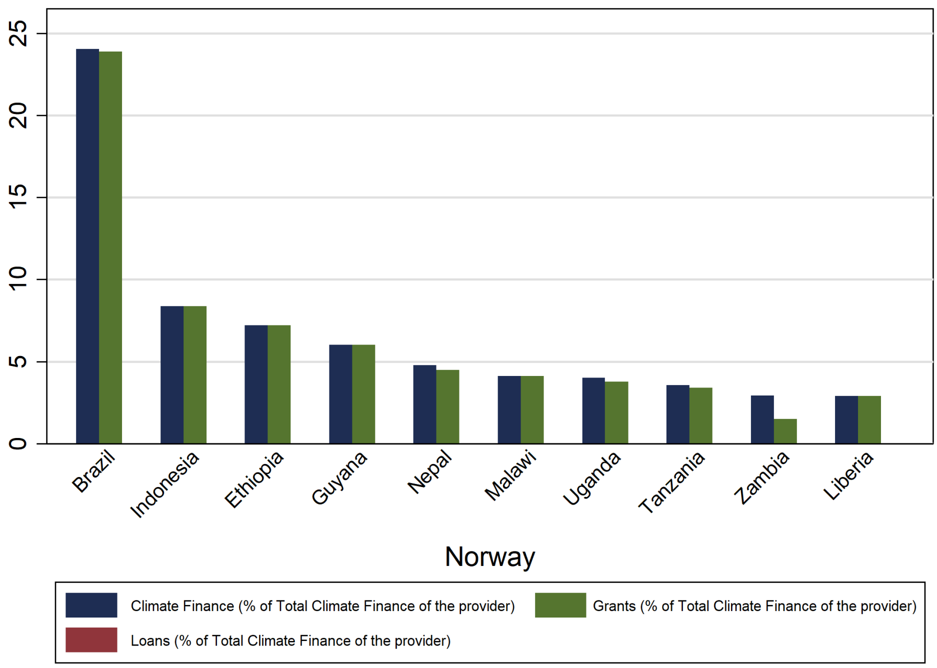

Figure B20: Norway and its 10 most recipients

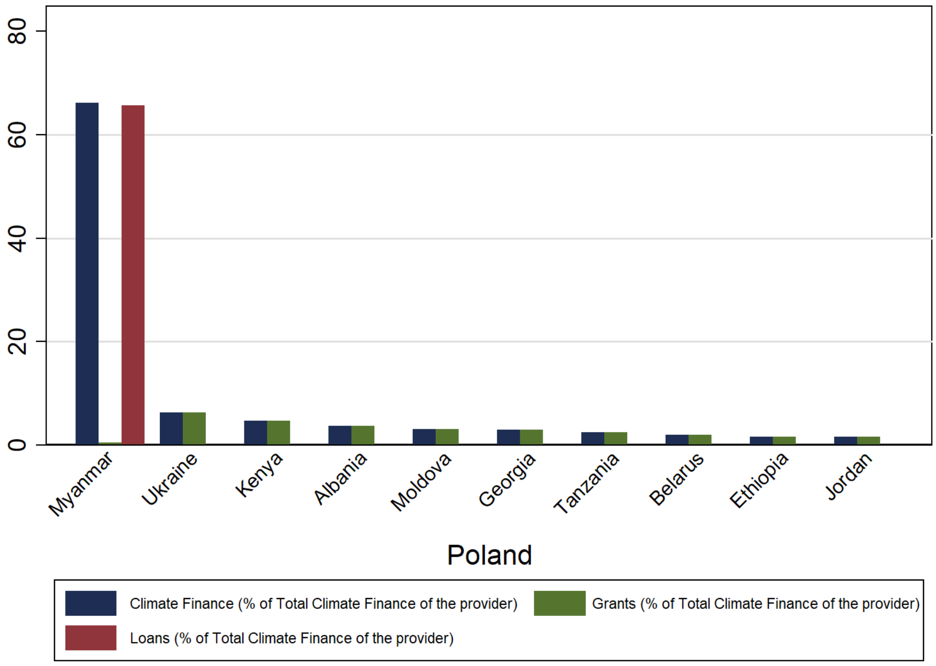

Figure B21: Poland and its 10 most recipients

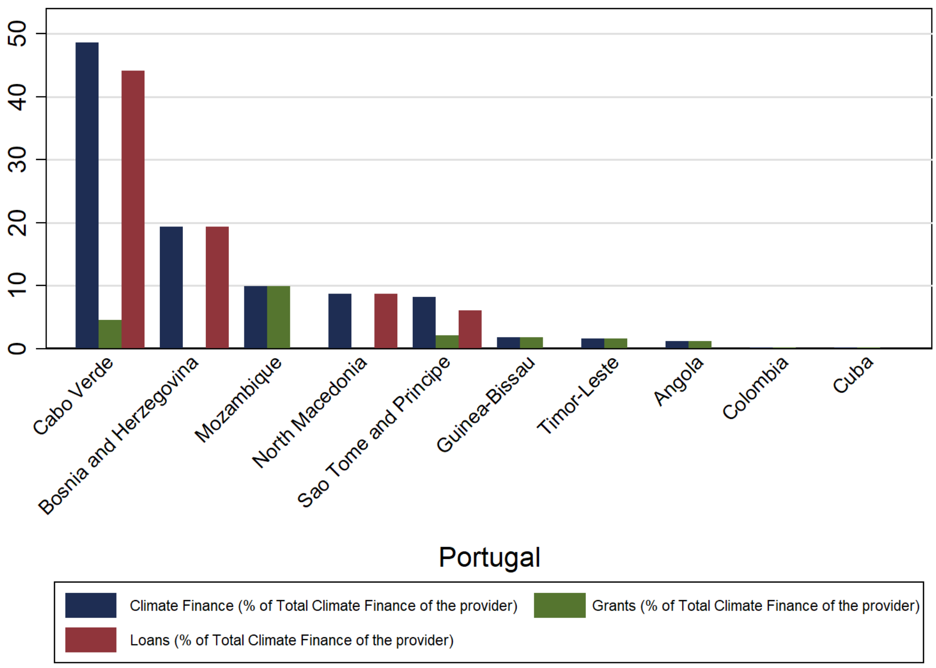

Figure B22: Portugal and its 10 most recipients

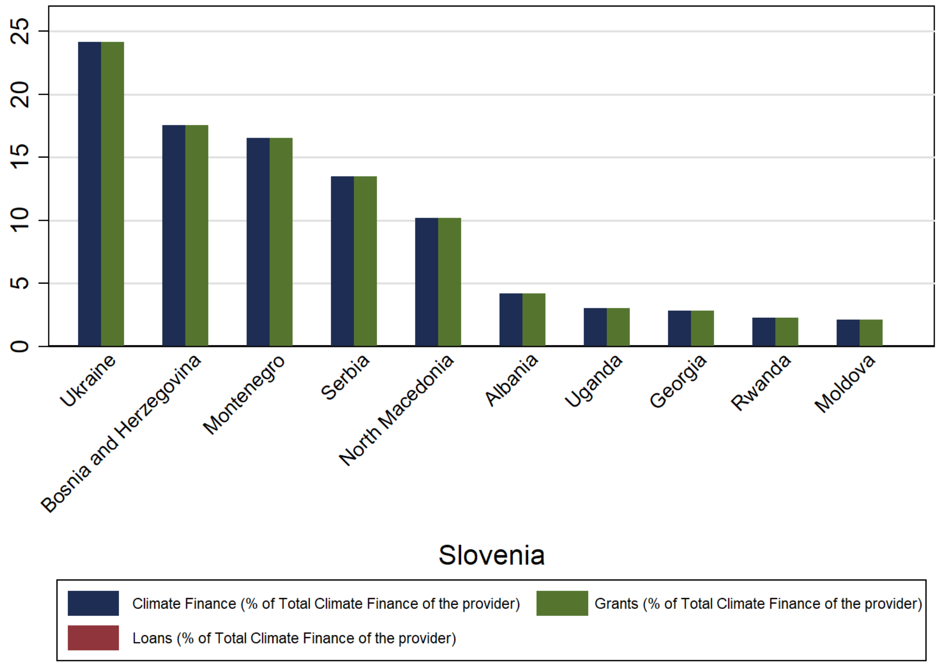

Figure B23: Slovenia and its 10 most 10 most recipients

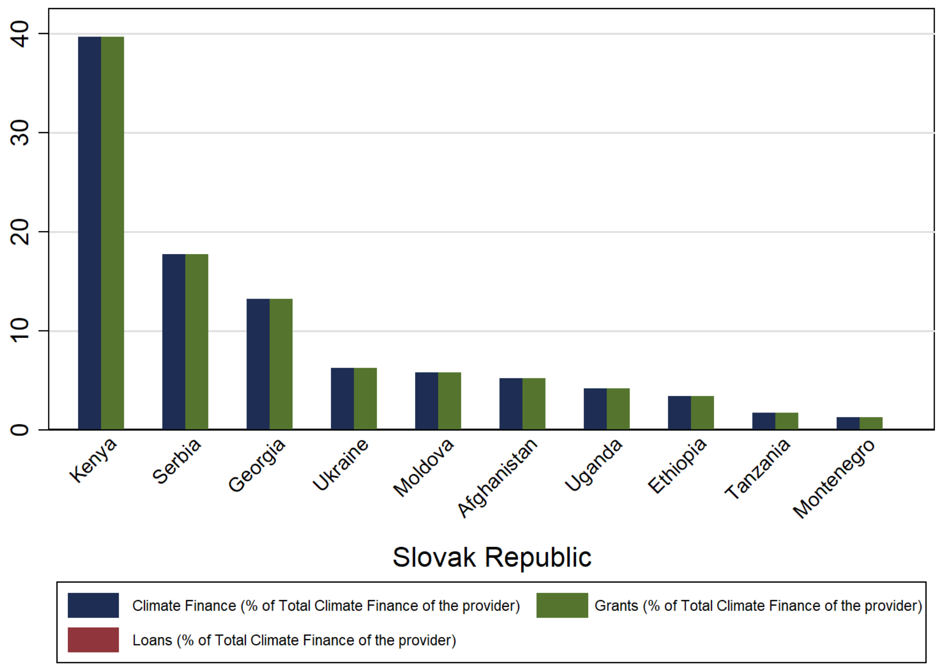

Figure B24: Slovak Republic and its 10 most recipients

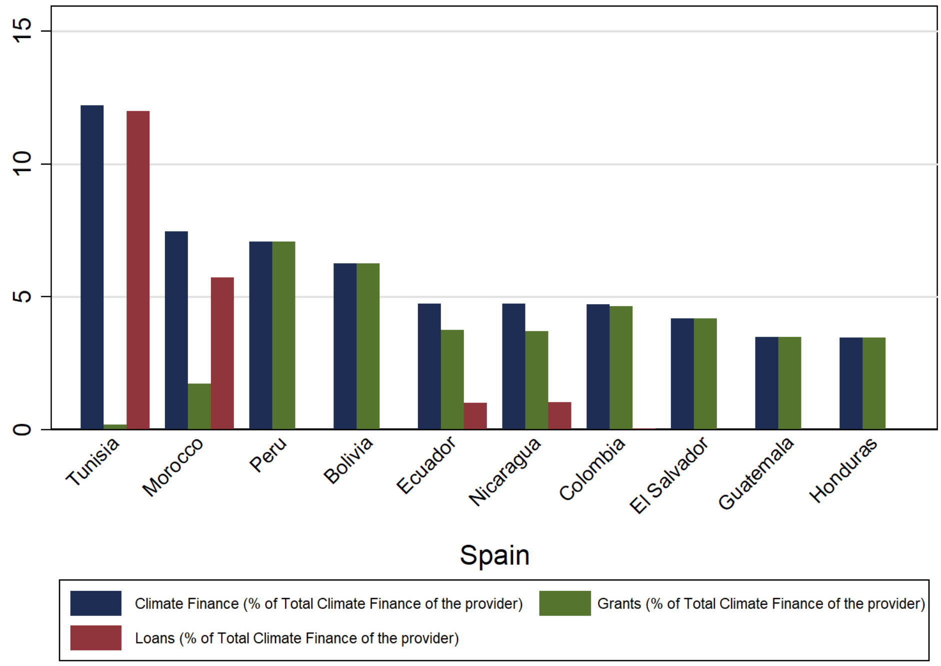

Figure B25: Spain and its 10 most recipients

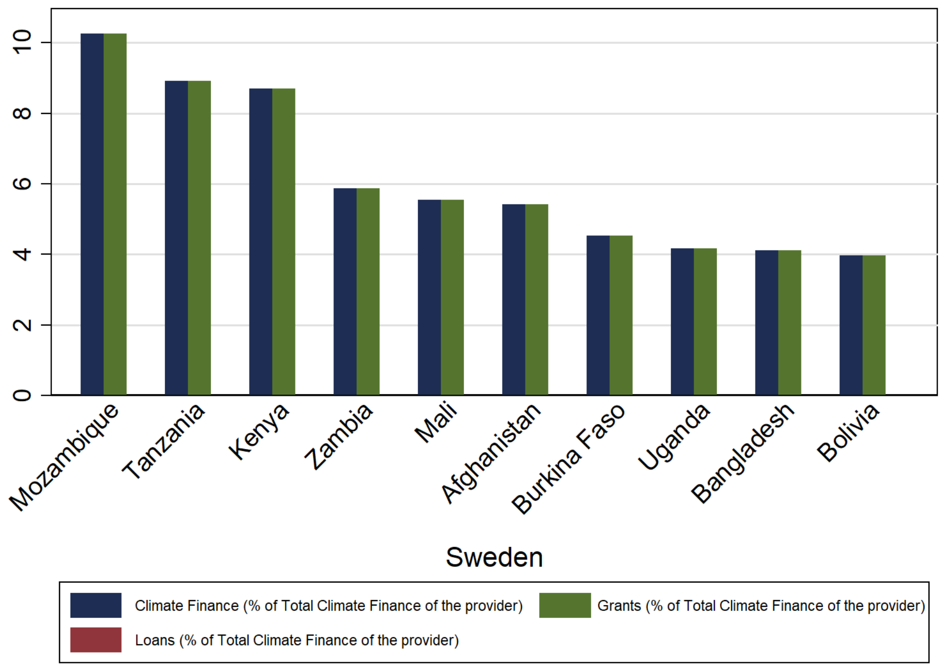

Figure B26: Sweden and its 10 most recipients

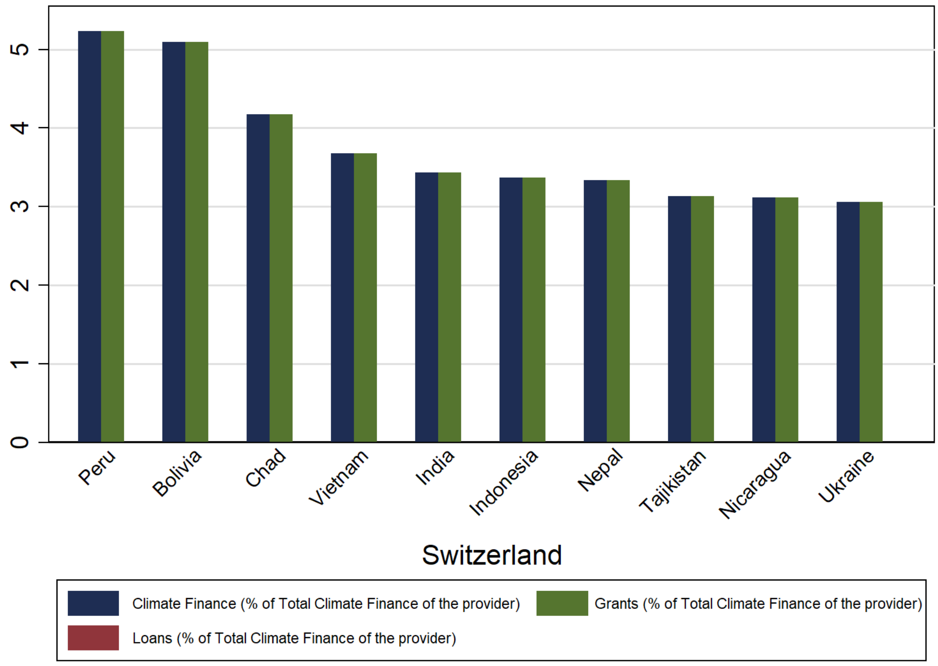

Figure B27: Switzerland and its 10 most recipients

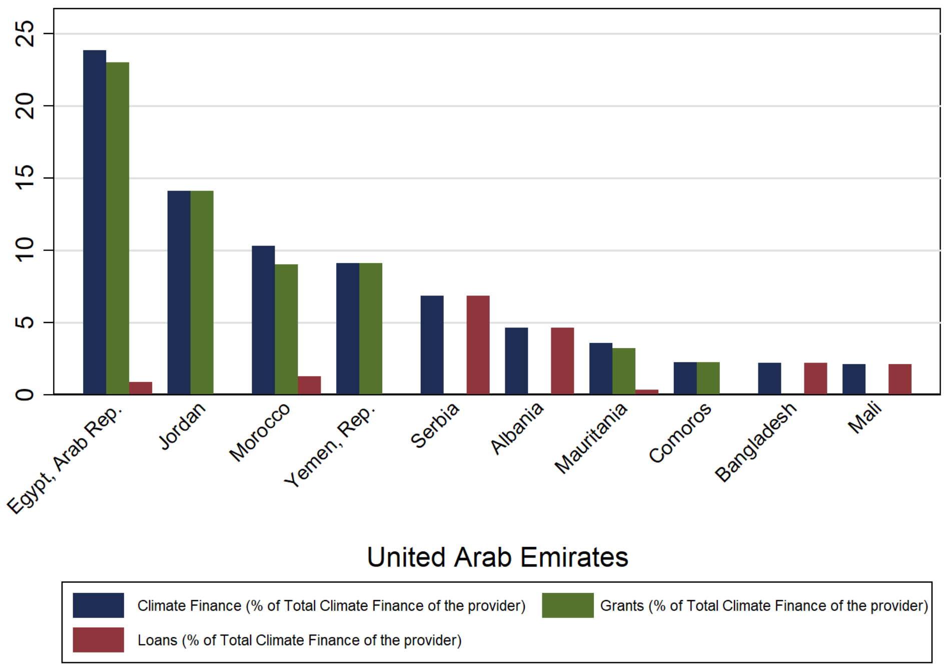

Figure B28: United Arab Emirates and its 10 most recipients

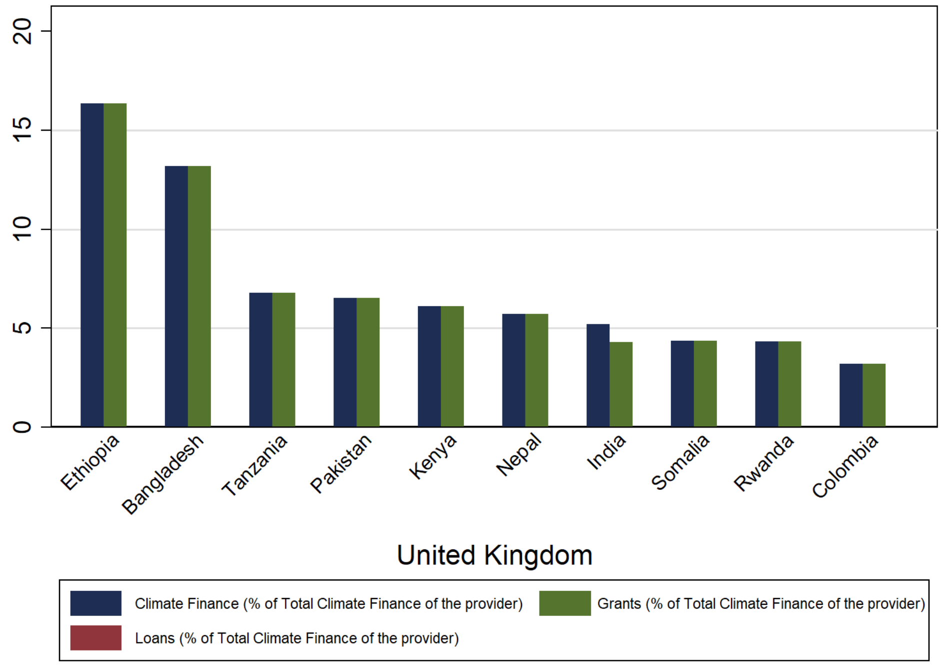

Figure B29: United Kingdom and its 10 most recipients

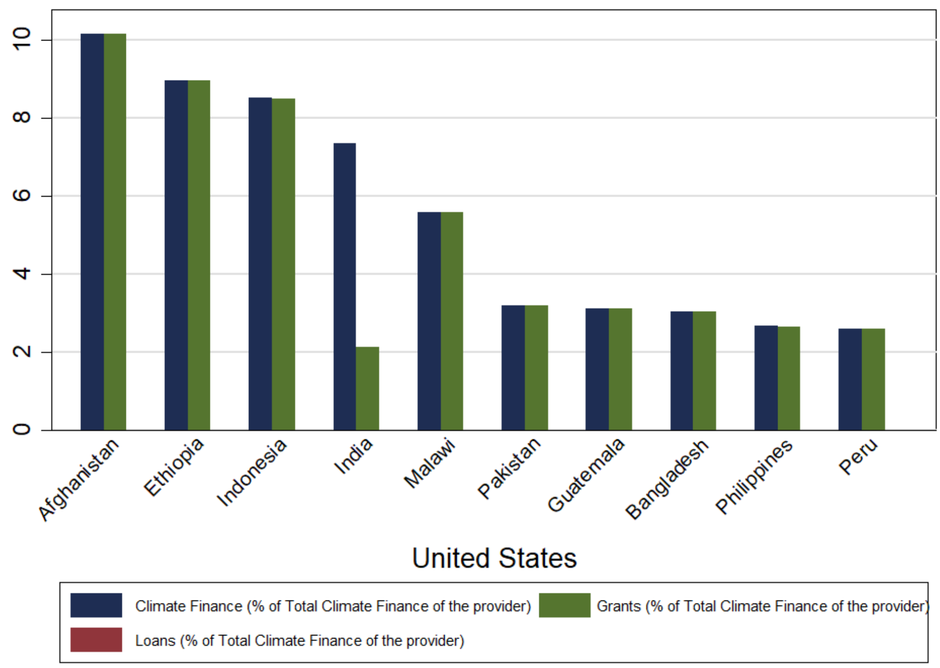

Figure B30: United States and its 10 most recipients

Conclusion Générale

Cette thèse a exploré d'une part l'interaction complexe entre le développement financier et la gestion des ressources naturelles et d'autre part les défis liés à la vulnérabilité et la finance climatique avec un regard particulier sur les pays riches en ressources naturelles. Chacun des trois chapitres a contribué à éclairer une facette de ces dynamiques, en soulignant les défis, mais aussi les opportunités, que les pays, en particulier ceux riches en ressources naturelles, rencontrent dans leur quête de stabilité économique et environnementale.

Le premier chapitre s'est concentré sur la relation entre l'abondance des ressources naturelles et le développement financier. Une question récurrente dans la littérature économique est de savoir si les ressources naturelles favorisent ou freinent le développement financier des pays qui en disposent en abondance (Beck, 2011; Beck et Poelhekke, 2017). Le concept de "malédiction des ressources naturelles" (Sachs et Warner, 1995) postule que l'abondance en ressources tend à ralentir la croissance économique, notamment à travers la corruption, la recherche de rentes, les conflits sociaux et la volatilité des revenus. Cette thèse a confirmé que, sans institutions solides, les ressources naturelles peuvent effectivement avoir un impact négatif sur le développement financier. Toutefois, elle a également montré que la qualité des institutions joue un rôle déterminant dans l'atténuation de cet effet négatif (Acemoglu et al., 2001). En d'autres termes, les pays riches en ressources naturelles peuvent tirer parti de cette richesse pour renforcer leur système financier, à condition de disposer de cadres institutionnels robustes et transparents.

Le deuxième chapitre a introduit une innovation méthodologique significative avec l'indicateur de vulnérabilité climatique "CV03". Cet indicateur est conçu pour s'affranchir des biais liés au niveau de développement économique, permettant ainsi une évaluation plus objective des risques climatiques auxquels sont confrontés les pays, qu'ils soient riches ou pauvres. La vulnérabilité climatique représente un défi majeur qui nécessite la mise en œuvre de mesures d'adaptation efficaces pour minimiser les conséquences néfastes du changement climatique. Il est donc crucial de disposer d'une mesure de vulnérabilité indépendante du niveau de développement économique des pays et qui reflète fidèlement la vulnérabilité aux effets directs du changement climatique. Ce chapitre s'est attaché à cette problématique, en proposant une évaluation macroéconomique de la vulnérabilité climatique détachée du contexte économique des pays. L'indicateur "CV03" a été construit à partir de variables de l'indicateur ND-GAIN, qui présentait des biais liés au développement et une tendance à minimiser la vulnérabilité au changement climatique, ce qui contredit l'augmentation des événements climatiques extrêmes comme les inondations, sécheresses, tempêtes et élévations du niveau des mers. Ce chapitre a donc mis en évidence l'importance de stratégies d'adaptation spécifiques, basées sur une évaluation rigoureuse de la vulnérabilité climatique plutôt que sur des généralisations liées au développement économique.

Le troisième chapitre s'est intéressé aux flux de financement climatique, avec un focus particulier sur les aides bilatérales. La finance climatique est aujourd'hui un pilier essentiel dans la lutte contre le changement climatique, notamment pour les pays les plus vulnérables (Ciplet et al., 2015). Bien que certains déterminants de la finance climatique bilatérale aient été identifiés, tels que les liens historiques issus du colonialisme et le faible niveau de développement des pays récipiendaires, des réponses ambivalentes subsistent quant à la priorité accordée aux pays les plus vulnérables face aux effets du changement climatique. Par exemple, Barrett (2014) avance que la finance climatique ne se dirige pas nécessairement vers les régions les plus vulnérables, tandis que Bayramoglu et al. (2023) soutiennent qu'elle est effectivement orientée vers ces pays. Cette thèse a démontré que les pays les plus vulnérables ne sont pas toujours les premiers à recevoir des aides climatiques, qu'il s'agisse de dons ou de prêts. Les résultats de ce chapitre ont ainsi révélé que l'allocation des ressources climatiques est souvent dictée par les intérêts politiques et économiques des pays donateurs, plutôt que par une évaluation objective des besoins climatiques . De plus, les fonds sont souvent distribués sous forme de prêts, augmentant ainsi l'endettement des pays vulnérables, au lieu d'être octroyés sous forme de dons, ce qui pourrait alléger leur charge financière.

Les conclusions de cette thèse appellent à une réflexion approfondie sur la manière de repenser la gouvernance des ressources naturelles et la gestion des risques climatiques. Premièrement, les pays riches en ressources naturelles doivent renforcer leurs institutions pour éviter la malédiction des ressources et favoriser un développement financier durable. Les politiques publiques devraient viser à diversifier l'économie et à réduire la dépendance à ces ressources, tout en mettant en place des cadres réglementaires solides pour garantir la transparence et la responsabilité. Deuxièmement, la gestion de la vulnérabilité climatique doit être revue. L'indicateur "CV03" a montré que l'évaluation des risques climatiques doit être plus nuancée, en se focalisant sur l'occurrence des événements climatiques plutôt que sur le niveau de développement économique. Il est essentiel que les politiques d'adaptation soient adaptées à chaque contexte national, en tenant compte de la diversité des défis climatiques auxquels les pays sont confrontés. Enfin, des réformes profondes sont nécessaires pour s'assurer que les financements climatiques parviennent aux pays qui en ont le plus besoin. Cela implique une plus grande transparence dans les mécanismes de distribution des fonds et une utilisation accrue des dons au lieu des prêts, afin de ne pas aggraver la dette des pays vulnérables . Une coopération internationale plus étroite, fondée sur des principes d'équité et de justice climatique, est indispensable pour garantir que les financements atteignent réellement les plus vulnérables. Une proposition clé serait la création d'une institution multilatérale internationale similaire au FMI ou à la Banque Mondiale, dont la mission principale serait de fournir des aides en prêtant une attention particulière aux pays vulnérables face au changement climatique.

Cette thèse soutient ainsi qu'il est urgent de renforcer les cadres institutionnels et de repenser les modèles de financement climatique afin de promouvoir un développement durable, inclusif et résilient pour tous les pays, qu'ils soient riches en ressources naturelles ou vulnérables au changement climatique.

Plusieurs pistes de recherche future peuvent être envisagées en prolongement des problématiques abordées dans cette thèse. Bien que cette thèse ait démontré que la qualité des institutions est cruciale pour transformer la richesse des ressources en croissance économique durable, il serait pertinent d'examiner plus en détail quels types d'institutions (politiques, judiciaires ou financières) jouent un rôle clé. Une autre piste de recherche pourrait consister à comparer les différentes stratégies de diversification économique adoptées par les pays riches en ressources naturelles. Certaines économies, comme la Norvège, ont réussi à éviter la malédiction des ressources en diversifiant leur économie et en investissant dans des secteurs non liés aux ressources naturelles. Une analyse comparative de ces cas pourrait offrir des enseignements précieux pour les pays en développement dépendants des ressources naturelles. De plus, les technologies émergentes, telles que la blockchain, les fintechs et les monnaies numériques, offrent des opportunités pour pallier les déficiences institutionnelles des systèmes financiers traditionnels dans les pays en développement. Ces technologies peuvent faciliter l'accès aux financements pour les PME et offrir des solutions plus transparentes et décentralisées. Une recherche plus poussée pourrait examiner comment ces innovations technologiques peuvent transformer le paysage financier des pays riches en ressources naturelles, en réduisant la dépendance aux systèmes financiers traditionnels (Beck et al., 2016).

Dans le contexte des défis environnementaux mondiaux, une piste de recherche intéressante serait d'étudier comment les marchés de capitaux verts peuvent contribuer au développement financier et à la transition écologique dans les pays riches en ressources naturelles. Des études futures pourraient examiner comment des politiques incitatives, telles que des obligations vertes ou des partenariats public-privé dans les infrastructures vertes, pourraient améliorer l'accès aux financements durables pour des projets écologiques. Enfin, cette thèse a révélé des déséquilibres importants dans l'allocation des fonds climatiques. Une recherche future pourrait se pencher sur une étude comparative entre les financements bilatéraux et multilatéraux afin d'apprécier également le rôle effectif des institutions internationales dans l'allocation des fonds climatiques.

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Résumé:

Cette thèse explore, d'une part, l'interaction entre le développement financier et la gestion des ressources naturelles, et d'autre part, les défis liés à la vulnérabilité climatique et à la finance climatique, avec un accent particulier sur les pays riches en ressources naturelles. Elle se structure en trois chapitres distincts. Le premier chapitre examine la relation complexe entre l'abondance en ressources naturelles et le développement financier, en mettant l'accent sur la manière dont la qualité des institutions peut atténuer l'impact négatif de l'abondance en ressources naturelles sur le développement du secteur financier. À partir de l'analyse d'un panel de 100 pays sur la période 1996-2017, ce chapitre démontre que des institutions solides peuvent significativement réduire les effets délétères associés aux ressources naturelles. Le deuxième chapitre propose une nouvelle mesure de la vulnérabilité climatique, dénommée « CV03 », caractérisée par son indépendance par rapport au niveau de développement économique. Ce chapitre met en lumière les défis spécifiques auxquels sont confrontés aussi bien les pays moins développés que ceux plus avancés en matière de résilience climatique, et montre comment une évaluation plus précise des risques climatiques peut mieux informer les politiques d'adaptation. Enfin, le troisième chapitre s'intéresse aux flux de financement climatique, notamment ceux provenant de l'aide bilatérale internationale. En examinant les allocations financières à travers un modèle de gravité, il démontre que les pays les plus vulnérables au changement climatique ne sont pas toujours priorisés dans la répartition des fonds, qu'il s'agisse de dons ou de prêts. Ce chapitre révèle que les décisions de financement climatique sont souvent influencées par des considérations politiques et économiques des pays donateurs, ce qui soulève des questions sur l'équité et l'efficacité de ces aides. Les résultats soulignent la nécessité de réformes pour mieux aligner les financements climatiques avec les besoins réels des pays les plus vulnérables. Les conclusions de cette thèse ouvrent des perspectives pour des recherches futures, notamment sur les marchés de capitaux verts, les innovations technologiques financières et des mécanismes de distribution plus équitables pour la finance climatique.

Mots-clés: Développement Financier, Pays riches en Ressources Naturelles, Changement Climatique, Vulnérabilité Climatique, Finance Climatique, Modèle de Gravité

Abstract:

This thesis explores, on the one hand, the interaction between financial development and natural resource management, and on the other hand, the challenges related to climate vulnerability and climate finance, with a particular focus on resource-rich countries. It is structured into three distinct chapters. The first chapter examines the complex relationship between natural resource abundance and financial development, emphasizing how institutional quality can mitigate the negative impact of resource abundance on the development of the financial sector. Based on an analysis of a panel of 100 countries over the period 1996-2017, this chapter demonstrates that strong institutions can significantly reduce the deleterious effects associated with natural resources. The second chapter introduces a new measure of climate vulnerability, called "CV03", which is characterized by its independence from the level of economic development. This chapter highlights the specific challenges faced by both less developed and more advanced countries in terms of climate resilience and shows how a more precise assessment of climate risks can better inform adaptation policies. Finally, the third chapter focuses on climate finance flows, particularly those coming from international bilateral aid. By examining financial allocations through a gravity model, it demonstrates that the countries most vulnerable to climate change are not always prioritized in the distribution of funds, whether in the form of grants or loans. This chapter reveals that climate finance decisions are often influenced by the political and economic considerations of donor countries, raising questions about the equity and effectiveness of such aid. The results underscore the need for reforms to better align climate finance with the actual needs of the most vulnerable countries. The conclusions of this thesis open up prospects for future research, particularly on green capital markets, financial technological innovations, and more equitable distribution mechanisms for climate finance.

Keywords: Financial Development, Resource-Rich Countries, Climate Change, Climate Change Vulnerability, Climate Finance, Gravity Model