Climate Change, International Security, and Compliance

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Abstract

This research aims to examine how risk perception and extreme weather events influence public policy development. It uses theories such as alliance formation and the security dilemma to clarify the logic of political decisions. Using advanced methods, including machine learning and regression models, the study finds that the perceived threat of climate change has minimal impact on policy compliance. The research examines the case study of Brazil to provide a nuanced understanding of the interaction between different factors and actors in shaping public policies. In Brazil, the study shows that political, economic and social dimensions significantly influence the policy formulation processes. These factors often outweigh the direct impact of climate change threats. For example, political alliances and security concerns often guide policy decisions more than environmental considerations. The study also highlights the role of economic interests and social constraints in determining public policies. Businesses, interest groups and civil society organizations exert significant influence and often prioritize immediate economic benefits over long-term environmental sustainability. The findings suggest that while climate change is a recognized threat, its impact on public policy is often overshadowed by more immediate concerns. This perception challenges the conventional wisdom that climate threats are the main drivers of political change. Instead, it highlights the complexity of policy-making, where multiple interest groups and competing interests intersect. By providing a detailed analysis of Brazil's political landscape, the research contributes to a more comprehensive understanding of how various factors interact to shape public policy beyond the sole area of climate change. This multifaceted approach offers valuable insights for policymakers seeking to address climate change in a broader sociopolitical context.

Keywords: Climate Change · International Security · Compliance · Risk Perception

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Chapter 1

Introduction

Climate Change is an ongoing topic in the literature of political science and International Relations; this happens because of the growing importance of the impacts of these events in the world. In this sense, it is expected that some of the consequences of Climate Change may trigger International Security issues. Hence, this research aims to answer the following question: To what extent are countries that are more prominently threatened by Climate Change more prone to adopt and enforce environmental policies?" The logic behind this question is that, as Climate Change is a security threat, states should enact policies to defend themselves. To explain this behavior, this paper will transpose concepts such as Alliance Formation, advanced by Stephan Walt (1990), and the theories of Security Dilemma, by Snyder (1984), to elucidate the lenses through which environmental problems can be seen as security problems. Following this idea, the research aims to assess two hypotheses: the first being, "Countries that are more threatened by Climate Change will have higher compliance to International Environmental Norms" and the second, "Individual risk perception influences public policy on the macro level." Econometric models will be used to find whether these hypotheses hold or not. The methodology involves building a compliance index score using quantitative and qualitative methods. Firstly, a Principal Component Analysis (PCA) is used in the dataset. Secondly, clusterization using K-Means algorithms of unsupervised learning, and finally, values of compliance for the clusters are assembled based on the objects within those. Results show that compliance has a negligible effect when countries feel more threatened. As for the second hypothesis, the idea is to dive deep into the case of Brazil, an important actor in international politics, given the presence of the Amazon rainforest within its territory. Hence, by assessing the political trajectory of environmental policies and observing the role of the main stakeholders, it is possible to evaluate whether the hypothesis holds or not. The results point that, if assessed with the logic of the Selectorate Theory, advanced by Mesquita (2003), then indeed, in some instances, individual risk perception can influence policy making.

To understand this research better, it is crucial to consider the definition of two core concepts regarding climate policies. The first is mitigation policies, which aim to mitigate Climate Change or reduce the pace of these changes. According to the United Nations Framework Convention on Climate Change (UNFCCC), examples of those are the reduction of CO2 emissions, the use of renewable energy sources, and even the use and promotion of the Carbon Market REDD+. Those actions help the planet not to reach the tipping points, which are planetary boundaries before any change is irreversible (Pereira and Viola, 2019). The second is the adaptation policies, which seek to adapt the world to Climate Change, although they only work until certain temperatures increase. Examples, still according to the UNFCCC, are the use of chemicals to reduce ocean acidification and greenhouse gas removal from the atmosphere, as well as using genetically modified organisms in crops to adapt food production to a warmer region or to resist drier seasons, which with Climate Change must be more frequent and extreme. Brown and McLeman (2009) define it as: "Adaptation in this context takes place through adjustments to reduce vulnerability or enhance resilience to observed or expected changes in climate, and involves changes in processes, perceptions, practices and functions."

It is also important to acknowledge the role of Brazil in International Politics to understand why it was chosen for the case study. The country is 6th in the world in terms of population, 8th in the economy, and is one of the top 10 greenhouse gas emitters. [1] Moreover, the emissions profile consists of land use change, energy, and agriculture/cattle grazing sectors contributing to over 90% of Brazil's total emissions, with land use change being the primary driver. Historically, the country has suffered and been internationally criticized for its deforestation dynamics. In this sense, particularly in the Cerrado and Amazon biomes, results from the conversion of forests into areas for agriculture, ranching, mining, and infrastructure projects. It is essential to highlight that deforestation rates decreased between 2004 and 2012 due to various factors, including better monitoring, policies to preserve forests, international funding, and public attention to Climate Change. However, the country still faces many challenges; the deforestation problem is again due to economic crises, corruption scandals, rising security issues, and anti-environment actions under the Bolsonaro administration. Moreover, the complexity of the institutional arrangement, with various groups having fluctuating positions on Climate Change depending on broader circumstances. Hence, the problem seems to be more systemic than a single issue because of the Democratic system in the country, in which the majoritarian voting for executive positions and systemic corruption also contribute to challenges in addressing deforestation and Climate Change.

Given all of that, this research goes as follows: the second chapter is the literature review, in which the core topics of literature on Climate Change and International Security are explained to the reader, moreover situating this work through the discussion. The third chapter deals with the theories and frameworks used, explaining concepts of alliance formation, Security Dilemma, and arms race and using a game theoretic approach to illustrate those theories and possible issues and outcomes. The fourth chapter explains what compliance is and the problems and limitations of measuring it. The fifth chapter tackles the methodological part, explaining all the machine learning, feature engineering, and econometric methods employed to achieve the results obtained. This comprehends the first section of the work, which generally studies the effects of threat and security on compliance and environmental politics. The second section deals with Brazil. Hence, chapter 6 takes a chronological approach to Brazil, first explaining the background of the country and then the timeline of the discussions in the country. The seventh chapter explains the institutional framework of the country, as well as the actors and their interests. The third section deals with the discussion and the link between both findings. Therefore, the eighth chapter explains the Brazilian case through a data set of extreme climate events and afterward makes a reflection and a discussion of the results and some theoretical implications. Chapter 9 finally concludes the research.

[1] "Global Greenhouse Gas Overview," EPA, accessed May 22, 2024, https://www.epa.gov/ghgemissions/global-greenhouse-gas-overview

Chapter 2

Climate Change as a Security Threat?

Climate Change is an extensive topic that contains several subtopics. However, the literature assessed in this research solely focuses on the field of climate security and environmental policies. This field is characterized by plenty of arguments and constantly ongoing research. For instance, some authors advocate that Climate Change is now a security matter (Scheffran 2012; Brown and McLeman 2009; Barnett 2003; Goldstein 2016; McDonald 2018), while others criticize these approaches (Corry 2011; Selby 2017). Beyond this debate, some scholars assume that Climate Change is indeed a security threat; however, they discuss whether it should be conceived as a traditional or non-traditional threat (Barnett 2003; Huntjens and Nachbar 2015; Nevitt 2020; Campbell and Parthermore 2016). Another subject of research concerns which procedures can be taken to deal with the issue; in this sense, some authors address how the United Nations Security Council (UNSC) should act (Nevitt 2021; Penny 2007). Advancing to the arguments used, a significant part of scholars focus on the consequences of Climate Change (Brown and McLeman 2009; Huntjens and Nachbar 2015), such as the threat multiplier argument (Brown et al. 2007; Penny 2007), the war for resources (Brown et al. 2007; Ahmed et al. 2018), and climate refugees (Nevitt 2021; Brown et al. 2007; Ahmed et al. 2018; Penny 2007). Finally, there is research directing attention to risk perception (Poushter and Manevich 2017; Lee et al. 2015; Kulin and Johansson 2020; Linden 2017; Howe et al. 2019) and literature reviews (McDonald 2018).

The identified gap in literature does not regard arguments but rather the methodology employed. Many authors opt to test their argument by applying their frameworks to case studies (Nevitt 2020; Huntjens and Nachbar 2015; Penny 2007; Brown et al. 2007; Johnstone and Mazo 2011; Fasona and Omojola 2005; Selby 2017; Busby 2013). A different methodology was employed in the study conducted by Sakaguchi (2017). The author reviews sixty-nine peer-reviewed studies on Climate Change and conflict, employing specific criteria for selection, then carries out an exploratory analysis of the methodologies and results of these studies. Ultimately, Sakaguchi finds mixed evidence for the links between violence and Climate Change (Sakaguchi 2017). Bollfrass and Shaver (2015), on the other hand, find a positive correlation between temperature rise and political violence, employing a conditional logistic regression.

Regarding legal cases, scholars use them predominantly to study the role of the UNSC (Penny 2007; Nevitt 2020; Nevitt 2021). Other authors execute an analysis based on a historical approach (Campbell and Parthemore 2016). In addition to that, some use the methodology of surveys for measuring risk perception (Lee et al. 2015; Poushter and Manevich 2017), while others choose literature reviews for the same purpose (Linden 2017; Howe et al. 2019), therefore using survey data and literature-based research (Kulin and Johansson 2020). The research carried out in this paper will use a methodology rarely used in the literature assessed, firstly a Principal Component Analysis (PCA), then an unsupervised Machine Learning clusterization method (k-means), and finally a Fixed Effect Regression Analysis using panel data. Conducted methods will be explained later.

When we focus on the logic of consequences approach, in the literature on Climate Change, Scheffran (2012) discusses the effect of temperature increases across the globe, leading to the argument of climate refugees and a higher occurrence of natural disasters. The author, moreover, highlights how wealthier regions may also face extreme conditions exacerbated by already stressful environmental conditions. Distinctly, Brown and McLeman (2009) suggest that in the existing literature, there is a consensus that poorer countries are more vulnerable to Climate Change. Following the same line, Raleigh (2010) elucidates the causal pathway between scarcity and governance. According to the author, weaker domestic institutions lead to weak governance related to higher resource competition. Barnett (2003) further adds to the Consequences Logic argument by highlighting problems such as territorial loss given the increase in sea level, which results in sovereignty issues. The scholar, moreover, discusses the consequences of migration and resource scarcity, following other authors in literature, and points out how institutions play in this logic. In this sense, a consensus in the literature is composed of the assumption that underdeveloped states or poorer areas have a higher probability of conflict due to scarcity, which is reflected in the weak or inoperant institutions existing in these areas.

Brown and McLeman (2009), besides adding to the literature on environmental stress and security (Threat Multiplier argument) using Ghana and Burkina Faso as case studies, develop a framework of five ways of undermining peace and security. First, they state that volatile weather patterns, which are changes in rainfall and temperature variations, have the potential to reshape productive capacities, exacerbating scarcities of food, water, and energy. Second, more frequent and intense natural disasters, alongside increased disease burdens like malaria, may overwhelm the coping abilities of developing countries, potentially leading to fragile or failed states. Third, climate refugees, natural disasters, and environmental shifts could drive destabilizing population movements, creating competition among groups for diminishing resources. Fourth, melting sea and land ice may unlock previously inaccessible resources, such as oil and gas reserves in the Arctic, and new transit routes like the North-West Passage, triggering disputes over ownership and control. Finally, processes like salinization, rising sea levels, and prolonged droughts could render entire regions uninhabitable, posing existential threats to small low-lying countries (Brown and McLeman 2009). The authors finally remark that some consequences are gradual while others are abrupt.

Furthermore, Campbell and Parthermore (2016) aim to redefine the idea of security threats, military and non-military.To do so, they base themselves on the literature and historical timeline analysis. They highlight the first conference in Toronto, "The Changing Atmosphere: Implications for Global Security," in 1988. In the summer of that same year, globally, people's risk perception regarding Climate Change increased due to extreme climate events, including droughts and record temperatures, which aligns with what the literature on risk perception argues. The authors also highlight the role of Bill Clinton in advocating for climate policies during his presidential terms, namely the BTU tax and other policies. The authors debate the presumption that security-framing problems must always involve military forces. On one hand, authors argue that environmental and security fields are different, and that threats are often likened to war to create a sense of urgency. On the other hand, others argue that Climate Change is more likely to affect international politics, and all sorts of political, environmental, and military threats are becoming intertwined and a part of the bigger picture. In the end, Campbell and Parthermore (2016) claim that Climate Change must figure along with other security threats.

Following the logic of the argument about consequences, Dupont and Pearman (2006) continue to identify the effects of Climate Change that correspond to security risks. Their main argument concerns food production dynamics that may be affected by changes in, for instance, rain and drought patterns, leading to exacerbation of scarcity. The authors also point out the increase in intensity and frequency of climate-extreme events as relevant to the analysis, representing another consensus in the literature. The scholars lean towards arguing about the impacts of deforestation, for instance, being one of the occurrences of pandemics due to new viruses showing up. Another consequence is the inhabitability that arises with droughts and sea-level rise, following Barnett's (2003) argument. Finally, there is another link to climate refugees and how the movement of people to other areas increases stress over resource competition. This argument is further developed by Myers (2001), who noticed the rise of environmental refugees since the 1990s for both internal and external movements. It is also possible to observe how the literature reaches common ground regarding competition over resources by incorporating variables such as already-existent ethnic tensions and demonstrating how the dispute over water, land, or stress situations may occur due to intergroup tensions. Dupont and Pearman (2006) highlight not only the competition for scarce resources but also how new oil reserves, previously inaccessible, may cause disagreement. Following the same line, Ahmed et al. (2018) also advance the mass migration argument and its consequences, such as the war over natural resources. The authors' contribution to the literature lies in incorporating the Resource Curse theory, which suggests that natural resources are a curse because they disrupt democracy (Ahmed et al., 2018). Given the decrease in agricultural land, the reduction of agricultural activities is another aspect that has been pointed out.

Following the literature, Goldstein (2016) argues that Climate Change can be seen as a security threat through three different approaches. Firstly, geographical changes; the rationale is that polar ice melting reshapes military dynamics globally and will demand adaptation from militaries. Secondly, the direct relationship between armed conflict and Climate Change; however, the author shows more skepticism regarding this idea given the lack of a clear pathway between both. Thirdly, the logic of the consequences, following the same argument most encountered in the literature that Climate Change itself represents a threat, akin to the effects of war; an increase in temperatures will lead to hunger, populational displacement, change in economic patterns, and infrastructure destruction. Here, we observe a broader definition, encompassing also global economic hazards. Huntjens and Nachbar (2015) develop this argument by providing direct evidence of how the exacerbation of already existing socio-economic problems that threaten human security are linked to Climate Change. The authors paint a bigger picture, dividing state security into social conflict and climate migrants.

Regarding state security, Huntjens and Nachbar (2015) classify threats that put states and their functions at risk in terms of institutional capacity, territorial integrity, and national sovereignty. Huntjens and Nachbar (2015) also advance the threat multiplier argument that will be further explained in the next paragraph, as well as discuss the problem of resource competition, and add to the literature by demonstrating that, given the resource dispute, states can become threats to one another. This falls into the security dilemma that one cannot be entirely certain of another's intentions. Hence, if one country is rich in resources, another may see it as an opportunity, and the resource owner sees other states as a potential threat. As for social conflicts and climate migrants, the authors claim that there is no direct evidence linking Climate Change to armed conflicts. However, the stresses over socio-economic structures will threaten human security (Huntjens and Nachbar 2015). They also argue that, rather than significant conflicts, disruption of the environment tends to lead to small-scale communal violence, especially where institutions have little efficiency and power. They also contribute to the debate by showing that in developing countries, stress situations may exacerbate poverty and marginalization of low-income individuals. Another contribution is that framing climate migration and refugees as a security issue reinforces negative perceptions and hinders effective addressing. It is also shown that in certain areas, such as Small Island Developing States (SIDS), the movement of people is inevitable due to parts of the territory becoming uninhabitable. Finally, they highlight how legal and normative frameworks are underdeveloped when addressing climate-migrants. In addition, they also argue that poorly implemented adaptation policies can also be a driver of international conflict.

Some scholars also focus on explaining the threat multiplier argument. To summarize, they argue that climate extreme events can trigger conflicts indirectly by creating stressful situations. However, no clear relationship exists, so this argument represents an ongoing debate. Johnstone and Mazo (2011) demonstrate how droughts affected wheat prices leading to the Arab Spring. Similarly, Fasona and Omojola (2005) studied the rain patterns in a region in Nigeria. They found a relationship between the change in these patterns and clashes between communities in the country. Brown et al. (2007) used the situation in Darfur to explain the threat multiplier argument; the authors created a framework that elucidates the dynamics. A population is in balance with its resources. Excessive consumption or environmental changes disrupt the balance, leading to scarcity and competition, and then conflict and the breakdown of the institutional arrangement follow, concluding in violent conflict between parties. Brown (2007) tackles the same issues, claiming that Climate Change threatens water and food security, the allocation of resources, and coastal populations due to rising sea levels, leading to displacement and forced migration which may raise tensions and trigger conflicts. The author also leans on the threat multiplier argument and argues that current problems will be exacerbated due to stressful situations. However, scholars such as Selby (2017) challenge the threat multiplier argument. The author defines the links between the Syrian Civil War and Climate Change in his work by studying crop production patterns using data analysis. In the same line of criticism of this argument, Corry (2011), in a more general argument, stresses that not every risk can be translated into a broad security matter. In this sense, there is a movement of securitization of all risks, making them cover all forms of danger and harm, disregarding the notion of existential threat.

While some authors still debate the relationship between Climate Change and conflict, Sakaguchi (2017) aims to address the discussion using a novel approach. The author assesses sixty-nine peer-reviewed studies in the area and then conducts an exploratory analysis of the methodologies employed in the studies. The author then finds mixed evidence, with most results showing a positive relationship and studies showing neutral or harmful links. The author also criticizes the empirical strategies and methodologies approaches in current research. In conclusion, most studies suggest a causal pathway; however, there is no apparent direct relationship between cause and consequence. Instead, evidence points to the threat multiplier argument. Some authors dismiss the debate and instead focus on other topics by assuming one of the sides is correct. Busby (2013) focuses his research on measuring which areas have a higher risk of disruption due to Climate Change. To do so, the author conducts mapping vulnerability research in African Countries. The author's framework goes along with the proposed research here, given that Busby and this paper seek to explain environmental and political disruption as a consequence of Climate Change. The author focuses on climate risk, while in this research the subject is compliance.

Other approaches give a holistic perspective and a summary of the primary debate. McDonald (2018) conducts historical research on the evolution of this debate. It is important to note that during the 1970s and '80s, the focus was set on the likelihood of conflicts due to the lack of competition for resources. In contrast, in the 1990s, the literature focused on wars for water access. McDonald contributes to the debate by supporting that Climate Change is a human security threat and arguing that military forces in certain countries are critical actors in providing climate security. McDonald (2018) also introduces the Ecological Security Framework. This manifesto advocates focusing on ecosystems and their resilience instead of the environment. In other words, the core of the discussion should be maintaining the capability of ecosystems to sustain life.

Penny (2007) and Nevitt (2020 and 2021) have used different approaches. These authors opt to analyze the subject using as framework international law and regulation. Penny (2007), beyond only explaining the threat multiplier argument and the problems related to climate refugees, also examines the role of the UNSC in addressing the cause and consequences of Climate Change. The core argument consists of the assumption that the highest decision-making body of the United Nations has the authority and power to deal with the issues. According to the author an immediate adoption is not advocated , although Chapter VII enforcement measures are viewed as an extreme response to the complex issue of Climate Change in this paper. However, the effectiveness of current voluntary international measures to address Climate Change may need to be improved, necessitating consideration of other options. It is also suggested that assessing alternative options, considering their legal and political limitations, is essential to respond effectively. Furthermore, the author highlights the Security Council's authority to address Climate Change's causes and consequences, should its members decide to invoke it (Penny 2007).

Penny conducts a comparative case with terrorism before 2001, the author highlights that the approach of the UNSC was ad hoc and incident-specific due to challenges in defining the problem precisely and conflicting national interests. The author suggests developing mechanisms, such as establishing an "Environmental Security Committee" to oversee domestic greenhouse gas reduction, which are proposed as potential avenues for the UNSC to exercise authority on Climate Change matters (Penny 2007). Nevitt has two papers with the same lens but different approaches; in one, Nevitt (2020) studies the relationship between environmental law and National Security Emergency Law, using the United States as a case study. The author demonstrates how US national security and intelligence services address non-traditional threats like Climate Change. Nevitt (2021), like Penny (2007), analyzes by observing the Security Council. The author's central argument is that, when the physical environment is affected, they also have spillover effects on governance structures. A comprehensive framework has been developed to include Climate Change in security topics. Hence, there are four ways to do so: extreme weather, climate migrants, Climate Change and armed conflict, and nation extinction. Both authors understand that the Security Council has the power and authority to deal with those issues. However, a change in approach by the permanent members is needed.

Another area of the literature aimed to be explored in this literature review is the risk perception field. There, the authors seek to examine factors that influence awareness of Climate Change as a threat on a personal level. This thesis will use the frameworks developed by the authors explored here to explain how individual risk perception, combined with selectorate theory, shapes environmental policy in Brazil. Some authors choose to deal with the topic using survey methodology (Lee et al. 2015; Poushter and Manevich 2017), others use literature reviews (Linden 2017; Howe et al. 2019), while a third group prefers mixed methodologies, using both elements of the literature and surveys (Kulin and Johansson 2020). Lee (2015) identifies and explores the lack of a global risk perception theory. To address this problem, the author collects existing survey data from around the world and builds a global analysis. These results should be considered despite the limitations of using different surveys that asked different questions in different time frames. Lee finds that educational level and individual beliefs about the causes of Climate Change are factors that shape with more relevance risk perception on the issue on a global level. Following the same methodology, Poushter and Manevich (2017) conducted global research to identify, among several factors, those with a higher raise awareness globally. The authors found that among several security threats, terrorism (in the form of ISIS) is the only one that ranked above Climate Change. Among the possible choices are cyber-attacks, the global economy, refugee flows, great powers (the USA, China, and Russia), power, and influence. In Brazil, 67% of the people believe Climate Change is one of the biggest threats (Poushter and Manevich 2017). The limitation of this research is the time frame, as some topics are more salient in some years than others; however, this at least shows some awareness of the problem of Climate Change.

Howe et al. (2019) approach the same topic with a different methodology; the authors seek to link subjective experiences with risk perception to Climate Change using a literature review. However, the scholar finds it difficult given the challenges concerning the different approaches used by various authors within literature and the geolocalization of each study. Both aspects are crucial when it comes to assessing risk perception. Howe concludes that specific factors, such as climate trends in warmer summers and colder winters, play a significant role in individual awareness. The central argument and evidence align with the psychological concept of experiential processing, suggesting that the closer one is to a particular event alters the perception of risk one has (Howe et al. 2019). Linden (2017), who also reviews the literature, takes a broader approach; the author aims to identify the causal pathways between several factors (social, psychological, cultural, political, and physical) to risk perception. The author finds most evidence for the Western world suggesting that several factors indeed influence the awareness of individuals on Climate Change, experiential and socio-cultural factors being those particularly relevant, particularly those with adverse effects. In this sense and going in the same direction as Howe, awareness is built when individuals face extreme events. It is also important to highlight that Linden points out that the relationship between behavior and the adoption of policies needs to be clarified, meaning that, even though individuals internalize the risk, it does not translate directly into action or advocating for pro-environmental policies. This research will come back to this argument, testing if this also holds for the macro level of analysis. Finally, Kulin and Johansson (2020), by using mixed methodology, describe the relationship between concern behavior and quality of government (QoG). The findings point out different behaviors based on whether the public or the private sphere is investigated. Both spheres show a positive relationship; however, in countries with good QoG scores, the public sphere contains a stronger and more robust relationship than the private sphere (Kulin and Johansson 2020).

The literature on environmental politics and Climate Change within International Relations is well-established and explored, making it challenging to identify overlooked gaps. Therefore, this research will not participate in discussions on whether Climate Change is a security threat. This paper will also not focus on identifying transparent causal relationships between disruptions or climate extreme events and armed conflict. Instead, it will lean on several arguments presented by authors in the logic of consequences, such as the threat multiplier argument and problems resulting from forced displacement. Moreover, it will follow the conducted research, assuming that Climate Change should be seen as a security threat because of its consequences on states and individuals.

Given all of this, the focus and contribution to the literature will be based on assessing state behavior in response to Climate Change, with the advancement of methodological approaches being the core contribution. As pointed out in this section, many scholars rely on simple quantitative methods, literature reviews, or mixed studies. Within this research, the use of machine learning techniques along with consolidated econometrics methods is proposed. The next part will dive deeply into building the argument, whereas methodology will be further explained and detailed in Chapter 5.

Chapter **3**

How do traditional Security Theories of International Relations apply to this?

This part of the research will first explain traditional concepts and theories of international relations, then adapt them to make sense in a Climate Change framework, and finally use a game theoretical approach to apply the newly translated ideas. Moreover, this paper will rely on Stephen Walt (1990) for Alliance formation to explain the traditional theories, both Balancing and Bandwagoning, and on Snyder (1984) to elaborate on the Security Dilemma. In this context, the framework developed by Gray (1971) of the arms race will also be helpful. In summary, the original idea of this paper posits that since extreme climate events are a global security threat, for any of the reasons enumerated in the previous chapter, states would form alliances (Balancing) to collaborate against them. As Mearsheimer (2001) states: "with Balancing, threatened States seriously commit themselves to contain their dangerous opponent." However, some constraints appear when putting this concept under environmental politics. For instance, threatened countries will not form alliances with others feeling threatened; instead, they will acknowledge the threat and adopt a pro-climate approach to the international system.

The rationale for the Security Dilemma theory is the same. In the traditional view, the construction of defense weapons, or the arms race, is driven by uncertainty about others' intentions (Snyder 1984). Hence, extreme climate events contain uncertainty (Barnett 2003) despite being predictable; furthermore, the threat aspect is reminiscent. Thus, States would "arm" themselves to mitigate the potential effects that Climate Change could have on their territory.

3.1 Alliance Formation Theory

Walt (1990) describes two core dynamics of alliance formation, Balancing and Bandwagoning, based on power relations rather than ideology. In short, Balancing involves allying with others to confront a common external threat, whereas Bandwagoning is about aligning with a more powerful actor. A great example of the bandwagoning dynamic occurred during the Cold War, when countries aligned with one of the two superpowers. Walt (1990) also outlines behaviors that can lead to Balancing against one State: aggregate power, geographical proximity, offensive power, and aggressive intentions, despite those not making sense when applying Climate Change logic.

In the logic of Balancing, Walt (1990) argues that under certain circumstances, states ally to balance a threat, not to face it alone. Hence, the behavior is defined as "allying with others against the prevailing threat" (Walt 1990). In this sense, alliances protect themselves from other states or coalitions that are superior and could pose a threat, and two main reasons guide this choice. First, it is a survival logic under anarchy, curbing a potential hegemon before the relative power gap is too big. Second, it serves to gain influence within the alliance, since the weaker side has a greater need for assistance (Walt 1990). Under the circumstances mentioned by the author, some assumptions consider aggregate power. For instance, the greater aggregate power one has, the greater the tendency for balancing increases.

Regarding geographical proximity, neighboring states feel an existential threat, making them more likely to balance. If the offensive capabilities are too prominent, this may lead others to balance in order to defend themselves. The same happens with aggressive behavior. It is also important to highlight that the alliances formed during wartime are to be undone once the enemy is defeated. As for Bandwagoning, Walt's (1990) pure definition is "alignment with the source of danger." In the International system, States are attracted by strength, hence in this logic, the more power one unit has, the more it will be considered a good ally. States opt to bandwagon for two reasons. Firstly, as a form of appeasement, it ultimately guarantees survival or not being attacked by the much stronger counterpart. Secondly, an alliance with the dominant side may mean sharing the spoils of victory in an eventual conflict (Walt 1990). Moreover, great power has both the effect of punishing enemies and rewarding friends since aggregate power plays a fundamentally important role in this logic. The same logic applied to the Balancing dynamic can also be employed here, meaning that the choice of alignment or Balancing depends on the State‘s rationale. Walt (1990) also emphasizes that when allying to make opposition to a threat, this alliance may not endure when the threat becomes more serious.

Facing the reality of Climate Change, it is possible to notice that this phenomenon has been causing more severe and destructive impacts each year. An example is the Atlantic Ocean hurricanes, which are getting stronger and faster, according to The New York Times [1]. When looking at Walt's argument for alliance formation, the author highlights several points: aggressive intentions, aggregate power, geographical proximity, and offensive power. In this context, those aspects also have to be reshaped. For instance, the element "aggressive intentions" changes from perceiving an intentional aggression, such as Nazi Germany in the Second World War, to indeed acknowledging Climate Change as a security threat. It is impossible to say that natural phenomenons have perverse intentions. Hence, the rational actors must perceive it based on data and observational analysis. When more than one country identifies Climate Change as a threat to its security, the trend, according to the traditional theory discussed by Walt, is to ally, either balance or bandwagon. In this case, Bandwagoning is impossible, given that the source of the threat is intangible. Considering that Climate Change is the recognized threat, hence it is impossible for a country to ally itself with it, as it is not another State, or actor, it is a force of the nature. Furthermore, the logic of Balancing would be given not through assigning military resources to combat actively but instead by promoting compliance with norms aimed at mitigating Climate Change.

Another point to consider is that, unlike traditional alliance formation literature, which suggests that alliances formed during wartime may dissolve during peaceful times (Walt, 1990), alliances formed to address climate change cannot end once the problem is mitigated. Decarbonization is seem as a non-return process, this happens because, first mitigation of climate change is based on technology switch, hence demanding investments, in

[1]Delger Erdenesanaa, "Atlantic Hurricanes Are Getting Stronger, Faster, Study Finds," The New York Times, October 19, 2023, https://www.nytimes.com/2023/10/19/climate/hurricane-intensity-stronger-faster.html.

this sense once the technology is already present and working going back would not make sense, and second, it would be costly. Moreover, it is illogical that years of investment will be disregarded and States would go back to old fashioned technologies. However, there are two situations in which this can happen, the first is when economic cycles are delaying the transition. That is, as decabornization demands constant investment, governments sometimes face situations in which other priorities are higher than investing in technology development and implementation, in this sense, carbon intensive sources may be reemployed or reactivated. The second example is governments facing emergency situations. This happens when an external shock happens and then governments are forced to, for example, restart using coal facilities to provide electricity to the population. Given these two scenarios, it explains why alliances should never end. Because the problem if humanity reduces emissions for a time span (t) and in (t + 1) carries out peak emission activities, the problem will be back. Therefore, alliances formed to mitigate climate change may not and likely will not be dissolved, as countries will continue to comply with international norms to address this global challenge. Thus, translating the concept of Balancing involves countries aligning themselves to address common external threats posed by climate change. However, this alignment entails compliance with international norms rather than traditional alliance formation with conscripted personnel.

3.2 Security Dillema

The Security Dilemma is a baseline concept in International Relations theory and happens as a consequence of the anarchical attribute of the International System (Jervis 1978). It is a problem of international cooperation because it works similarly to a Stag Hunt game (Jervis 1978). Two hunters go out to hunt; however, they only have enough resources to capture one animal each. Both hunters can capture a stag or a rabbit if they cooperate. The stag has more meat but demands cooperation to be captured. As a simultaneous game, one player will only cooperate if it is understood that the other will not have a worse payoff (Jervis 1978).

	Stag	Rabbit
Stag	$3, 3$	$0, 2$
Rabbit	$2, 0$	$1, 1$

Table 3.1: Payoff Matrix

This game has two strategies: Nash Equilibriums, the first (Stag, Stag) and the second (Rabbit, Rabbit), suboptimal. Bringing this to the International Relations study, it is possible to see that even if cooperation is desirable, it may be challenging under some circumstances. Jervis (1978) points out two aspects that explain the difficulties of the Stag Hunt scenario. First, the fear component, commitment to the current status quo, can be a characteristic of current governments; with the advancement of time, this commitment might cease existing. Second, to guarantee survival, sometimes it is necessary to abandon the status quo position. This leads to the Security Dilemma problem given that States work in the self-help logic; in this sense, to maximize their gains or guarantee security, they may abandon cooperation. In the case of security, given the anarchy of the system, increasing one's security implies decreasing the others' (Jervis 1978). In this sense, the traditional Security Dilemma theory posits that states seek security when uncertain about others' intentions in an anarchic system, leading them to build defenses (Snyder 1984; Posen 1993). In this logic, when a neighboring state starts arming itself, it can unleash another state to answer by building more weapons to protect itself against a potential threat (Snyder 1984; Posen 1993). The game is played infinitely until two possible outcomes emerge: an arms race or alliance formation (Snyder 1984). This happens because alliances help increase the information within the system, thus reducing uncertainty.

An example is the relationship between Argentina and Brazil in the atomic field. During the 50s, both South American countries had nuclear programs that caused uncertainty (Owens 1995). Hence, each discovery or acquisition of new technology by one part would create a reaction in the other part (Owens 1995). The cycle repeated until 1991 both countries agreed on institutionalizing cooperation to mitigate uncertainty between countries, forming the Brazilian-Argentine Agency for Accounting and Control of Nuclear (ABACC). In the scenario of an arms race, Colin Gray (1993) explains that, at first, antagonism between two parties must exist. The structure of their military personnel should be focused on efficiency and deterrence, and competition must be held in quantity and quality. Finally, there must be a rapid increase in amount or improvement in quality over a short period.

The Security dilemma concept applies to climate change, focusing on the rationale instead of specific outcomes such as arms race or alliance formation. Following this logic, fear of the threat prompts States to take measures to ensure survival. Hence, a country acquiring certain weapons may trigger another State to acquire weapons to defend itself. Therefore, climate change should follow the same logic since States, when perceiving it as a threat, should prompt action to protect themselves, mitigating climate change and complying with international regulations. Another critical element is the uncertainty aspect. Despite being predictable, extreme events have uncertain impacts or unvoidable consequences, contributing to the Security Dilemma. When it comes to adaptation measures, the IPCC provides framework concerning forecasting better when extreme events will happen, and technology evolved in this sense, aiming on mitigating damages and losses. The uncertainity lays on the fact that one cannot predict the destructive power and the exact consequences of these events. However, one must understand that different States perceive the climate threat differently, given the unproportionality of climate change's implications across the globe. Thus, once countries acknowledge the potentially destructive impact of climate extreme events, they should adopt climate change mitigation policies as a defense mechanism. In the end, the outcome of this Security dilemma should be an alliance formation, addressing a common external threat through policy alignment.

3.3 Game Theory Approach

Many authors rely on a game theoretic approach to explain some logic regarding Climate Change (Wood 2010; Jervis 1978; Chander 2018). Developing models range from small cooperation to solve the general problem to auction strategies to explain more complex dynamics within the area. This research will exclusively treat three cases, based on Wood (2010), to explain the argument developed in this session. At first, the prisoner's dilemma for Climate Change will be elaborated, afterward the repeated version of it, and finally, the treaty ratification game. One of the arguments that claim that Climate Change cooperation is so challenging to achieve concerns the fact that there are many incentives for being a free rider, given that not having Climate Change is a public good. All countries would benefit from it, although no one wants to face the costs of complying with specific policies to mitigate this phenomenon (Wood 2010). In this sense, the prisoner's dilemma approach can be brought forward. Therefore, reducing emissions promotes a collective good; however, the States are better off by continuing to pollute individually.

	Abate	Pollute
Abate	10, 10	0, 11
Pollute	11, 0	1, 1

Table 3.2: Payoff Matrix

In this game, the Nash Equilibrium is (Pollute, Pollute), the dominant strategy for any player to choose Pollute, providing a suboptimal outcome for the players. Despite being a very simplistic view of the problem, because Climate Change is much more than just polluting or not, this game illustrates the problem of cooperation in the field well. Now, a more complex model, in which countries play this game several times repeatedly, is regarded. Here, it is crucial to notice that the Nash Equilibrium is not changed when this game is played a finite number of times. However, when this game is played an infinite number of times, we have several subgame perfect equilibria which lay on the "folk's theorem" (Wood 2010).

	Cooperate	Defect
Cooperate	3, 3	0, 5
Defect	0, 5	1, 1

Table 3.3: Payoff Matrix

Game theory says that the trend for an infinite number of games is to cooperate, given that collectively, it produces a higher payoff for the players. Moreover, Axelrod's tournaments showed the strategy called Tit for Tat in which players mimic their opponent's previous move (Wood 2010). However, two limitations emerge from this model. The first is that gas emissions are cumulative throughout the years, and the second is that the effects of emissions are not immediate, meaning that the payoff will not be granted at the moment (Wood 2010). Finally, the treaty ratification game is a two-stage game, the first being the negotiation and the second being whether to ratify it. In this scenario, ratification has to do more with domestic politics, which are pivotal to assessing whether a treaty will be ratified (Wood 2010).

In this sense, the interactions between countries in the sense of Climate Change can also be explained using game theory. As for the argument presented in this research, the relevance of risk assessment and perception by one country prompting cooperation is crucial and supports the argument described here. Moreover, it is essential to acknowledge Climate Change as a risk, hence taking action and building trust through institutionalization or alliance formation. Therefore, following the traditional International Relations theories is essential to understanding cooperation in the field and why countries more threatened by Climate Change should comply more.

3.4 Hypothesis

Given all that has been explained, the argument posits that the higher the risk of devastation due to climate extreme events or landscape changes, the higher the actors will advocate for climate cooperation and proactively engage with the international regime, complying with international norms. This will happen because, while putting their survival at stake, internalizing Climate Change as a security threat will trigger harsher responses, explained both by the Security Dilemma theory and the compliance and cooperation with other actors in the same situation, having a common threat, described by the alliance formation theory. All of this is exemplified by the game theoretical approach of infinite games, triggering cooperation and punishing deviances. In this sense, countries experiencing more significant impacts from Climate Change are expected to comply more with international environmental norms, as they have already acknowledged the threat and are more willing to cooperate globally in mitigating Climate Change. Having considered these essential aspects, two main hypotheses emerge:

H1: "Countries more threatened by Climate Change will comply more with International Environmental Norms."

H2: "Individual risk perception influences public policy on the macro level."

Chapter 4

How to Measure Compliance?

Measuring compliance is one of the core challenges in this research. Environmental politics is different from atomic energy politics in that checking nonproliferation is much easier than checking if all targets proposed to comply with are being followed. Furthermore, enforcement is also tricky because, compared to the atomic field, there are many ways to realize and notice if a country is trying to acquire nuclear weapons, given that there is a specific place and process for this to happen. Meanwhile, there is a rough estimate of data for the reduction of emissions. However, it is only possible to go to some of the factories in one country and assess whether they comply with a framework from an international accord. In this sense, there is no available data classifying countries throughout time on a scale from non-compliant to very compliant. This chapter will focus on first explaining what compliance is, then benchmarking some metrics on how to measure compliance in other areas, and finally explaining the framework used in the methodological part to create a compliance score.

4.1 What is Compliance?

One can define compliance in many ways; this article will adopt the definition used by Slaughter and Raustiala (2002). They describe the term as a "state of conformity or identity between an actor's behavior and a specified rule" (Slaughter and Raustiala 2002). From this perspective, being compliant means adhering to a specific law and conforming with what was proposed. To illustrate, a technical example such as the International Organization for Standardization (ISO) 1 may be more valuable. This organization produces a set of rules, frameworks, and guidelines for standardization ranging from technology sectors to education, health, environment, and so on. This process guarantees the object complies to acquire a stamp, demonstrating that such a thing correctly follows predefined rules. In the case of Climate Change, compliance with, for example, the Montreal Protocol of 1987, which regulated the synthesis and utilization of approximately 100 synthetic compounds, denoted as ozone-depleting substances (ODS)[1], would mean correctly following the timelines agreed upon to reduce the ODS.

It is also important to note that the concepts of effectiveness and implementation are closely related to compliance, as Slaughter and Raustiala discuss. Therefore, implementation is an essential step towards compliance, despite not being necessary in 100% of cases. The authors highlight the importance of institutional building and legislation in some cases to achieve compliance and point out two scenarios in which compliance is not a consequence of implementation. The first is when the practices already adopted by a state comply with what was accorded. The second is due to exogenous factors. Hence, one of the externalities of the collapse of the USSR was that it was more compliant with environmental norms due to the shutdown of many industries, reducing emissions (Slaughter

[1] UN Environment, "About Montreal Protocol," Ozonaction, accessed May 23, 2024, https://www.unep.org/ozonaction/who-we-are/about-montreal-protocol.

and Raustiala 2002). In this context, implementation is not a necessary causal pathway to have compliance. In the same direction, effectiveness is not strictly related to compliance because some regimes can be inefficient, or a minimal degree of compliance already indicates efficiency (Slaughter and Raustiala 2002).

The authors also provide a list of explanatory variables clustered into six groups. The first is the problem structure, given that there are different incentives for compliance and, in adopting a game theoretic approach, coordination games are different from collaboration games. The second is solution structure, which refers to the institutional design chosen to address the problem, whether it will be a punitive or capacity-building approach. The third is the solution process, referring to the inclusiveness, perceived legitimacy, and fairness of the institutional framework adopted to comprehend the cooperative solution. The fourth concerns the quality and strength of international norms. The fifth is the domestic linkages, concerning how the international institutions operate with domestic politics, either through domestic actors with incentives to enforce the framework, the agreement shaping actors' preferences, or the reshaping of legal systems, an approach that does not demand the role of actors. The sixth is the international structure, meaning that highly institutionalized systems have a higher probability of generating spirals of compliance, referring again to what was explained in Chapter 3, about the prisoner's dilemma with infinite repetitions.

The scholarship also criticizes some approaches concerning measuring compliance, which is the biggest challenge in this research. Alvarez (2002), in his essay "Measuring Compliance," criticizes how scholars measure compliance levels up to that moment. The author points out three critical problems to be acknowledged in this research to develop the framework for the data analysis. The first criticism relies on using quantitative methods without an appropriate date or period. Alvarez also criticizes how the work was focusing too much on doctrinal debates. The second is about the confusion surrounding implementation and compliance, corresponding with Slaughter and Raustiala. Alvarez argues that it is impossible to merely assume compliance if a state has just ratified a treaty or made domestic laws in accordance with an international treaty. In addition, there are endogeneity problems, leading one to ask if a country is highly compliant because it implemented an accord correctly and has high enforcement on a treaty or because it adhered to a regime that better suits its domestic situation. Thirdly, the author advocates for "scrutinized and confined case studies" (Alvarez 2002). This means that a better option is to assess individual cases to get a better and more accurate classification of the extent of compliance a country is in a determined field.

4.2 Framework to Measure Compliance

While developing this framework, one must be aware of the risks in measuring compliance, such as confusing effectiveness with compliance, as highlighted in the previous section. Another risk is the possibility of assigning degrees of adherence to international norms. That happens because, for many international standards, a state must either adhere to and comply with them or disregard them completely. Bearing all this in mind, as well as the criticism of the literature presented by Alvarez and the variables proposed by Slaughter and Raustiala, the focus of this research when evaluating compliance will be to develop a metric that makes sense throughout time. The technical specificities of the process will be explained in the next chapter, and this section will discuss only the rationale and the justifications for this approach. In summary, the choice was to have a mixed approach using quantitative analysis and a single in-depth case study.

Environmental politics is a topic that has been gaining traction and strength throughout the years. Hence, we cannot expect compliance to be fixed over time. The degree of a country's complaints varies at different levels, depending on the domestic policy, as discussed by Slaughter and Raustiala, and on the regime being discussed. In the case of the environmental regime, there are over 3700 international environmental treaties, conventions, and other agreements from the 1850s to the present, according to the International Environmental Agreements (IEA) Database Project, hosted by the University of Oregon [2]. Because of this, it is easy to understand the challenges of measuring compliance and why no ultimate dataset containing this information is available. The first limitation of this research is that it is only possible to have highly accurate compliance metrics consistent throughout time. Domestic policies are reshaped, and regimes change; there is always a new goal every year. Therefore, some accords are more accessible to implement than others.

In this sense, the approach will not directly assign a score to a country in a particular year for compliance. Instead, the approach will be to cluster countries into groups of compliance. Moreover, with the groups assigned and the observables included in one of three groups, the next step is classifying manually what is a low level of compliance, then average, and finally high. The strategy is to observe which countries are assigned to each group for determined years. This approach is limited because it relies on the author's subjectivity. However, to mitigate bias, the idea is to use the existing literature to support the decisions based on observing which countries are assigned to specific groups. Despite Alvarez criticizing quantitative approaches such as the one proposed here, using qualitative analysis may provide a more trustworthy classification. Moreover, despite limiting the analysis, not using a specific number range for every country and clustering instead has the advantage of having a bigger space for countries to fall in, the problem with this is that outliers will also be assigned in groups, and hence need special treatment before the conduction of the analysis.

Another issue to be solved concerns not confusing implementation and effectiveness to compliance. Slaughter and Raustiala claim these three concepts do not follow cause-consequence logic. Implementation is not a prerequisite to compliance and is not a condition for effectiveness. Clustering may also represent a promising approach because, despite the authors arguing that there is not necessarily a relationship between these three phases, this is usually the logic of an international accord. However, I acknowledge that in some cases, this link may be nonexistent. This problem is solved primarily by the amount of data used, some instances in which no implementation occurred, or ineffective regimes present in the dataset. However, the number of cases in which all the phases occur is higher, and therefore, the results of clustering will be consistent, even encompassing these outliers. There is just one point in which this research will not agree with the literature presented in the first part of this chapter, and that is bringing effectiveness to the analysis. In environmental policies, results are expected given the implementation of some treaties,

[2] "IEA Database Home," IEA Database Home | International Environmental Agreements (IEA) Database Project, accessed May 24, 2024, https://iea.uoregon.edu/.

hence if a state adheres to a regime of reducing emissions, it is likely that CO2 releases will be mitigated throughout time, that is, if there is compliance with the government, at any level. In this sense, this research will opt to include data on CO2 emissions and other pollutants in the analysis to assign clusters and classifications to compliance in countries.

The variables used and the complete detailed strategy employed are explained in the next chapter. However, it is essential to highlight the rationale behind the choice to deal with compliance in this way. The literature on compliance is focused on different senses, ranging from private sector activities to government compliances, which demonstrate how difficult it is to have a definitive answer. This happens mainly because compliance is a behavior, and measuring behaviors is difficult because they are not fixed over time. Even in private companies, a boss cannot keep track of all the employees complying with the firm's rules and contracts. When escalating this logic to the international relations arena, in which there is not a supranational authority dealing with all the actors, and where the main logic is the one of self-help, it is not easy to assemble safeguards for monitoring whether one state is following everything accorded in an agreement.

Moreover, incumbency changes over time; for instance, a clear example is the environmental policies in the United States and, more recently, the Paris Agreement of 2015. Signed by the Obama administration, then withdrawn from by Trump in 2020 [3] and reinstated by the Biden administration in 2021 [4]. This is a clear example of why clustering is a better option, at least for this research, to deal with endogenous factors within domestic policies. Despite the challenges and limitations, this will provide an excellent data analysis and modeling framework, which will be explained next. Furthermore, qualitative analysis within this part ensures higher reliability on the outcomes of the cluster analysis.

[3] Jim Daley, "U.S. Exits Paris Climate Accord after Trump Stalls Global Warming Action for Four Years," Scientific American, February 20, 2024, https://www.scientificamerican.com/article/u-s-exits-paris-climate-accord-after-trump-stalls-global-warming-action-for-four-years/.

[4] Leggett, Jane A. (2021). https://crsreports.congress.gov/product/pdf/IF/IF11746

Chapter 5

Methodology

This chapter will discuss the methodology employed in this part of the research. It is divided into these core parts: explaining the datasets used, Principal Component Analysis (PCA), K-Means clustering, Fixed Effect Regressions, Results, Implications, and Limitations. The first part will explain how I found the datasets already compiled by other scholars, followed by a brief exploratory analysis of what is contained in each set and the preparation process for each of them. The PCA part will explain theoretically and apply it to the data. Following is the K-means section, which will also have a theoretical framework backing the application and, therefore, will get the results for the PCA to build a compliance index, with some brief case studies of the results obtained. Then, theory and modeling are applied to both lagged and unlagged models on the Fixed Effect Regressions part. The results section will discuss the findings, while the implication section will situate those findings in the literature. Finally, the limitations section will outline the limitations of this study. All the code sets will be available in the document's appendix for reference, replication, and data.

5.1 Data

This research uses three datasets, two of which already exist: one compiled by the Quality of Government (QoG) Institute from the University of Gothenburg and another developed based on yearly reports published by the German Watch Institute.

5.1.1 QoG Environmental Indicators

This dataset is a compilation of several variables concerning the environment done by researchers in Gothenburg. Moreover, it ranges from policy strictness, ecological footprint and emission levels, public opinion, and background geographical data.

The dataset is organized by compilation of data, having always the first part of the name of the variables referring to the study it was taken from, and the second part related to what it is measuring. It starts with the Identification Variables, those are all variables used to find a specific observation, in this case containing the names of the countries, the years, and some codes based on other datasets, such as the V-Dem, to facilitate possible merging actions for the user handling the data. Followed by a variable called "Accountable Climate Target", which measures whether a country in a specific year has an emission target or not. Then it begins the data collections, with the "Aquastat" compilation that is the official Food and Agriculture Organization (FAO) dataset for water resources, measuring freshwater resources in countries and water stress situations. Next, the "Bertelsmann Transformation Index", which relates to public perception, among the variables, measurements of environmental concerns measured in surveys.

Following it there is the “Climate Change Knowledge Portal” provided by the World Bank, it compiles geographical data such as average rainfall and average temperature. Then it is the first set of variables used by this research, the “Climate Change Laws” of the World by the Grantham Research Institute on Climate Change and the Environment, among those data related to laws and policies based on legal documents and that aim the promotion of low carbon initiatives, which demonstrate a level of commitment and compliance. The next cluster of data is provided by Baettig, Brander and Imboden, called “Cooperation in International Climate Change Regime”, it is an aggregate of five indicators and is only available for the year of 2008, it follows the United Nations Framework Convention on Climate Change (UNFCCC) and Kyoto Protocol Indicators to assess countries’ commitment to shared international goals, while the Reporting, Finance, and Emission Indicators to evaluate how effectively countries fulfill their respective commitments within the global framework, it is worth to highlight that there is no global metric, rather it is just the compilation of those 5 indicators in 5 variables within the dataset.

The QoG Environmental dataset also contains data provided by the European Commission on Fossil CO2 Emissions on all countries, across several years. The commission also shares emissions on other air pollutant gases, such as black carbon, methane, carbon monoxide, nitrous oxide, ammonia, non-methane volatile organic compounds, nitrogen oxides, organic carbon, and sulfur dioxide. The dataset also contains variables on Environmental governance in Europe, with measurements of quality of water, policy instruments for environmental protection. There also variables concerning specifically regulations in 24 OCDE countries. In addition to that, there is the “Emergency Events Database” by the Centre for Research on the Epidemiology of Disasters, that compiles Climate Extreme Events. Along with it, date about land use, provided by the FAO and a binary variable if countries have or not environmental ministries and the presence of NGOs. The dataset also contains data related to biodiversity and ecosystems.

In summary, the QoG Environmental dataset contains many variables and information on several areas ranging from technical aspects such as emissions, to public opinion, ecological data and policies adopted. However, the main limitation of this dataset is that, despite containing data from 1946 until 2020, it has a lot of missing values, which will demand feature engineer to be tackled. The dataset has over 400 variables compiled within it and about 12,000 observables, being a very extensive dataset to work with. In order to use this set, it was necessary to first go through the codebook and sort which variables would help measure compliance and which were not applicable and could be dropped. In this sense, the choices were: Climate Change Laws of the World by the Grantham Research Institute on Climate Change and the Environment (2021); International et al. (2020); Environmental Ministries by Michaël Aklin and Johannes Urpelainen (2014); and the Stock of Climate Laws and Policies by Eskander and Fankhauser (2020).

The next step was to rename the variables using the snake case convention; hence the variables were renamed to:

Among these variables (Go to Table 5.2)

This data summary shows two specific things: the number of missing data, which will be explained further, and the distribution of the data and the possible occurrence of outliers that will have to be treated during the analysis. In this sense, boxplots are very

Previous Name	New Name
ccl_lpp	laws_adopted_per_year
ccl_mitlpp	mitigation_laws
ccl_nexep	cumulative_number_of_laws_exec
ccl_nlegl	number_of_laws
ccl_nlp	cumulative_number_of_laws
ccl_nmitlp	cumulative_mitigation_laws
iead_eif1	enforced
iead_eif2	enforced2
iead_inforce	in_force_all
iead_inforce_noterm	in_force_except_terminated
iead_rat	ratifications
iead_sig	signatures
iead_term	terminated
iead_withdraw1	withdraws
em_envmin	environmental_ministry
slaws_mit_ex_lt	exec_policies_last3yrs
slaws_mit_leg_lt	leg_policies_last3yrs
slaws_mit_lt	gov_policies_last3yrs

Table 5.1: Previous and New Names

good for exploring the presence of outliers:

As we can see, many variables have outliers that will have to be treated to have better functionality of the PCA and later of the K-means clusterization. When it comes to checking the correlation among the numeric variables chosen:

Some variables may have a strong positive correlation, even though correlation is different from causality, which raises another point that needs to be examined while conducting the analysis. However, one could expect that the cumulative number of laws and laws approved in a particular year could have a strong relationship, and those could also be closely correlated to laws passed by the legislative and the government. The last step of the exploratory analysis is to deal with the missing values using feature engineering.

Despite the high missing data in some variables, I opted to keep all variables, such as environmental ministry. Once a country inaugurates a ministry in this sense, the trend is that it will continue existing in the following years. Hence, it is possible to address the problem. As for the other variables, missing data goes up to 58%. Moreover, for the variables related to Climate Laws and International Agreements, the decision was to fill the values with 0, presumably because, in those countries, no law or agreement was ruled in those years. Therefore, for those related to Stock and Environmental Ministries, the option was to fill it with the global average of the variable. Having all the data complete now, the following steps with this data set will be explained in the section dealing with the PCA Analysis.

Variable	Count	Mean	Std
laws_adopted_per_year	2035	0.72	1.08
mitigation_laws	2035	0.53	0.92
cumulative_number_of_laws_exec	2035	4.77	4.43
number_of_laws	2035	3.51	3.55
cumulative_number_of_laws	2035	8.28	6.2
cumulative_mitigation_laws	2035	6.09	5.14
enforced	1928	7.11	5.41
enforced2	1928	0.04	0.22
in_force_all	1928	214.04	83.43
in_force_except_terminated	1928	255.38	110.62
ratifications	1928	1.48	1.72
signatures	1928	0.55	0.83
terminated	1928	0.39	0.78
withdraws	1928	0.13	1.57
envinromental_ministry	177	0.73	0.44
exec_policies_last3yrs	931	2.59	2.47
leg_policies_last3yrs	931	3.44	4.12
gov_policies_last3yrs	931	6.03	5.21

Table 5.2: Summary of each Variable

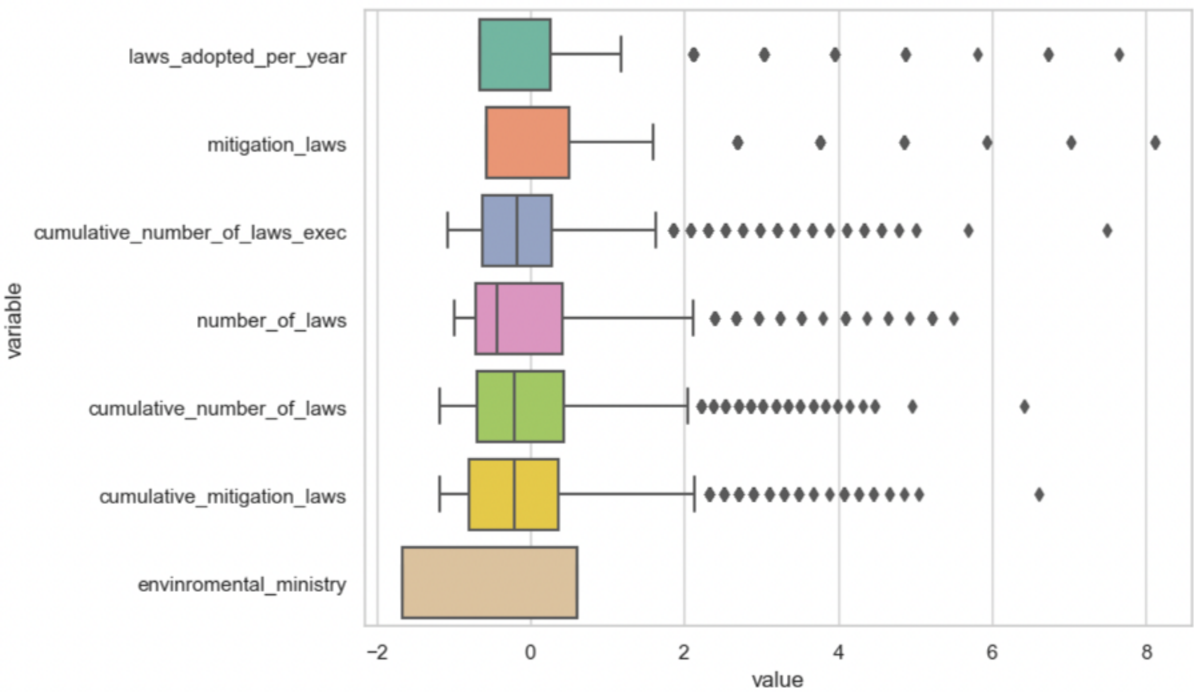

Fig. 5.1: Box Plot of the Variables with outliers

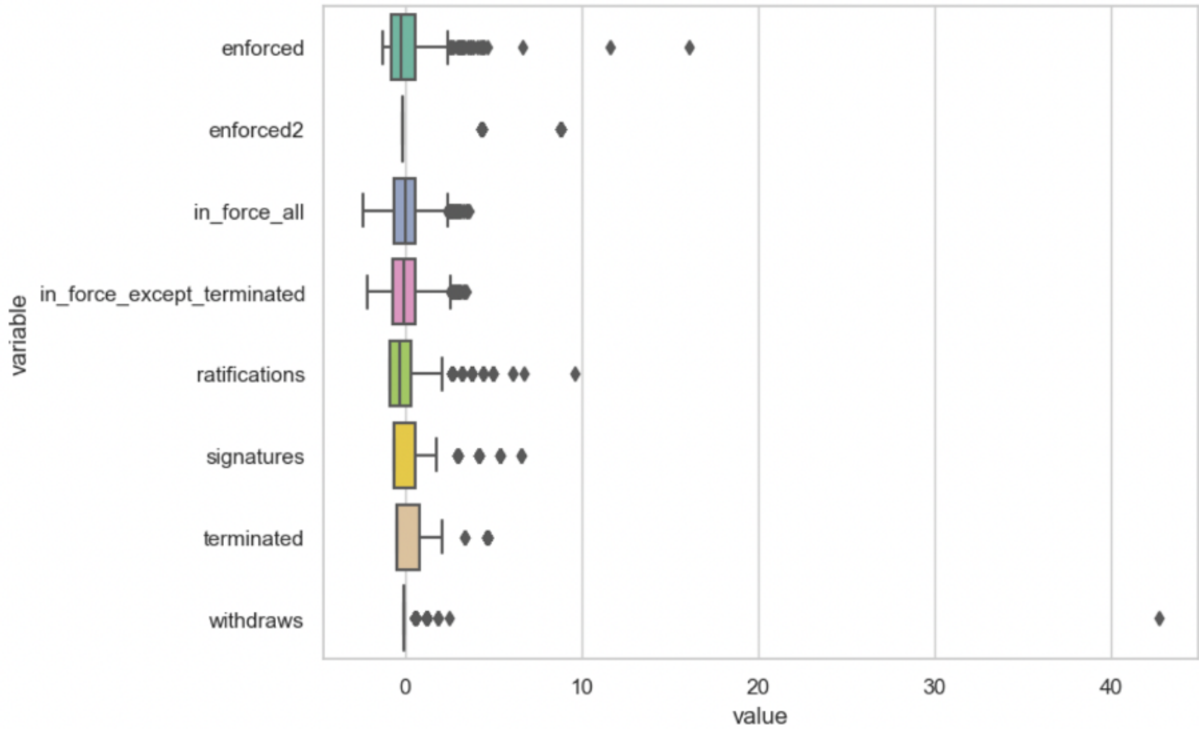

Fig. 5.2: Box Plot of the Variables with outliers

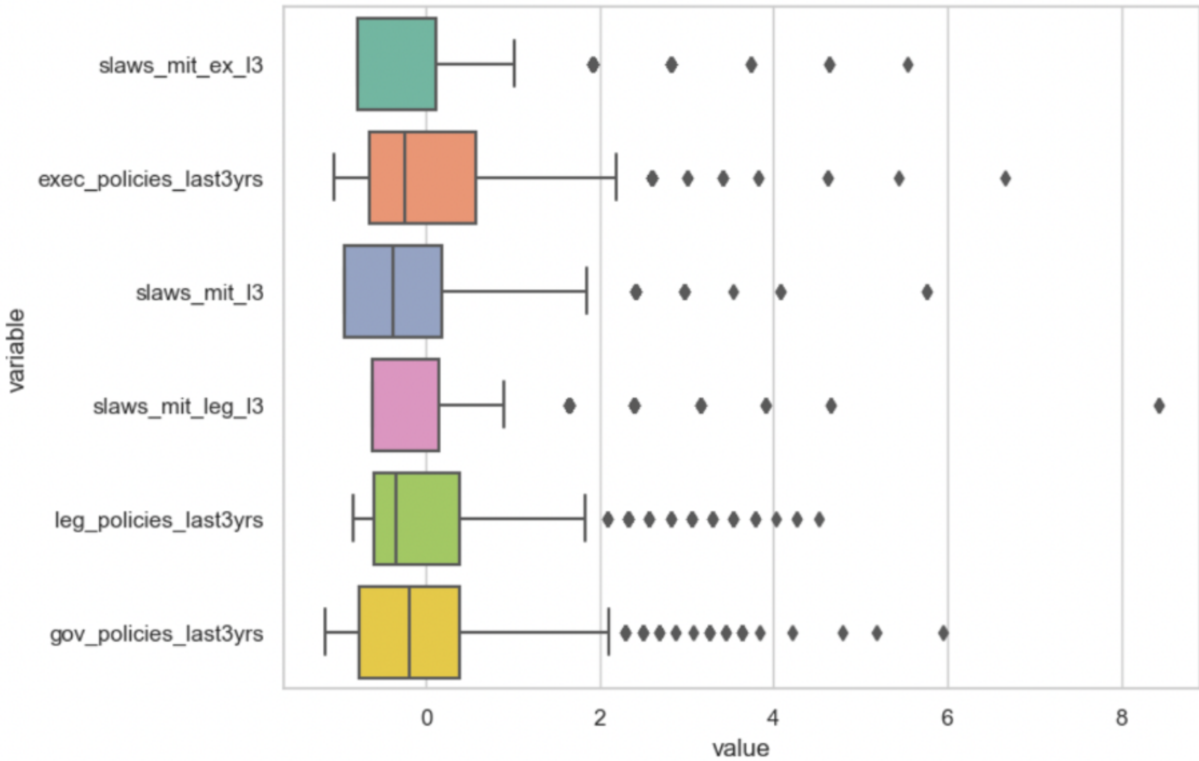

Fig. 5.3: Box Plot of the Variables with outliers

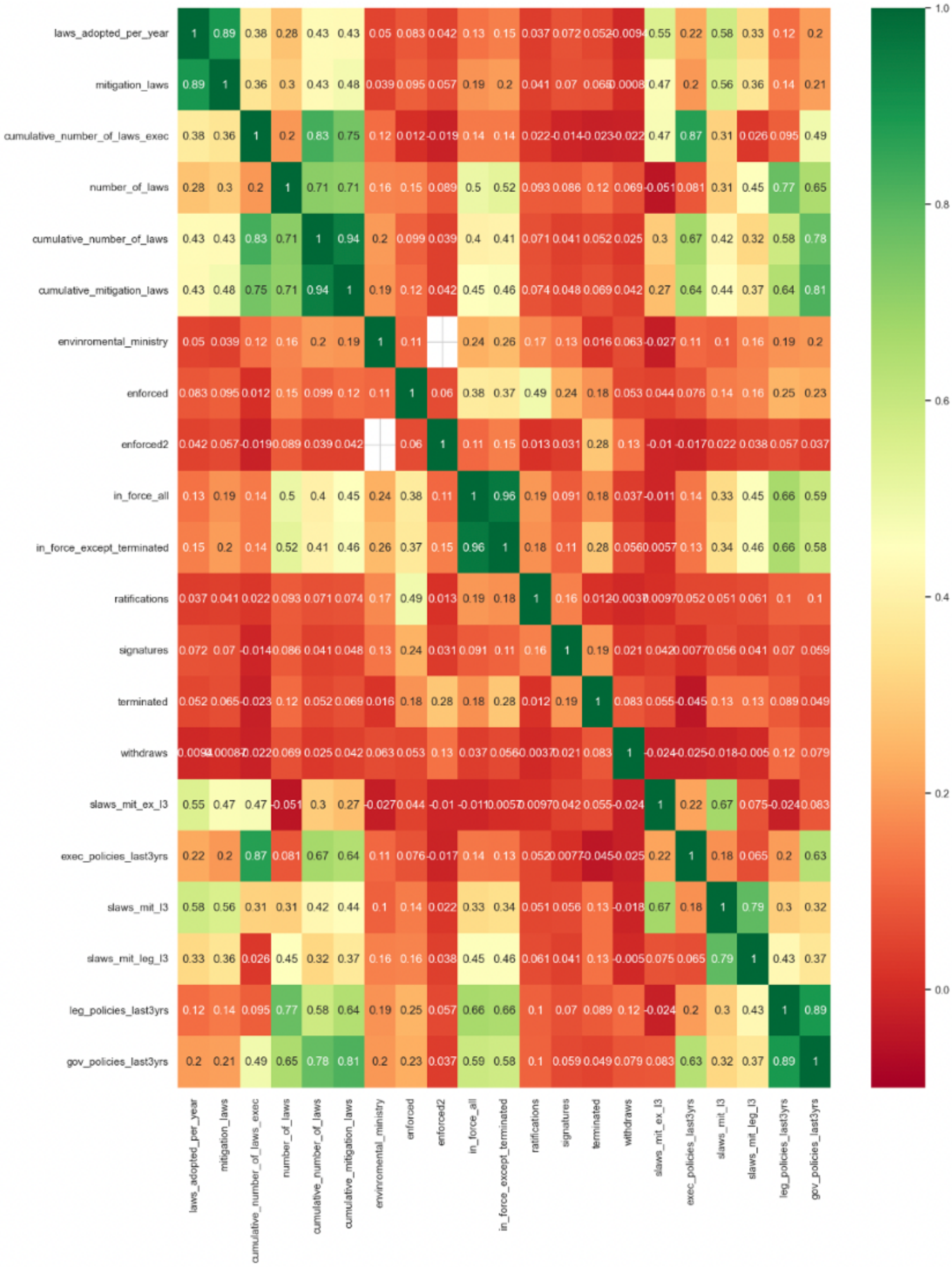

Fig. 5.4: Correlation Matrix

Variable	Missing Ratio
envinromental_ministry	92.073444
country_year	85.714286
gov_policies_last3yrs	58.307210
leg_policies_last3yrs	58.307210
slaws_mit_leg_l3	58.307210
slaws_mit_l3	58.307210
exec_policies_last3yrs	58.307210
slaws_mit_ex_l3	58.307210
signatures	13.658755
withdraws	13.658755
terminated	13.658755
ratifications	13.658755
in_force_except_terminated	13.658755
in_force_all	13.658755
enforced2	13.658755
enforced	13.658755
mitigation_laws	8.866995
cumulative_mitigation_laws	8.866995
cumulative_number_of_laws	8.866995
number_of_laws	8.866995
cumulative_number_of_laws_exec	8.866995
laws_adopted_per_year	8.866995

Table 5.3: Missing Values in %

5.1.2 QoG Basic Dataset

The Basic Dataset is another compilation of data built by the QoG department of the University of Gothenburg. It has more than 400 variables coming from over 80 sources. Among those, it is possible to see data related to civil society, population and culture, such as political participation, demographic data, and trust. There are also variables on conflict, measuring use of force and military informational data. Education, such as scholarity scores, human development index and literacy. Information on Energy and Infrastructure is also present, with data on access to electricity, gas and oil production, and other data on production and distribution of energy. Environmental data providing a comprehensive overview of various environmental and sustainability metrics, including ecological footprints, environmental policies, CO2 emissions, and land usage, highlighting the ecological challenges and performance indicators of a region or country. It also contains data on gender issues, contemplating various aspects of gender equality, including equal opportunity, representation of women in politics and diplomacy, female employment across sectors, and key indicators like fertility rate and life expectancy, shedding light on the status and challenges of gender equality in a given region or country.

The data also encompasses various aspects of health, judicial systems, and social well-being, covering topics like health policies, subjective well-being, COVID-19 impacts, and life expectancy. Additionally, it delves into the judicial landscape, exploring civil liberties, freedom of expression, and the prevalence of corruption within the legal system, providing a comprehensive overview of health and judicial frameworks in a given context. Moreover, data insights into labor market conditions, including employment distribution across sectors, unemployment rates, and gender disparities in the workforce. It also touches on media freedom, with metrics related to press freedom, media bias, and public confidence in the press and television. Additionally, it covers migration trends, including internal displacement, remittances, and refugee populations. The legal framework around labor, such as child work, the right to strike, and protections against slavery, is also highlighted. In addition to that it provides a detailed overview of political parties, elections, and political systems, highlighting aspects such as electoral integrity, voter turnout, the distribution of parliamentary seats among various parties, and public trust in political institutions. It also covers the effectiveness and democratization of political systems, examining elements like the separation of powers, the rule of law, and central bank independence, alongside measures of democracy and political globalization.

Additionally, the data touches on aspects of the private and public economy, including economic freedom, trade, and fiscal policies, as well as quality of governance, focusing on corruption, government effectiveness, and rule of law. There is also a section on religion, examining the role of official religion, religious freedom, and the importance of religion in life. The welfare system is addressed, covering social safety nets, sustainable social policies, and various aspects of social protection, indicating the broader socio-economic context within the country or region.

The advantage of using this dataset for gathering economic, social, and emissions data is that merging with the Environmental dataset is easier since they have the same nomenclature for the observations. In this sense, the variables chosen were the "Expanded Trade and GDP Data" by Gledistch and the "World Development Indicators" by the World Bank. The focus is to use those variables as a control for filtering the data to use only in the research-developed countries, as well as control for inequality variables and have a proxy with the number of emissions. The data preparation was simple. First, all the variables not used were dropped, achieving several eight variables and over 15,000 observables, then renaming all the variable names:

Previous Name	New Name
gle_cgdpc	gdp_pc
gle_gdp	gdp
gle_rgdpc	real_gdp_pc
wdi_co2	co2
wdi_gini	gini

Table 5.4: Renaming Variables

Considering the exploratory analysis, the option to only look to certain countries stems from the fact that Italy and Germany are big European economies, Brazil is the case study of this research, and China is one of the countries responsible for the most emissions in the world. When comparing GDP, we observe the great ascension of China in recent years, with exponential growth, when Germany has a higher GDP, and Brazil and Italy are similar in this sense.

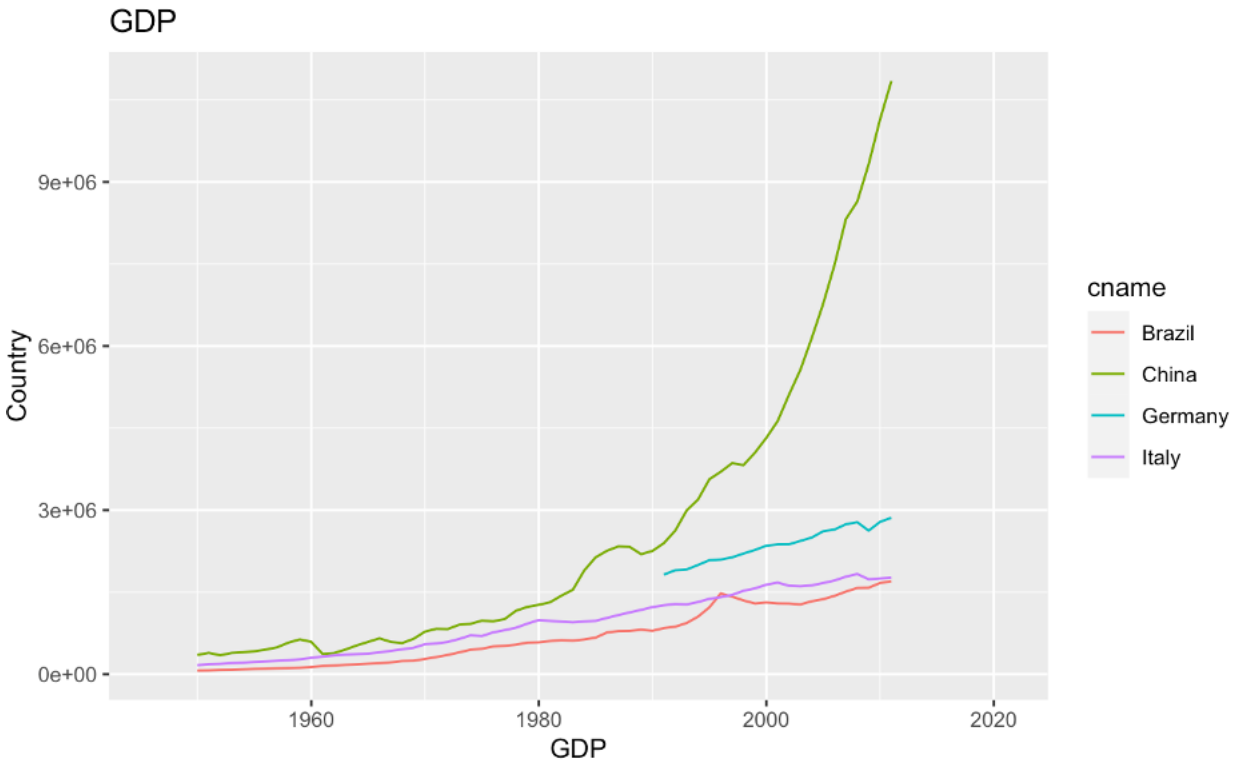

Fig. 5.5: GDP versus Country through the years

Figure 5.6 shows the emissions through time, measured in metric tons per capita. In this sense, it is possible to understand why the pattern does not follow the above GDP growth graph.

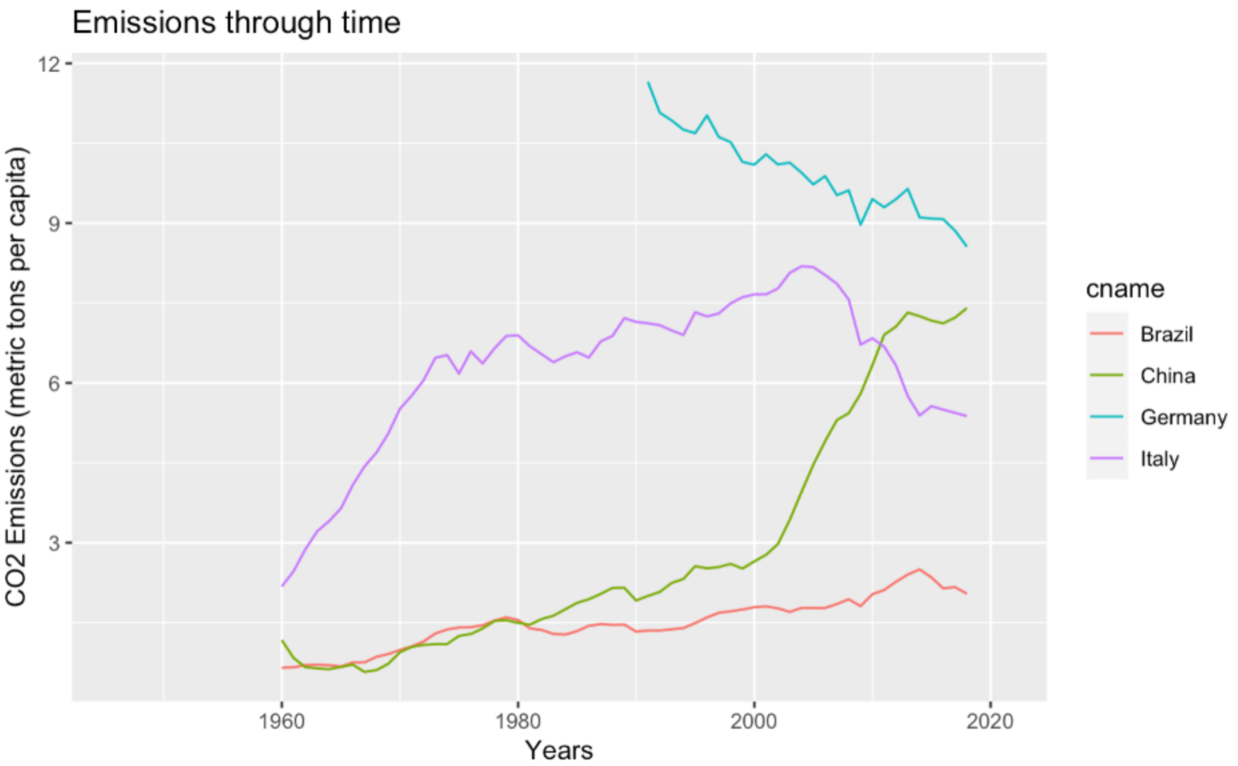

Fig. 5.6: Emissions through time

Another variable worth exploring is the Gini index. On this scale, less unequal countries have smaller values. It is interesting to note the scale's variance, with more observables contained in the first two quantiles.

Lastly, the correlation matrix. Here, it is possible to see that Gini, smaller and better than the others, has a negative relationship with economic power and emissions variables. In the same way, we see a strong positive relationship between emissions and economic growth.

5.1.3 Risk

This dataset was built using the reports produced by the German Watch Institute; in these documents, the authors, Eckstein, Künzel, and Schäfer, assess how much certain countries and regions have been affected by Climate Change in a particular year. Moreover, the authors consider data not only from the current year analyzed but also from previous years. The methodology used by the authors is based on the collection of data conducted by MunichRE, a reinsurance company. The data collected concerns fatalities, infrastructure damage, and economic losses related to climate events such as floods, storms, and droughts. One of the limitations is the lack of continuous effects such as those captured with the decrease in rainfall in a particular region. With the data collected and sorted, the Climate Risk Index (CRI) is calculated using the following equation based on the ranks of the countries in all variables assessed:

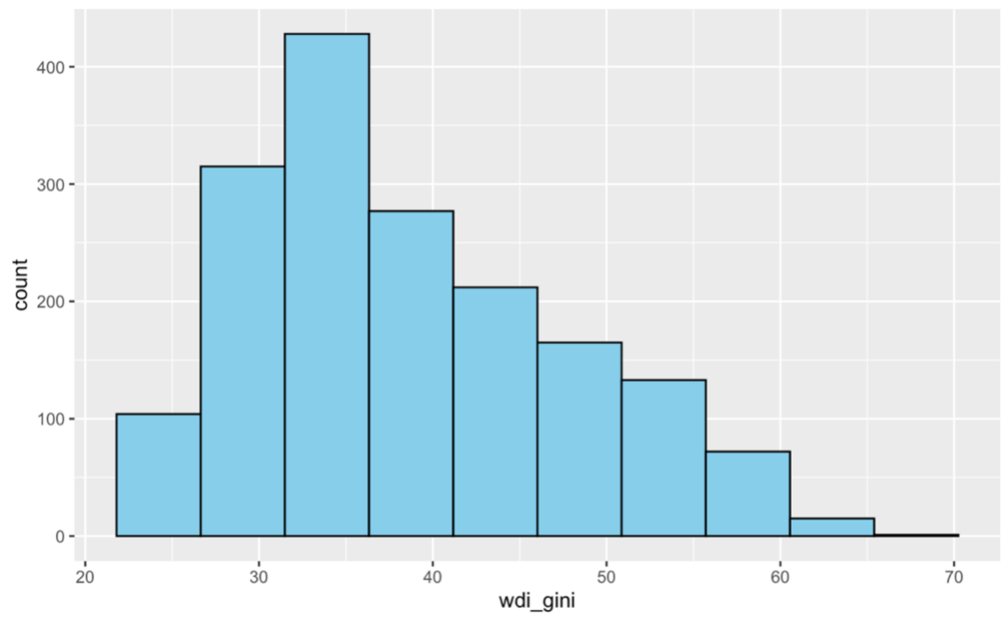

Fig. 5.7: Gini Histogram Distribuition

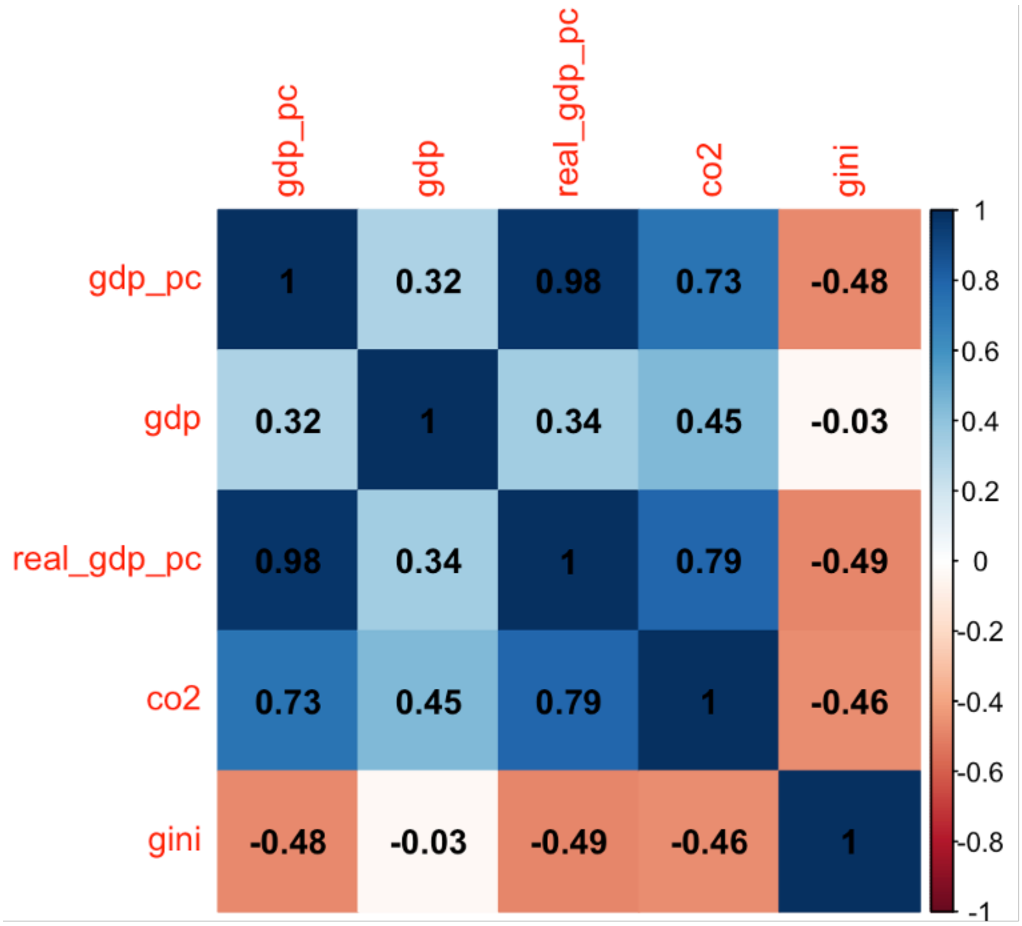

Fig. 5.8: Correlation Matrix

$$\text{CRI Score} = \frac{X_1}{6} + \frac{X_2}{3} + \frac{X_3}{6} + \frac{X_4}{3} \tag{5.1}$$

X_1 being the rank in fatalities, X_2 the rank in fatalities per 100,000 inhabitants, X_3 the rank in losses, and finally X_4 the rank in losses per unit GDP. In this sense, we observe that the smaller the score, the higher the position in the ranking will be, meaning that a smaller number leads to a more significant climate risk score. After compiling all the reports into a single data frame, eliminating the rank variables, and adding a year indicator, the outcome is a dataset with more than 1600 observables and only three variables.

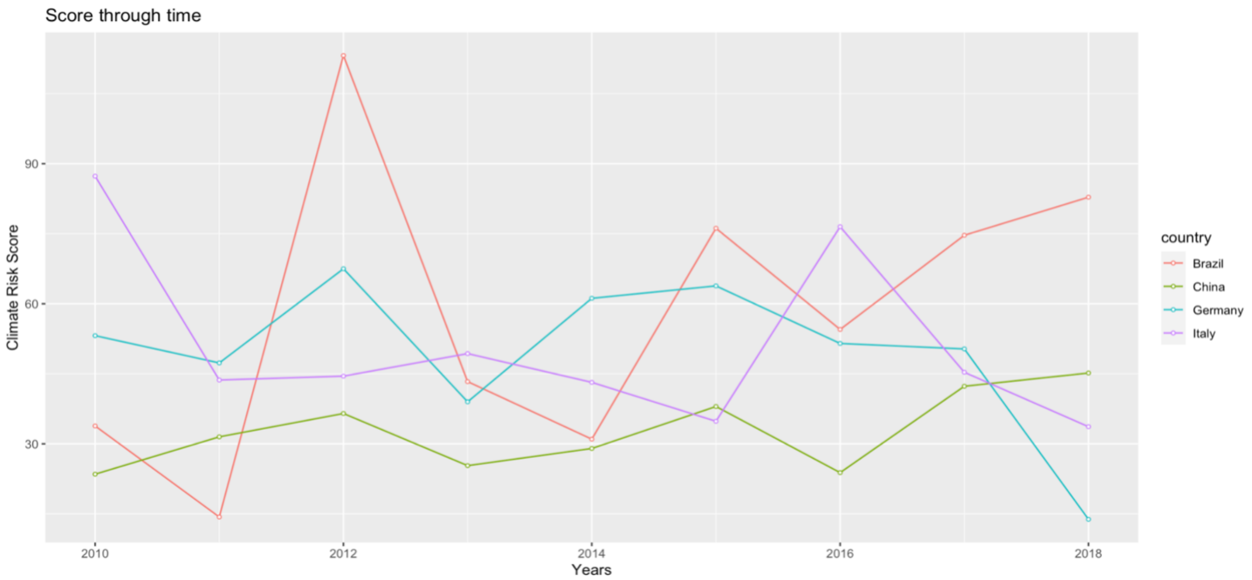

Fig. 5.9: Climate Risk Score through time

A preliminary analysis shows the evolution of the graph between 2010 and 2018, with countries such as Germany having a stable score over time but with a more miniature score in 2018, meaning that the risk was higher in that year. In contrast, Brazil performed best with the lowest risk in 2012. It is important to remember that the higher the score, the lesser the climate risk. The following steps for this data set are concatenating the variable "country" with the variable "year"; hence, merging it with the other datasets and proceeding with the analysis will be possible.

5.2 Principal Component Analysis (PCA)

As explained in the previous chapter, one of the core issues in conducting this research concerns building a framework for measuring compliance. In this sense, the approach for tackling this problem is to use a Principal Component Analysis (PCA) and then an unsupervised machine learning technique. This approach allows for a comprehensive analysis of compliance levels without relying on predefined indices, providing insights into the compliance behavior of countries about international environmental norms. One of the core reasons for choosing a PCA analysis is the size of the Environmental Dataset by the QoG. The original idea was to assign weights to specific variables and build a compliance index. However, concerns arose regarding potential biases in assigning weights to calculate a compliance score. Furthermore, the choice of PCA is also a more efficient technique that reduces bias and could be introduced using mean or weighted mean. This part of the methodology is available in the appendix in Jupyter Notebook format.

5.2.1 Theory

PCA is widely known in statistics, with literature tracing back to 1901 on this method. The concept is easy: when one has a high number of observables and variables, one often needs to improve on interpreting and assessing the data. In this sense, a PCA is a method used to reduce the dimensionality of datasets containing numerous variables, making them easier to interpret (Hsieh 2022). An easy way for the reader to picture it is by imagining that every variable in a dataset represents a dimension. If we want to analyze a single variable, many graphical options exist for interpreting and understanding it. The same happens when comparing two variables simultaneously; when it comes to three, there are still options, however scarcer. Regarding four variables, a graphical representation with four axes is impossible in a 3D world. This method basically combines the variables, generating new uncorrelated variables that maximize the amount of variance captured in the data (Hsieh 2022).

There are two approaches within PCA, the geometric and the eigenvalue (Hsieh 2022). The geometric approach begins by identifying the axis along which the bulk of the variance is observed, then determining the optimal axis by minimizing the distance between the data points and this axis. First proposed by Pearson in 1901, PCA treats all variables equally, unlike linear regression, and seeks to find the best-fitting hyperplane in the dataset's n-dimensional space, where n is the number of variables (Hsieh 2022). Alternatively, Hotelling (1933) introduced a more systematic eigenvector approach to Principal Component Analysis (PCA). In this approach, each data point is transformed from its original coordinates, (x,y), to new coordinates, (u,v), through a coordinate system rotation. This rotation allows for identifying the principal components, which are orthogonal directions in the dataset's space that capture the maximum variance. In the 2-D example, the transformation involves rotating the coordinate system to align with the principal components of the dataset (Hsieh 2022).

The literature on PCA is vast, and this study's objective is not to understand the mathematical implications of this method. Thus, only this brief introduction will be given to the reader. However, an important aspect to highlight is that using PCA is widely accepted within the Machine-machine-learning community to reduce the dimensionality of datasets while maintaining variance (Ding and He 2004; Metsalu and Vilo 2015). In addition to that, using a PCA followed by the K-means method is not exclusive to this research; Ding and He (2004) found that principal components serve as continuous solutions of cluster membership in K-means clustering. Hence, this approach aligns with the study's objective of reducing dimensionality to enable visualization through scatter plots and facilitate clustering using K-Means.

5.2.2 Application

Completed all the processes of data preparation and exploratory analysis, it was time to begin the PCA analysis. The framework was in Python, and two different methods were used, resulting in more than one score, as I will explain later in the K-Means section. The first, proposed by Kaloyanova [1], after the data processing the first step was to choose the number of components used by conducting the "elbow analysis". It is important to highlight the necessity to standardize all the datasets, or at least the numerical features that will come into the analysis.

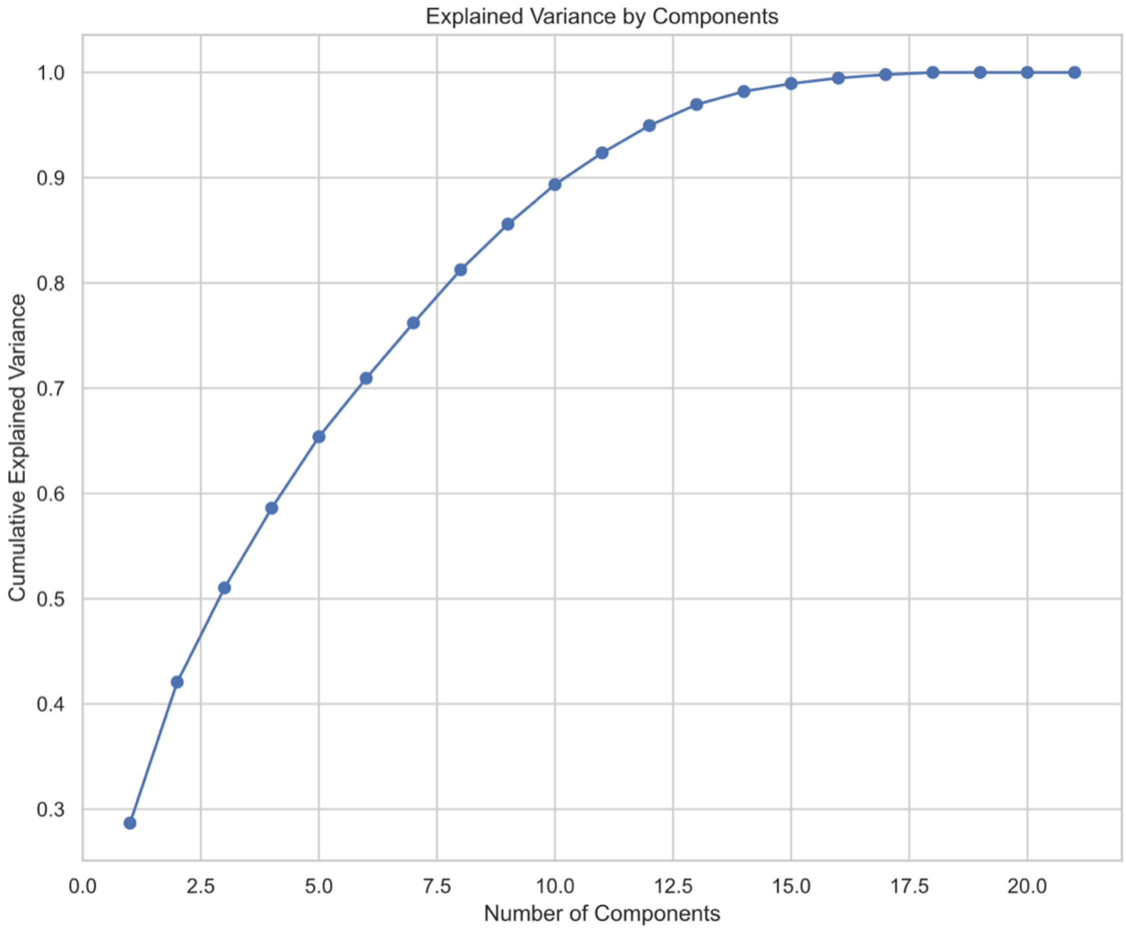

Fig. 5.10: Variance versus Number of Components

The initial option was to choose eight components, given that they explained more than 80% of the whole dataset, reducing the dimensionality from 21 to 8. The second approach was the one explained by Gebeyaw [2]. The idea is the same; however, in this

[1] Elitsa Kaloyanova, "How to Combine PCA & K-Means Clustering in Python," 365 Data Science, April 15, 2024, https://365datascience.com/tutorials/python-tutorials/pca-k-means/.

[2] Gebayaw, Mesfin. "Parsing HTML and Applying Unsupervised Machine Learning. Part 3: Principal Component Analysis (PCA) Using Python." DataScience+, May 19, 2019. https://datascienceplus.com/parsing-html-and-applying-unsupervised-machine-learning-part-3-principal-component-analysis-pca-using-python/.

case, the option is to use a different number of components.

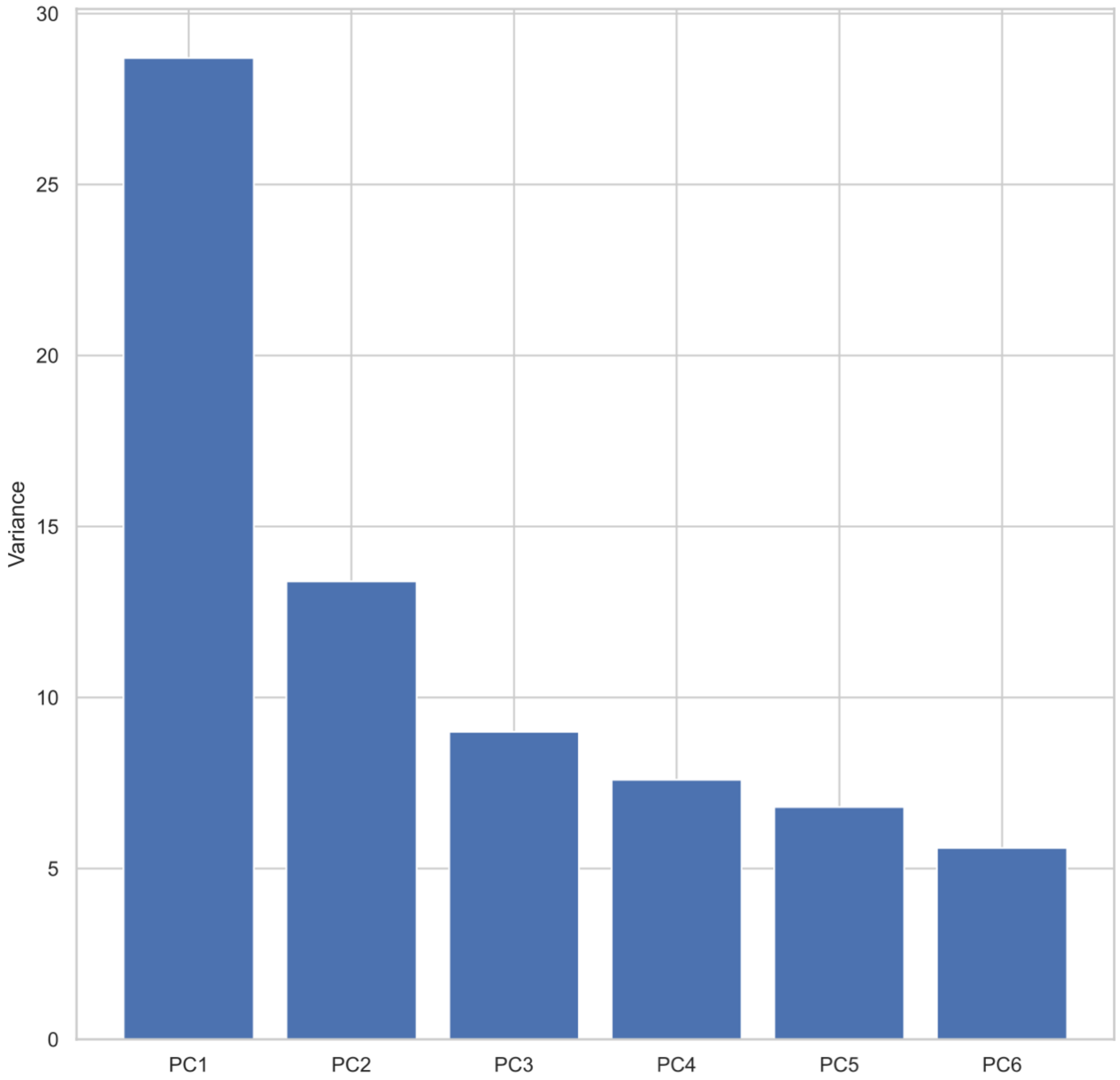

Fig. 5.11: Variance by Principal Component (PC)

In this case, with fewer components and using a different rotation of eigenvectors, we find that 3 components are enough to conduct the analysis. Having completed both methodologies, it was time to advance to the K-means processing.

5.3 K-Means

5.3.1 Theory

K-means is a clustering technique and a model for unsupervised learning in machine learning topics. When dealing with ML, there are often two approaches: supervised and unsupervised learning. The former is finding a mapping from input variables X to output variables Y using training data (X, Y). While the latter works with only input data X and aims to find structure within it (Hsieh 2022). Moreover, the concept of clustering is aggregating objects, or data points, into clusters based on their similarity. Therefore, there are two different approaches for clustering, hierarchical and non-hierarchical; the first refers to linking the pair of closest clusters until every data object is included in the hierarchy, resembling an upside-down tree (Hsieh 2022). The second approach can use either hard (assigns objects to a single cluster) or soft clustering (allows objects to belong to multiple clusters). K-means is a method used in non-hierarchical clusters based on grouping data points into k sets or clusters (Ck) to minimize the within-cluster sum of squares (Hsieh 2022).

5.3.2 Application

The clustering was done using the PCA analysis that was conducted and explained previously. However, with the first approach, I decided to test two different clusters, while for the second approach, I used just a certain number of clusters. They resulted in three scores that will be tested qualitatively below. A cluster analysis starts by evaluating how many clusters are optimal to explain the data. To do so, one must conduct the WCSS analysis, which is the sum of the variance between the observations in each cluster. For the first PCA, the option was 6 clusters, because after that the variance would shrink abruptly:

Hence, we can observe the number of clusters and how some of them are very intertwined, not providing a clear separation. In this sense, I decided to reduce the number of clusters to 4 because it would provide a better aggrouping of data based on the two main components used to explain compliance. We can observe better-differentiated, less intertwined clusters than on the first try.

Using the second approach, the choice was to use only three clusters, given that using more than three would have significantly reduced the variance. In this sense, our third score for compliance used three clusters, as we can see in the graphs below, after testing different numbers, which can be checked out in the annex to this book.

5.3.3 Testing

The assigning of values to the clusters followed the same parameters so that all the clusters had consistent scores. A brief framework was adopted using proxies of countries with good compliance, such as Sweden, Denmark, and Chile. Countries such as Brazil figured

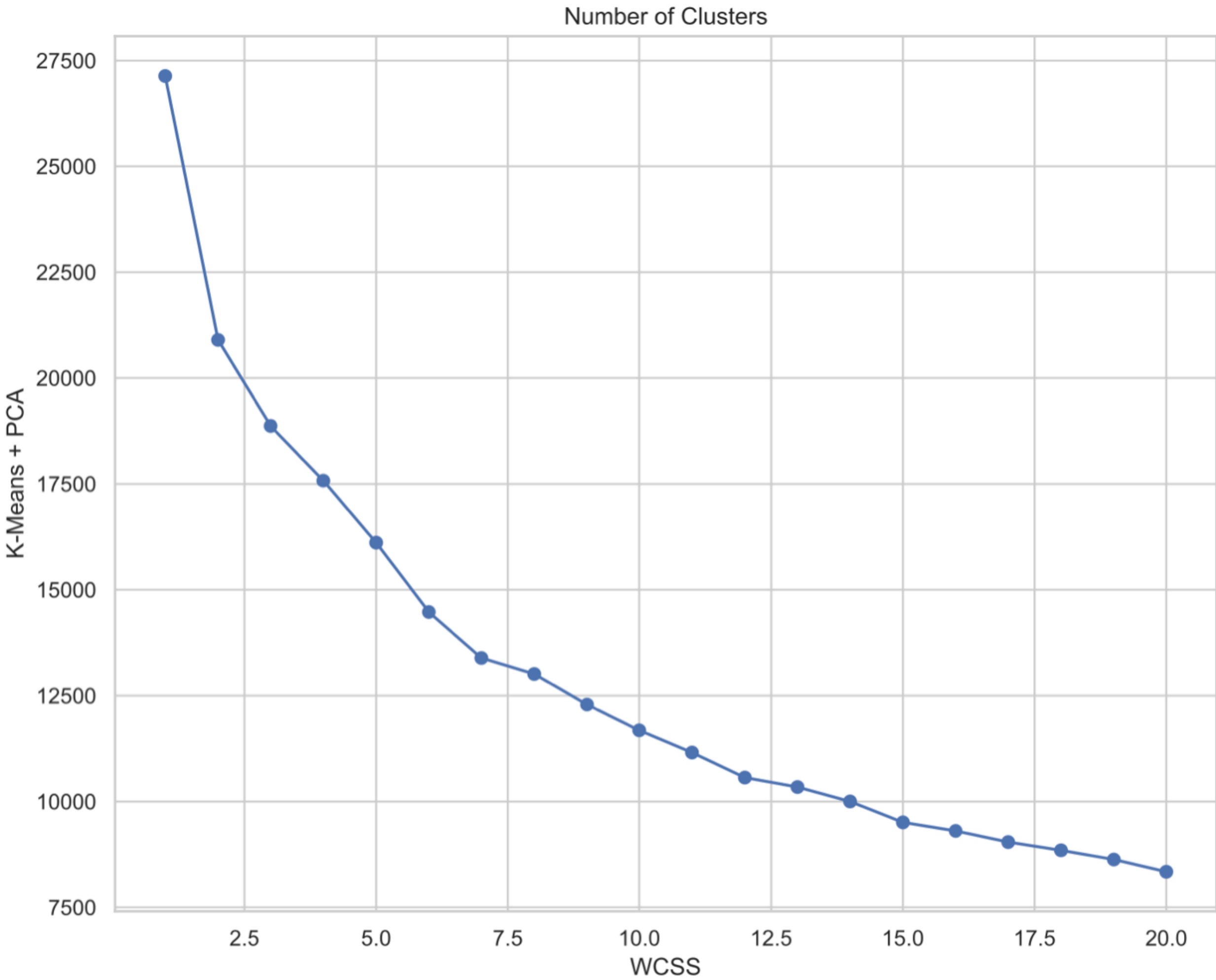

Fig. 5.12: Clusters and WCSS

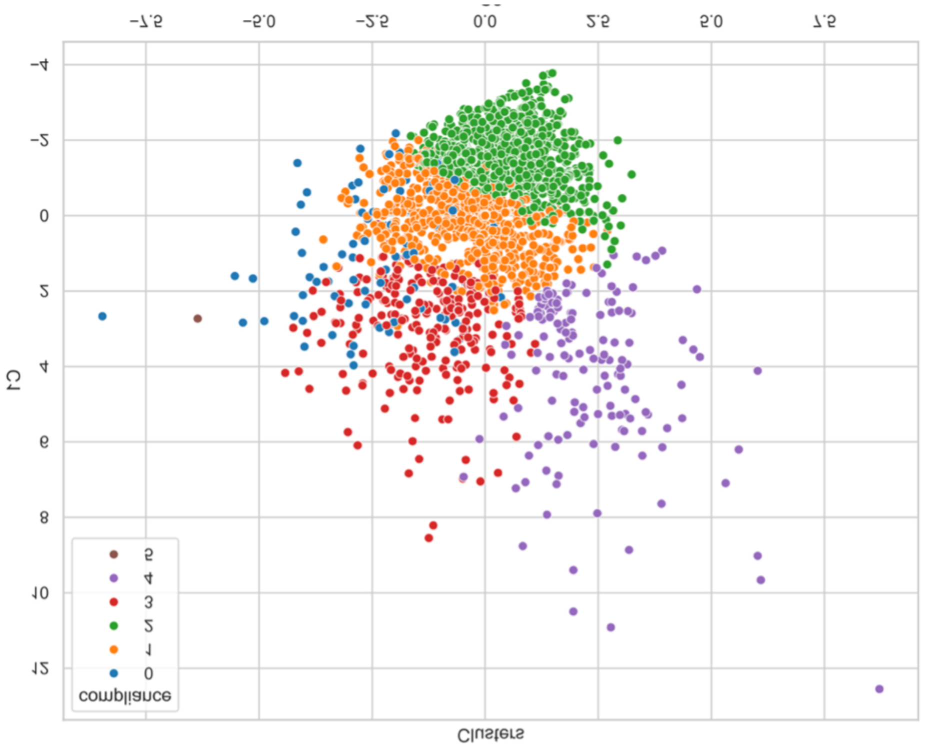

Fig. 5.13: First CRI clusters

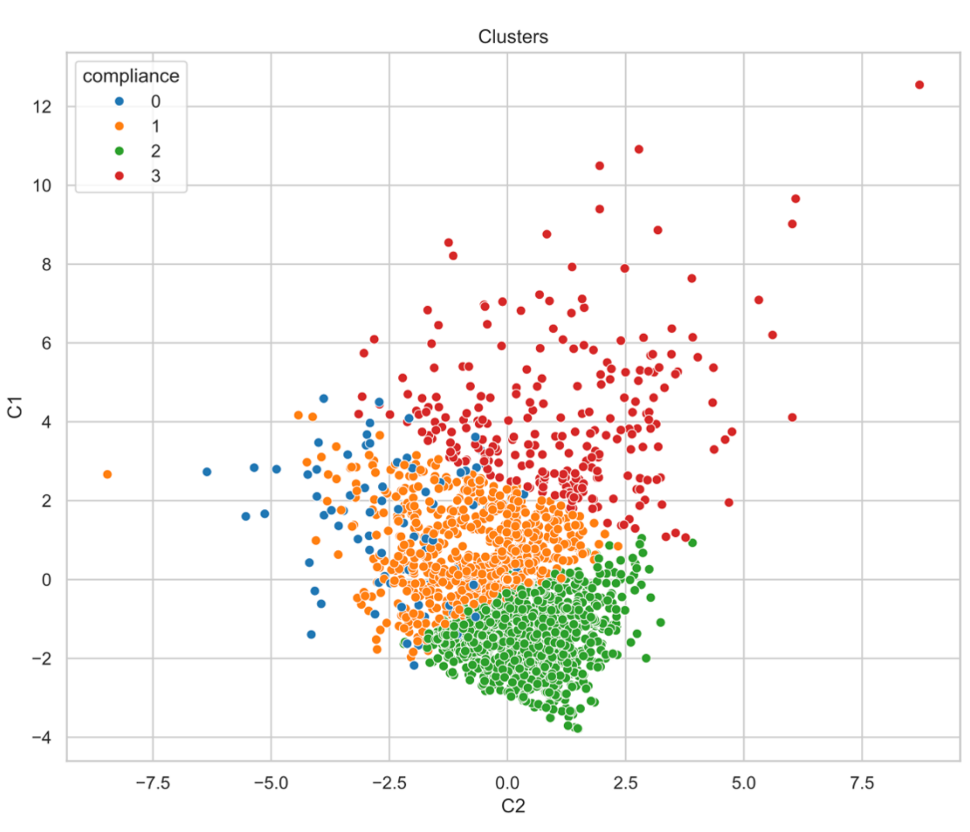

Fig. 5.14: Second CRI clusters

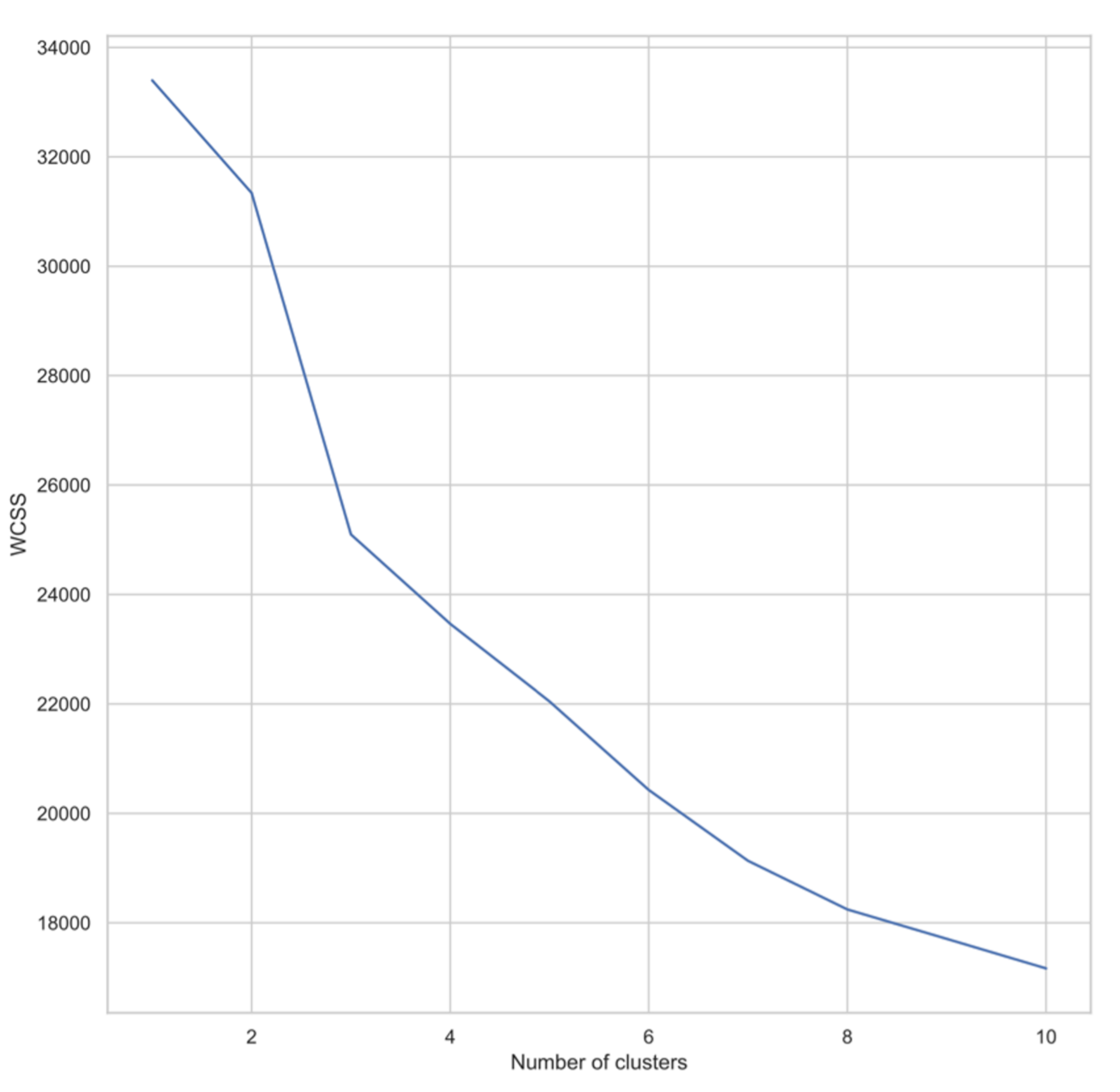

Fig. 5.15: Second PCA approach WCSS x Number of Clusters

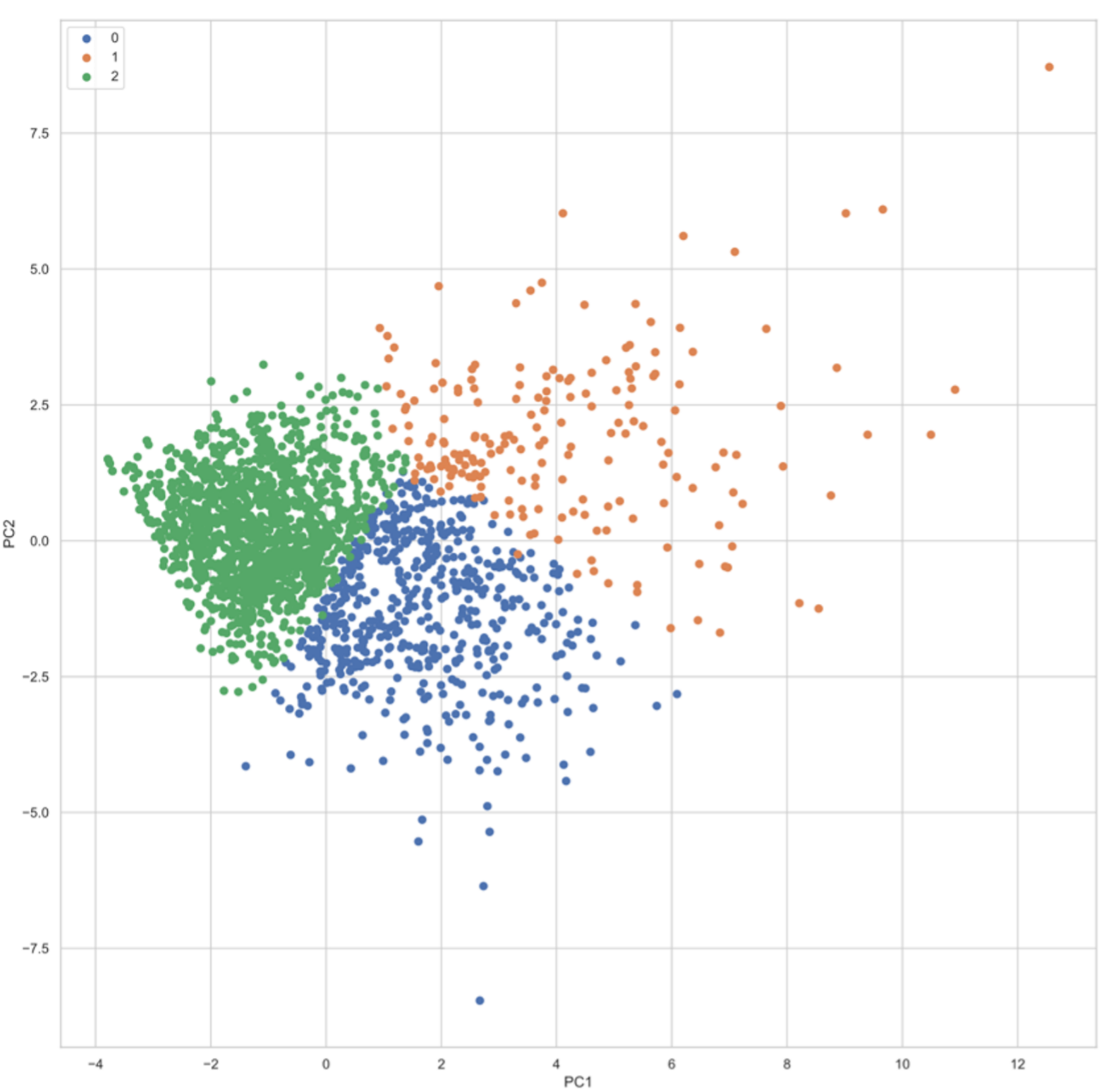

Fig. 5.16: Third CRI clusters

in middle score countries in terms of compliance, given that there is compliance to some extent. The United States of America was also a proxy, especially during the years of the Trump administration, with climate denial and the withdrawal of the Paris Agreements, indicating low commitment and compliance with environmental policies that were internationally discussed. In this sense, evaluating in a table how many times certain countries would figure in specific clusters was the way of assigning the values of compliance between 0 and 10. Indeed, there are ways of improving this, but there are limitations to this method. However, later in this chapter, those will be better explored in the limitations session.

5.4 Fixed and Random Effects Regression

5.4.1 Theory

The dataset is organized using panel data, with observables going through time series from 2010 to 2018. In this sense, Wooldridge (2012) explains that the fixed effect estimator is a method used to handle variables with fixed effects in panel data. The process consists of averaging the model equation over time for each entity to create a demeaned equation (Wooldridge 2012). The next step is subtracting the demeaned equation from the original equation, eliminating the fixed effect term. Once this transformation is done, a pooled OLS model can be applied. Moreover, the estimator can capture time variation within each cross-sectional observation. In addition to that, the author also explains that for multiple explanatory cases, such as here, the demeaning process is applied, and pooled OLS regression is conducted without prejudice (Wooldridge 2012).

One question that may arise is: why the Fixed Effect (FE) model instead of a Random Effect (RE) or First Difference (FD)? Wooldridge (2012) explains that the former is preferred for estimating ceteris paribus effects between FE and RE because it allows for arbitrary correlation between the fixed effect and explanatory variables. The latter is applied when the key explanatory variable is constant over time, and FE cannot be used. A good approach the author proposes is applying for both and checking which is more statistically significant. Wooldridge also points out the importance of conducting the Hausman test. He claims that FE is usually more convincing than RE for policy analysis using aggregated data, regardless of the philosophical debate about the nature of fixed effects (Wooldridge 2012). When it comes to FE and FD, it depends on the case, for $T > 3$, it will depend on the relative efficiency of the estimators, determined by the serial correlation in the idiosyncratic errors, when the idiosyncratic errors are serially uncorrelated, then FE is a better choice (Wooldridge 2012). In this sense, this research will test both Fixed and Random effects.

5.4.2 Application

After creating an index based on Machine Learning models, it is time to apply fixed and random effects regression analysis on panel data. The dependent variable is the three scores of the PCA plus K-Means clustering analysis produced using the Quality of

Governance Institute data on environmental indicators. At the same time, the independent variable remains the same: the Gini Index from the QoG Basic Dataset, which serves as a proxy for education level due to inequality correlation. CO2 emissions from the QoG Basic Dataset, a control variable for emissions reduction compliance assessment, and real GDP per capita give a proxy for the economic development of the countries. The variable measuring climate risk comes from German Watch Institute data and is measured by climate extreme event impact, loss events, human impacts, and economic losses.

Moreover, this variable will be used in two ways: first, without any modification, and then lagged, given that a response to an event does not happen immediately but rather after some time. It is also important to highlight that a lower Climate Risk Index indicates a higher threat level. Hence, the equations of each regression will be put before the regression and followed by the tables. After that, the results will be discussed.

5.4.2.1 Normal

Fixed Effects

$$\text{M1: } Y_{Compliance\ 1} = \beta + \beta_{Climate\ Risk} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.2)$$

$$\text{M2: } Y_{Compliance\ 2} = \beta + \beta_{Climate\ Risk} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.3)$$

$$\text{M3: } Y_{Compliance\ 3} = \beta + \beta_{Climate\ Risk} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.4)$$

Regarding the P-value, the model containing "comp_score1" as the variable should be disregarded because the value is above 0.05, making the model statistically insignificant. In this sense, observing the other two models, it is possible to see that despite the score, all the other variables have similar effects on compliance; this model shows that, more significantly, having higher compliance is related to the decrease of CO2 emission. As shown in model 3 with comp_score2, in addition to that, models 1 and 3 also show a negative relationship between Gini, meaning more development and more compliance.

Random Effects

$$\text{M4: } Y_{Compliance\ 1} = \beta + \beta_{Climate\ Risk} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.5)$$

$$\text{M5: } Y_{Compliance\ 2} = \beta + \beta_{Climate\ Risk} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.6)$$

	Dependent variable:		
	comp_score	comp_score1	comp_score2
	(1)	(2)	(3)
score	0.006	−0.0003	−0.001
	(0.004)	(0.004)	(0.005)
gini	−0.137*	−0.039	−0.144*
	(0.075)	(0.069)	(0.081)
co2	−0.057	−0.023	−0.426**
	(0.179)	(0.165)	(0.194)
real_gdp_pc	−0.0001**	0.0001**	−0.00004
	(0.00003)	(0.00003)	(0.00003)
Observations	798	798	798
R^2	0.019	0.008	0.017
Adjusted R^2	−0.116	−0.128	−0.118
F Statistic (df = 4; 701)	3.305**	1.462	3.006**
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.5: Regression Model for FE and Compliance Scores

$$\text{M6: } Y_{Compliance\ 3} = \beta + \beta_{Climate\ Risk} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.7)$$

When using Random Effects in the normal score, M4 must be disregarded given the high p-value assumed. Instead, M5 and M6 have great statistical relevance. Using Random Effects on the normal score has proven more relevant than the Fixed-Effect model. Consistently with the models M1 and M3, both current approaches show a negative relationship between Gini and Compliance. They also show higher emissions, contrasting with what was noticed before. Regarding the score, higher compliance is related to a higher threat, even though it is insignificant.

5.4.2.2 Lagged

Fixed Effects

$$\text{M7: } Y_{Compliance\ 1} = \beta + \beta_{CR\ Lagged} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.8)$$

$$\text{M8: } Y_{Compliance\ 2} = \beta + \beta_{CR\ Lagged} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.9)$$

	Dependent variable:		
	comp_score	comp_score1	comp_score2
	(1)	(2)	(3)
score	0.001	-0.007^{**}	-0.009^{*}
	(0.004)	(0.004)	(0.004)
gini	-0.030	-0.028	-0.121^{***}
	(0.028)	(0.026)	(0.035)
co2	-0.006	0.009	0.119
	(0.067)	(0.063)	(0.083)
real_gdp_pc	0.00000	0.0001^{***}	0.00002
	(0.00002)	(0.00002)	(0.00003)
Constant	5.076^{***}	5.136^{***}	8.957^{***}
	(1.283)	(1.210)	(1.602)
Observations	798	798	798
R^2	0.001	0.036	0.028
Adjusted R^2	-0.004	0.031	0.023
F Statistic	1.643	34.451^{***}	27.114^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.6: Regression Model for RE and Compliance Scores

$$\text{M9: } Y_{Compliance\ 3} = \beta + \beta_{CR\ Lagged} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.10)$$

	Dependent variable:		
	comp_score	comp_score1	comp_score2
	(1)	(2)	(3)
as.numeric(lag_value)	−0.008**	−0.001	0.0002
	(0.004)	(0.004)	(0.004)
gini	−0.143*	−0.034	−0.143*
	(0.075)	(0.069)	(0.081)
co2	−0.119	−0.016	−0.424**
	(0.180)	(0.166)	(0.196)
real_gdp_pc	−0.0001**	0.0001**	−0.00004
	(0.00003)	(0.00003)	(0.00003)
Observations	797	797	797
R^2	0.022	0.008	0.017
Adjusted R^2	−0.112	−0.128	−0.118
F Statistic (df = 4; 700)	3.878***	1.378	2.994**
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.7: Regression Model for FE and Lagged Compliance Scores

Now, in the models using Fixed Effects and lagged score value, we incur the same problems as in the model without lags, having good p-values for models 7 and 9, disregarding M8. The findings concerning Gini remain solid and consistent to all models so far; CO2 goes according to M1 and M3, and remains statistically significant we see a small negative effect of the lagged score on compliance, meaning that a higher threat will trigger more compliance, with the advancement of time, going in the same direction as M5 and M6.

Random Effects

$$\text{M10: } Y_{Compliance\ 1} = \beta + \beta_{CR\ Lagged} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.11)$$

$$\text{M11: } Y_{Compliance\ 2} = \beta + \beta_{CR\ Lagged} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.12)$$

$$\text{M12: } Y_{Compliance\ 3} = \beta + \beta_{CR\ Lagged} + \beta_{Gini} + \beta_{CO_2} + +\beta_{Real\ GDP\ Per\ Capita} + \epsilon \quad (5.13)$$

	Dependent variable:		
	comp_score	comp_score1	comp_score2
	(1)	(2)	(3)
as.numeric(lag_value)	-0.012^{***}	-0.006^{*}	-0.005
	(0.004)	(0.003)	(0.004)
gini	-0.037	-0.025	-0.118^{***}
	(0.027)	(0.027)	(0.036)
co2	-0.023	0.007	0.110
	(0.066)	(0.064)	(0.085)
real_gdp_pc	0.00001	0.0001^{***}	0.00003
	(0.00002)	(0.00002)	(0.00003)
Constant	6.338^{***}	4.884^{***}	8.617^{***}
	(1.246)	(1.211)	(1.599)
Observations	797	797	797
R^2	0.012	0.033	0.024
Adjusted R^2	0.007	0.028	0.019
F Statistic	11.596^{**}	31.864^{***}	24.036^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.8: Regression Model for RE and Lagged Compliance Scores

As for the lagged version of the Random Effects, all models are statistically significant, and show the same effects on all variables, except CO2, in which M10 shows a decrease in polluting for more compliance, which is factual. Gini is the more consistent of the findings that will be discussed next, when it comes to threat versus compliance, having a negative relationship as well, meaning that there is a specific effect on threat, leading to more compliance, given that the smaller the score, the more threatened a country is, leading to an increase in compliance.

5.5 Results

The results here show that in all models evaluated, regardless of lagging one of the variables or using different econometric approaches, the Gini index has a positive causal relationship with the compliance scores used. While CO2 emissions found mixed findings, majorly the findings are supporting that higher compliance necessarily means a reduction of emissions. As for GDP per capita, the results are insignificant. Ultimately, the findings indicate that there is more evidence supporting a positive relationship between environmental threats or risks and compliance, meaning that higher threats lead to higher compliance. Supporting the hypothesis: "Countries more threatened by Climate Change will have higher compliance to International Environmental Norms." It is essential to notice, although, that the effect, despite being overall supportive of the hypothesis, is not very strong, meaning that other factors may play a more significant role.

5.6 Implications

Despite not being very expressive, having a threat affecting political behavior shows that the worse the climate threat gets, the more action will be taken or taken more seriously. The biggest implication of these results is that climate change is actually perceived as a security threat, it brings with itself one extra limitation to the model, that will be explained in the next paragraph. Moreover, having public opinion influencing the risk perception of governments in terms of climate change might reshape politics in the following years, with economic and security issues being less salient than environmental policies, given that this can influence all the other sectors of society. In this sense, if threats are triggering environmental response and compliance, a progressive green agenda might be enough to win votes and elections. The effects of the second hypothesis are yet to be studied in the second part of this book. Hence, the discussion of implications will be done in Chapter 8.

5.7 Limitations

Among the limitations that must be acknowledged, the number one must be assigning the compliance score; despite being very backed by the literature, measuring qualitative compliance of every country throughout the years would provide a more accurate metric. Followed by the fact that in any moment seriousness, or commitment with global climate change is put into the equation. That is, some incumbents are known for denying climate change, cases of Donald Trump and Jair Bolsonaro, hence downplaying climate change in public discourses should also be a control variable in this model design. Another limitation of this method is that other factors triggering compliance should be tested. In this sense, future research should focus on dealing with it; another suggestion would be to increase the time frame used, expand the panel size, and employ more sophisticated forms of regression analysis and even Machine Learning to assemble more accurate clusters. In addition, one could measure the distance of the observable to the cluster's center and create a more advanced compliance metric by using the distance as inversely proportional to the score the cluster will give. Thus, many modifications can be done to improve the methodology, and those are acknowledged.

Chapter 6

The Case of Brazil

6.1 Background

According to scholars, Brazil is an "underachieving environmental power" because it has vast natural capital, although it remains underdeveloped given the limitations of its socio-environmental capital (Viola and Franchini 2017). The primary emission source in Brazil comes from land use, land-use change, and forestry (LULUCF), with the deforestation of the Amazon as a critical factor. This has been drastically reduced since 2005 onwards with successful policies controlling deforestation in the first mandate of Lula (Viola and Franchini 2017). Brazil's emission profile has changed since the early 2000s, with the decline of deforestation and the rise of the energy sector in emissions. It is essential to highlight that it is complex to calculate the country's greenhouse gas (GHG) emissions because it is hard to track the exact amount coming from deforestation, especially in the Amazon and Cerrado (Viola and Franchini 2017). However, in favor of Brazil there is the Brazilian scientific community and the country's democratic system, which represent an advantage when compared to other emergent countries. Thus, the principal sectors impacting environmental policy in Brazil are LULUCF, energy, and agriculture (Viola and Franchini 2017).

Brazil is the most extensive South American country, the 5th in the world in area, and the 6th in population size. In the 1990s, it ranked 4th among the highest GHG emissions, dropping to 6th in 2018 (Climate Watch and Data 2021). At the same time, per capita emissions rose to 10 tCO2e/capita in 2019, more than double compared to the 1990s. On the other hand, Brazil managed to grow its GDP, achieving the status of one of the biggest global economies, while reducing GHG intensity by 4.7 times compared to 1990 (Climate Watch and Data 2021). Moreover, Brazil is a democracy, despite being characterized as low-quality and unable to provide long-term policies for common goods given the weak political institutions in the country (Viola and Franchini 2017). Those will be elucidated and further discussed in the next chapter. However, one of the biggest problems in the institutional design is the fragmented representation in the government branches. In addition, poor education and civic culture in the population as well as the active role of businesses and unions in political parties and campaigns often lead to big corruption scandals (Viola and Franchini 2017). Another factor that needs to be improved in the institutional design is that decisions concerning climate and energy policies are not centralized. Hence, many ministries, such as the Environment, Mines and Energy, Agriculture, and Foreign Affairs, are involved in this discussion. Historically, individuals who favor a sustainable cause have controlled the Ministry of Environment. However, a shift occurred in 2011 with a more conservative approach that lasted until 2023, with the return of Minister Marina Silva (Viola and Franchini 2017). Regarding the minister of foreign affairs, the conservative trend concerning Climate Change is noticeable, given concerns over national sovereignty, especially in the Amazon region, and the trade-off between economic development and environmental policies pursued by other ministries.

Looking at the data, between 1990 and 2019, total GHG emissions increased by 16.83%.

LULUCF emissions decreased by 18%, while agriculture rose by 48.58% (Basso 2019). Breaking down by biome, in the Amazon, it is possible to see the highest deforestation rates in absolute numbers; forests decreased by almost 12% over the period due to pasture growth for cattle grazing expansion in the region (Basso 2019). Moreover, agricultural land for the culture of soybeans also accounted for much deforestation, as well as the expansion of local cities and urban areas, and mining activities. When it comes to the Cerrado biome, the decline of forest was about 20%; the drivers were the same: agriculture for soybean production, pastures, and mining; finally, in the Pantanal, where forested areas decreased by 18% and wetlands by 75%. The drivers remain the same as the other biomes: pastures, agriculture, urban expansion, and mining areas (Basso, 2019). Over this period, energy emissions more than doubled, growing 113.59%, while industrial processes rose 92.5% and waste 186.52%. This data shows how LULUCF remains the most significant source of emissions despite the reduction, and other sectors have increased their participation in the emission pool (Basso 2019). In summary, Brazil's GHG emissions result from the change in land use practices, industrialization processes, and energy consumption.

In this sense, it is noticeable that during the 1990s and early '00s, cattling became a significant driver for deforestation. Being followed by soybean cultivation, because the investment for cattle is low, whereas soy is more significant, demanding access to credit. This happened due to the region's land speculation and infrastructure development, reshaping the deforestation dynamics in Cerrado and Amazon (Pessoa and Inocencio 2014). One factor contributing to the lack of fiscalization is the undesignated land problem, which comprises about 15% of the region. These areas lack precise legal classification. Hence, the chance of speculative activities and illegal practices succeeding in those areas increases. Data shows that about 25% of the deforestation between 2010 and 2015 was due to uncertainty concerning land classification (Azevedo-Ramos and Moutinho 2018; Garrett et al 2021). Another issue concerns beef production and the role of Brazil as a global food supplier, being the second biggest beef producer globally, holding 20% of the market share. For instance, in 2020, half of the exports were destined for China, making the Asian country a major player in the dynamics of Brazil, as will be explained in the next chapter. However, only some of the beef production in Brazil generates high deforestation, as regions in the Southern part have lower deforestation impacts than the Cerrado and Amazon biomes (Viola and Franchini 2017). Exporting to China, Egypt, and Russia often comes from the northern part, creating pressure for deforestation. In contrast, the European Union and the United States generate less environmental impact, often from the southern part. However, even though Brazil accounts for high beef exports, the vast majority of the production is consumed within the country, associated with 85% of the deforestation caused by cattle feeding the internal market (Viola and Franchini 2017).

In summary, Brazil has a vast natural environmental capital, with water, forests, biodiversity, and low-carbon energy potential, making the country relevant to the economy and environment. However, the institutions and political elites in the country need more socio-environmental capital, prioritizing other policies over sustainability. Moreover, despite reducing the deforestation rates, Brazil still needs help controlling, monitoring, and combating this practice. It is essential to understand that Brazil is still a country going through a development process; in this sense, it faces many economic problems, high unemployment rates, low confidence among economic actors, and a low-quality democracy, with clashes between powers occurring very often (Viola and Franchini 2017), as it was possible to see during Bolsonaro's term and the Supreme Court. Thus, the narrative that

Brazil is a climate leader, as is sometimes portrayed, is problematic. Next, this paper will develop a timeline of governments and actions conducted to understand to what extent Brazil is a leader when it comes to environmental matters.

6.2 Historical Timeline

6.2.1 Before 1990s

From 1964 until 1985, Brazil went under an authoritarian military regime, following the military logic of occupation of the territory in order to make the Amazon region more urban and flourish. Among the objectives of this strategy, a core point was to restrict international influence, controlling the borders aiming to maintain federal control and sovereignty in the region; in addition to that, many infrastructure projects in the region, such as the Transamazonica and Porto Velho-Manaus Highways, telecommunication lines, and hydro powerplants were started (Becker, 2001). Hence, they connect the region with the rest of the country through better communication, transport, and industrial activity. Moreover, the project started by the military governments intended to alleviate social tensions in Southern Brazil, where agrarian reforms and mechanization of production led to social unrest. Settlement projects that provide land and economic opportunities to those who migrate to the northern region help ease the pressure in other areas (Viola and Franchini 2017). Finally, the strategy to establish modern regional activities, such as agriculture and mining, stimulated growth and development. However, some problems arose, especially with land tenure, given that, in the 1970s, the occupation of the north was encouraged through the sale of large properties and granting property titles to settlers, leading to conflicts and land grabbing, also known in Portuguese as grilagem (Viola and Franchini 2017). To solve this problem, the government enacted laws to regularize property titles, even for those illegally occupied areas. However, it only aggravated land tenure issues in the region.

Still, a modernization strategy was implemented during the military period, focusing on modernizing the agriculture sector without holding a land reform. Moreover, the focus was on establishing agro-industrial complexes and integrating agriculture and industry (Muller, 1991). The government invested in developing and researching science, technology, and infrastructure to develop crops that can grow in other biomes, such as the Cerrado and the Amazon. Thus, the EMBRAPA (Brazilian Agricultural and Research Corporation) was founded in 1973 in Brasilia, as a hub for research and development of technologies for agriculture and livestock. It plays a core role in enhancing farming activities and productivity in Brazil still to the present day (Viola and Franchini 2017). In summary, under military dictatorship rule, the encouragement and subsidy of occupation of the Amazon biome led to massive deforestation in the area. In addition, the infrastructure projects increased the demand for timber in the region. Population growth and the weak enforcement of the existing environmental regulations made Brazil a villain in environmental topics before the 1990s.

6.2.2 Fernando Collor (1990-1992) and Itamar Franco (1992-1995)

After the military regime, Brazil went through a period of transition to democracy once again, in which José Sarney was the first president in this period. However, Collor was the first elected through popular vote. Having neoliberal ideas, Collor brought to Brazil the debate of the economic paradigm of the 1990s, reducing the state's role and increasing private sector participation. Investment in technology then emerged, and production units grew in size, achieving higher output levels. Hence, along with market deregulation, Collor created a globalized market for primary commodities and reduced the influence of domestic politics (Viola and Franchini 2017). Brazil was finally open to global trade and capital; this increased the tensions between economic development and environmental conservation. This was aggravated by the economic situation in Brazil at that time, with the greatest heir to the military government being a high inflation rate.

Moreover, high deforestation rates were recorded, with little advancement in creating environmental protection mechanisms. One of the highlights of the Collor government was the reduction of the military influence on environmental issues. Brazil also hosted the 1992 Earth Summit in Rio, which helped to improve the country's international image on environmental concerns (Viola and Franchini 2017). However, given the economic situation and growing corruption, Collor was impeached. Vice President Itamar Franco took power, shifting the country's focus to solving currency problems; Franco, along with his economic team (headed by Fernando Henrique Cardoso), developed the Plano Real, which would save the Brazilian economy after many failed attempts by previous administrations (Sarney and Collor). Due to that, no significant changes in environmental policies were noted during Franco's period.

6.2.3 Fernando Henrique Cardoso (1995-2002)

Fernando Henrique Cardoso (FHC) was elected given the success of Plano Real and was the first president to serve two terms in Brazil as he allowed reelection. Moreover, with the economic stability and the market reforms during his administration, the conditions for a "capitalist revolution" in Brazil were there. Hence, land prices decreased, and the business environment improved; this led to higher crop outputs with higher emissions from land use and the agriculture sector. In this sense, Cardoso faced international criticism given the deforestation in the Amazon biome (Viola and Franchini 2017). Due to that, several restrictions on legal deforestation were implemented, though they were ineffective. 1997, under the FHC administration, Brazil participated in the Kyoto Conference and signed the Kyoto Protocol, despite only being ratified in 2002 at the end of his term (Hochstetler 2021). Moreover, in 1999, a new commission on Climate Change was formed, turning the Ministry of Science and Technology's key role into making the environmental cause a foreign policy and a technology issue. This commission was the National Authority for the Clean Development Mechanism, and was responsible for compiling Climate Change statistics (Viola and Franchini 2017).

Regarding domestic policy, Brazil had a poor commitment to Climate Change during this period, despite Rio 1992 and its leadership role in Kyoto 1997. For instance, Brazil had a high emissions profile and high deforestation indexes in that period. This activity was supported by a robust domestic lobby within the political institutions of loggers, farmers, and marginalized populations. An example is the Forest Code reform of 1996, which aimed to increase land protection in the Amazon (Hochstetler 2021). This policy faces severe resistance from the lobbyists and the economic and political elites of the Amazon states (Amazonas, Para, Mato Grosso, Rondônia, Tocantins, Roraima, Acre, Amapá, and Maranhão). In terms of mitigation measures, no specific mitigatory action was taken in this period, going along with the mainstream flow of common but differentiated responsibilities. The problem of deforestation was mainly driven by the logging industry and the agri-business sector, which was a consequence of the economic stability that occurred given the reforms that Cardoso approved. However, the period also faced small advancements; for instance, in the shift in perception concerning the Amazon rainforest, politicians changed the idea of the Amazon as a territory to be exploited into a national treasure. This is illustrated by Brazil hosting the Global Summit in 1992, still under Collor, the leadership role in Japan, and the Forestry Code reform in 1996. Despite backlash in Congress and the Senate, the idea was to raise the amount of land on private properties that must be protected from deforestation. In the Amazon biome, this number, which was previously 50%, would be increased to 80% (Viola and Franchini 2017). This was seen as fundamental in limiting further deforestation and, despite lobbying, was approved by the Brazilian legislative branch.

6.2.4 Luis Inácio Lula da Silva (2003-2010)

Lula was elected in the 2002 elections and was the first left-wing Brazilian president; his mandates occurred in a moment of high economic and political stability, benefiting from the commodities boom. In summary, the main focus of environmental policy is law enforcement, monitoring, conservation, and attempting to mitigate deforestation (Viola and Franchini 2017). Moreover, Lula believed Brazil should be a significant actor in international relations. In the context of internal stability, it was possible to advance environmental policies in the country. Hence, between 2003 and 2010, significant progress was made in building institutional capacity through domestic policy to deal with Climate Change (Hochstetler 2021). In 1992, Brazil realized its environmental challenges, and in Kyoto, it acknowledged the Climate Change problem. The first climate policy was then enacted in 2004: the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) (Viola and Franchini 2017). The main goal of this policy was to reduce deforestation based on three pillars: conservation areas, monitoring, and effective law enforcement. During this period, figures such as Marina Silva and Carlos Minc were prominent actors shaping the debate on environmentalism in the country. Thus, in this period, Brazil transformed from a "climate villain" to a leadership role among developing countries through efficient policies controlling emissions and reducing deforestation rates. For instance, a 55% reduction in greenhouse gas emissions happened between 2005 and 2010, just by controlling deforestation in the Amazon (Viola and Franchini 2017).

Designed by Marina Silva, the PPCDAm was responsible for improving the institutional framework and tackling deforestation. It is contained within the Programa Áreas Protegidas da Amazônia (ARPA), which seeks to protect conservation areas. It also counted on establishing a real-time monitoring system to track deforestation using the technology provided by the National Institute for Space Research (INPE). The PPCDAm also created the Serviço Florestal Brasileiro and Instituto Chico Mendes de Conservação da Biodiversidade, which expanded environmental capacity and biodiversity protection (Viola and Franchini 2017). It is possible to see that the environmental cause had become a crucial part of the government's agenda, given the action of many players, such as the pro-environment coalition, the connection with grassroots movements, and foreign policy objectives.

Moreover, in the international arena, Brazil started to relax its rigid position on forest regulation, such as the Amazon Paranoia. In fact, it became one of the first non-Annex countries to adopt a domestic climate law, hence showing commitment and compliance with international norms (Viola and Franchini 2017). An illustration of this change in mindset is the alliance of Lula with France, which is seen by the armed forces in Brazil as the biggest enemy, given the border with France. As previously mentioned, deforestation rates decreased from 2005 on, given the improved enforcement of legislation, creation of environmental protection areas, action of environmental NGOs, cooperation between federal and state governments, and better equipment. Therefore, the Ministry of Environment played a core role in the fight against deforestation, backed by Lula, who established the Amazon Fund to finance conservation efforts (Viola and Franchini 2017). In the same direction, incentives were created for access to credit by conditioning it to compliance with environmental norms. During this period, states such as Amazonas also implemented local incentives, such as the Bolsa Floresta, all of which attempted to reduce forest devastation.

Lula was reelected in 2006. During COP 12, Brazil proposed the creation of a global fund against forest devastations, putting the Amazon rainforest as an asset for foreign investment. In 2007, the Interministerial Committee on Climate Change was established, and a national plan on Climate Change was enacted in 2008. This plan sought to create mandatory quantitative targets for different sectors, such as forestry, energy, and waste management. By 2017, one of the goals was to reduce deforestation by 80% compared to the period between 1995 and 2005(Viola and Franchini 2017). In addition, a similar strategy to PPCDAm was introduced for the Cerrado biome, called PPCerrado, seeking to reduce land use change emissions in the other biome. It was still part of the plan for a carbon market proposal, although it caused internal division within the Worker's Party (Lula's Party) (Hochstetler 2021). The period also saw new sectoral plans to reduce energy and agriculture emissions and action of states, such as São Paulo and Rio de Janeiro, implementing their legislations to deal with the climate problem. With the Brazilian economy flourishing and stable during this period, public opinion on environmental issues was undeniably more comprehensive (Hochstetler 2021). However, the public attention and awareness in the period turned to Climate Change given the release of Al Gore's documentary "An Inconvenient Truth" in 2006 and the occurrence of extreme climate events across the globe (Viola and Franchini 2017). In 2009, during COP 15, Brazil pledged that reducing deforestation would reduce emissions by around 37% by 2020.

Moreover, in 2009, the National Climate Law was enacted. It established the National Policy on Climate Change (NPCC) and included mitigation targets for 2020 based on the conference of the parties' voluntary commitments (Viola and Franchini 2017). The law introduced a bureaucratic structure to support the NPCC, including the Inter-Ministerial Committee on Climate Change (CIM) and the Brazilian Emissions Market. Mitigation plans were regulated, ranging from deforestation to energy agriculture and the substitution of deforestation charcoal (Viola and Franchini 2017). The Climate Change National

Fund (CCNF) was also created to ensure financial support for mitigation and adaptation policies, as well as provide the necessary resources for implementing these measures.

However, not every stakeholder agreed with the government's agenda, including the rural caucus and the Ministry of Foreign Affairs. Moreover, the opposition from the agricultural interests, the so-called "ruralists", managed to overcome the collective action problem and organize themselves into a group that, since 2010, managed to increase its participation and representation in Congress. It is important to emphasize that not every ruralist opposed environmental measures; some opted to adhere to initiatives such as the Soy and Beef Moratoria transplantation initiative brought by NGOs that played a crucial role in reducing deforestation. Regarding the Ministry of Foreign Affairs and the Ministry of Science and Technology, the problem was that they did not consider Climate Change to be linked with deforestation (Hochstetler 2021). This point of view only changed after the Brazilian success in international climate negotiations, which elucidated the connection between both matters.

In summary, the emissions profile saw reduced emissions in this period, mainly driven by the effective policies reducing deforestation, from 3,800 MtCO2e in 2004 to 1,800 MtCO2e in 2010 (Viola and Franchini 2017). However, emissions in other sectors spiked, given the expansion of fossil fuel consumption and increased agriculture activities. In the energy sector, the government focused on advancing green energy by inaugurating new hydroelectric projects and expanding ethanol production; the discoveries of new oil reserves in Brazil by Petrobras also prompted an oil industry expansion. As for agriculture, the increase in emissions resulted from more significant outputs in the sector; Viola and Franchini (2017) explain that the agri-business sector embraced lower deforestation policies, aligned themselves with public opinion and market forces, and continued exercising their political power and influence. In terms of external affairs, the successful policies gave leverage to Brazil, fulfilling the role Lula wanted of protagonism in international relations. In addition, access to funding, primarily through the REDD+ discussion, was also seen as a victory for Brazilian efforts in forest conservation (Viola and Franchini 2017). Finally, it is essential to understand how actors were organizing concerning this theme; by the end of Lula's second term, the Ministry of Environment, environmental NGOs, Amazon state governors, and corporate coalitions exerted pressure for policy changes. In addition, business coalitions, such as the Alliance of Corporations in Favor of the Climate and the Coalition of Corporations for Climate, demanded climate policy reforms and ambitious emissions targets, driven partly by concerns over potential trade barriers. Playing a significant role, the agri-business sector grew in influence and power (Viola and Franchini 2017). The election of 2010 saw Marina Silva running for president against Dilma Rousseff and José Serra; her participation kept Climate Change a hot topic for public and media debates that year.

6.2.5 Dilma Rousseff (2011-2016)

Rousseff was elected as the successor of Lula in the 2010 presidential election. This event counted on the candidacy of Marina Silva, which influenced the Climate Change agenda, forcing the candidates to tackle environmental topics and low-carbon transitions more directly. Marina Silva's strong sustainability and forest protection stand impacted the Brazilian position at international climate conferences. Rousseff's election happened at the end of the commodities boom cycle, directly impacting government revenues. Moreover, the effects of the 2008 subprime crisis and the slow recovery from European and American markets reduced the overall momentum of climate cooperation (Viola and Franchini 2017). The Rousseff's government also faced strong discontentment given the lack of public service improvements, the slowdown of poverty reduction in the country, and the corruption scandals. In this sense, despite the reelection in 2014, Rousseff went through an impeachment process and was the second president after the military regime in the country to be impeached.

Regarding environmental policy, during Rousseff's administration the relevance of environmental topics were reduced. In addition, the growth of the rural caucus in the parliament put pressure on environmentally strict actions, given their size and decision-making power (Viola and Franchini 2017). Therefore, the debate on climate-related topics slowed, reducing the private sector's pro-climate engagement. In terms of policies, in 2012, the new forest law was enacted. However, given the backlash on deforestation, this was heavily criticized because the new legislation allowed farmers to devastate more and conserve less of the natural areas; it also canceled fines for environmental crimes before 2008. The law also needed to be more credible because it introduced an auto-declaratory registration in the Rural Environmental Registration, leading to concerns about a need for more accurate georeferencing coverage (Viola and Franchini 2017). The government also created the Bolsa Verde in 2011, a monetary incentive for poor communities engaged in environmental protection in the Amazon. It also enacted a national policy on managing indigenous lands in 2012 (Abers 2019). Thus, the environmental legacy can be disappointing, especially considering the previous administration's advancements. For instance, the pace for creating conservation units was slowed down.

Moreover, budget cuts were made to the Ministry of Environment and related agencies, leading to less monitoring and law enforcement. Moreover, the agencies' reduced capacity and the changes in the forest legislation led to increased illegal deforestation (Viola and Franchini 2017). Furthermore, the pressure from the ruralistas and the focus on agribusiness burdened the Plano ABC's effectiveness, a sectoral plan to reduce emissions from the agriculture sector that will be tackled further. Thus, despite some small advancements in the first years of government due to the National Policy on Climate Change (NPCC) and the Action Plan to Prevent and Control Deforestation in the Legal Amazon (PPCDam), both initiatives experienced budget cuts and defunding. Furthermore, support for forest protection actions in the Amazon declined, and the poor economic momentum made the government subsidize gasoline and electricity prices. Meanwhile, public investment in the national oil industry increased, given the discovery of oil in the pre-salt layer of Brazilian shores (Viola and Franchini 2017). Finally, the government granted tax incentives and exemptions to industrials, to the detriment of environmental progress.

Regarding foreign policy, Brazil stepped down from its leadership position and became more conservative and ambiguous, not very active in international climate political matters during this period. The country's commitments and prospects became uncertain because of the spike in deforestation, the economic crisis, and the Brazilian government's reduced capacity to enforce climate policies. In this sense, the Intended Nationally Determined Contributions (INDC) went from the ambitions and will of becoming a low-carbon economy to a conservative approach, postponing the targets, pledging, for instance, zero illegal deforestation by 2030 (Viola and Franchini 2017). Regarding the emissions profile, during Rouseff's government, the emissions increased among the moderate growth in GHG; for example, emissions rose from approximately 1,827 MtCO2e in 2011 to around 1,925 MtCO2e in 2015. Moreover, the GDP carbon intensity increased by around 10% in this period, showing the cause-and-consequence relationship between emissions and production output. Over the period, per capita emissions remained stable at around nine tCO2e. In this period, the more significant drivers for the spike in emissions were the high deforestation rates and the increased fossil fuel usage (Viola and Franchini 2017). In this sense, the comeback of deforestation, especially in 2015 and 2016, represented a significant setback for Brazil's environmental commitments. Hence, the likelihood of Brazil meeting the mitigation targets was low, and its international reputation was shaken; the country was not seen as a reliable climate player.

Regarding the energy sector, corruption in the state-owned oil company Petrobras, with illegal financing, contributed to the increase in public investment and leveraged the power of carbon-intensive industries. The agriculture sector, through the ruralistas, launched initiatives to relax the legislation on forest protection and pardon previous environmental crimes following the new position of the Brazilian government. This illustrates the situation described above in the new Forest Legislation enacted in 2012 (Viola and Franchini 2017). During Rousseff's term, the government enacted some sectoral mitigation plans within the NPCC; those included the continuation of the PPCDam and the Low Carbon Agriculture Plan (Plano ABC). While the PPCDam was a success during Lula's government, after 2011, it started to face challenges because of the reduced state presence in the Amazon region, hence being ineffective in controlling deforestation (Viola and Franchini 2017). The ABC was intended to promote sustainable practices among farmers; one of the problems of this plan was the lack of funding; less than 5% of the budget was dedicated to this. Regarding the energy sector, the government did not have specific mitigation plans, relying on outdated plans such as the Decennial Energy Plan (PDE), which was broad and lacked objectives and projections. In 2011, new plans were designed to tackle Climate Change ruled by climate law, but they were not included in the 2009 Copenhagen Pledge (Viola and Franchini 2017), despite the creation of the new plans. They lacked quantifiable mitigation targets, except for the manufacturing sector plan, and therefore, they only assessed the impact of existing policies on GHG emissions. The first plan was the transportation and urban mobility plan, which aimed to assess emission reduction from infrastructure projects, such as water and rail transport, and promote urban public transportation. The second was the manufacturing sector plan. The goal was to increase competitiveness through carbon emission management, energy efficiency, and technology development. Third, the low-carbon mining plan, which intended to present alternative scenarios for emissions reduction, highlighting new mining technologies and fuel-switching proposals. Finally, the health sector plan that focused on strategies to deal with the impacts of Climate Change on public health is more of an adaptation than a mitigation policy (Viola and Franchini 2017).

One of the problems of this period was the need for domestic and international pressure due to the perception that Brazil had accomplished its obligations for climate stabilization. This happened because of the successful policies and emissions decline of the 2000s. In this sense, Brazil had little pressure to make more ambitious commitments. In addition to the conservative positions internationally, during the COP in Warsaw, Brazilian officials have sustained the argument that developed nations have a historical debt. In contrast, developed nations must emit more to achieve developed status (Viola and Franchini 2017). This behavior was more evident at the RIO+20 in 2012. Brazil prioritized economic and social issues over the climate problem, shifting away from Climate Change themes in official discussions and agenda-setting. Several drivers can explain the decline in climate commitment. For instance, they prioritized short-term economic growth over long-term environmental problems, putting forth economic development at the expense of conservation and increasing emissions through energy consumption and fossil fuels. The prestige and influence gained during Lula's terms were downplayed, foreign policy was not a priority for Rousseff, and climate and environmental agendas were not essential for the government. This can be highlighted through the defunding of the Ministry of the Environment and the government's support of conservative policies, such as the reform of the Forest Law (Viola and Franchini 2017). Finally, new stakeholders, such as the rural caucus, were becoming more vital in the Brazilian political game, and they influenced decisions directly through solid lobbying and legislative seats.

Furthermore, the business sector used the economic crisis argument to organize themselves and protest against climate measures because they could not afford the economic costs, which would impact their competitiveness and increase the unemployment problem (Viola and Franchini 2017). Thus, all the problems in the period were related to economic or political crises amid the corruption scandals and dissatisfaction from the population. In this sense, the salience of Climate Change to the population was low, and Climate Change was a secondary topic. Rousseff was impeached in 2016, allowing vice-president Michel Temer to reach incumbent status.

6.2.6 Michel Temer (2016-2018)

Temer represented a political shift in Brazil, with the impeachment of the left-wing Rousseff to the center-right president. The political and economic situation in the country was a considerable adversity for governability, especially with political sectors accusing Temer of a coup d'etat. In this sense, the government faced record unpopularity, corruption investigations, and impeachment processes. Furthermore, to govern, he had to make concessions for the major political parties and caucuses in the parliament, including the ruralistas. In this line, laws legalizing property titles of land areas without questioning the legality of occupation were enacted, environmental fines were canceled, and farmers' debts were reduced (Viola and Franchini 2017).

Moreover, they suspended the ratification of indigenous lands and allocated resources for these caucuses to pass proposals to please their electorates. In addition, environmental institutions had their budgets cut, and programs such as the Green Grants were suspended, aiming to control the government's fiscal deficit. There were also attempts to authorize mining in protected areas and indigenous lands in the Amazon, which would increase deforestation. In this sense, it is possible to observe a continuation of conservative trends, majorly in emissions, for instance, the LULUCF sector, which saw deforestation rates increase, having an increase in emissions. The conservative stance was also apparent, with Brazil blocking negotiations of carbon market mechanisms in the climate regime (Viola and Franchini 2017). A good point of this new administration was the appointment of José Sarney Filho, an actor tied to the environmental movement. However, budget cuts affected the forest protection agencies, demonstrating a clear sub-prioritization of environmental concerns (Viola and Franchini 2017).

The new administration focused on the economy, given the period of turmoil the country was going through. Moreover, Temer opted for having a more rational and pro-market policy, prioritizing short-term growth and investment while reducing the government's fiscal deficit. However, some actions were still taken. For instance, in the energy sector, gasoline price subsidies were reduced and domestic fuel prices adjusted to the international oil market fluctuation. Despite not having a pro-climate approach, it had the externality of being good environmentally. Another action was the increase in oil production by Petrobras, which would negatively impact emissions (Pereira and Viola 2022). The climate policy stagnation domestically as well as the slow progress in implementing sectoral mitigation plans and forest protection efforts are related to the high influence of the agri-business sector, which leads to the relaxation of regulations, amnesty of previous crimes, and the pardoning of fines. In the international arena, the change in discourse was superficial and remained conservative; hence, despite the claims of being a low-carbon economy, the leadership acquired throughout the last decade was eroded, as well as the claims made by the country were questioned internationally (Pereira and Viola 2022).

Regarding awareness and risk perception, the population focused more on the economy, unemployment, crime, and corruption, making environmental issues secondary to the population. In this sense, the presidential campaign in 2018 was focused more on these topics than Climate Change (Pereira and Viola 2022). The presidential run counted candidates such as Fernando Haddad, Jair Bolsonaro, and former minister Marina Silva, while the ex-president Lula was incarcerated for corruption accusations. It is essential to notice that environmental topics were so secondary for the population that Marina Silva only received 1% of the votes.

6.2.7 Jair Bolsonaro (2019-2022)

In 2018, Bolsonaro was elected president. Known as Trump of the tropics, Bolsonaro made environmental politics secondary during his term. An anti-environmental agenda was established in the executive power. An example of this was merging the Ministry of Environment with Agriculture, though it faced resistance. Moreover, the minister appointed, Ricardo Salles, was directly aligned with the rural caucus and was responsible for dismantling environmental protection institutions and defunding agencies (Pereira and Viola 2022). Furthermore, Bolsonaro terminated the Ministry of Environment secretariat of Climate Change and forestry in an act of climate denial.

Moreover, the Brazilian Forestry Service was moved to be under the Ministry of Agriculture, and despite that, a reduction of personnel and defunding into monitoring deforestation also occurred. During his administration discourses, anti-environment and anti-science agendas were constantly fueled while attempting to change the legal framework and relax environmental protection. Bolsonaro also exonerated INPE's director over deforestation data, defended the use of resources from the Amazon Fund for land expropriation compensation, and advocated for reducing the protection of conservation units and indigenous lands. Bolsonaro also claimed they would like to withdraw from the Paris Agreement, but they backed it after much criticism (Pereira and Viola 2022). Towards the end of the term, they moderated the discourse given the pressure coming domestically and internationally; however, they did not translate this change in discourse into action. In the international arena, Bolsonaro also adopted a climate denial anti-environmental agenda, which affected the Brazilian position in the regime, causing a loss of credibility and damaging partnerships. It also marked a comeback of the Amazon Paranoia, making the military reuse an outdated platform for Amazon protection while allocating a substantial budget. During the period, a new region in the Cerrado went under heavy deforestation, the so-called MAPITOBA (Maranhão, Piauí, Tocantins, and Bahia) (Pereira and Viola 2022). The dynamics are the following: unoccupied areas near roads and infrastructures are cleaned up and converted into cattling fields. After that, they become agricultural lands, mainly soybeans. The core characteristic is acquiring land through land grabbing, similar to what happened in the Amazon. In this sense, soybean production rose almost 432% from 1976 to 2020, making Brazil the most significant producer, holding 1/3 of the total market share, and China as the biggest importer (Pereira and Viola 2022).

Thus, over the period, Brazil faced economic crises, unemployment, inflation, crime, and severe pandemic consequences. Moreover, even though deforestation and fires in the rainforest were recurring and climate extreme events, public opinion kept environmental concerns secondary, given the poor socioeconomic circumstances. On the positive side, a coalition of states named "Governors for Climate" made opposition to the federal government policies (Pereira and Viola 2022). They even negotiated with the U.S. (Biden administration) and European countries despite the sub-federal aspect of the coalition. Furthermore, mobilizing internationalized corporations to control deforestation and shape foreign policy because of their interest in not suffering restrictions against their products abroad also pressured Bolsonaro (Pereira and Viola 2022).

In summary, during this period, with skepticism and denial, climate action was tied to partisanship, leading to the dismantling of climate institutions, regulatory changes, and budget cuts. It also counted on the dispute of some farmers against traders over international agreements, such as the Moratoria. At the same time, the former claimed rights violations, and the latter highlighted the importance of environmental credentialing for market access.

6.2.8 Luis Inácio Lula da Silva (2023-)

There are roughly 18 months of the new administration. However, a few changes have already been noticed. One of the most significant changes was the substitution of Ricardo Salles for Marina Silva. Many policies enacted by Bolsonaro were undone, resulting in Brazil's comeback of conservation policies. In 2023, Brazil recorded reduced deforestation, which was already expected due to the return of the policies and control. Internationally, Lula returned with his progressive diplomacy, participating in the discussions at the Conference of Parties and regaining a small quantity of trust from the international community that Brazil is a severe environmental player. However, some statistics remain negative; for instance, the emissions in 2023 for the energy sector increased, and the burnt area of the Amazon was still significant. Thus, it is still too early to assess the progress or backlashes of environmental policy in Brazil in the current administration. However, there is the expectation that Lula can make considerable progress, as done in the period between 2003 and 2010.

6.3 Graphical Visualization

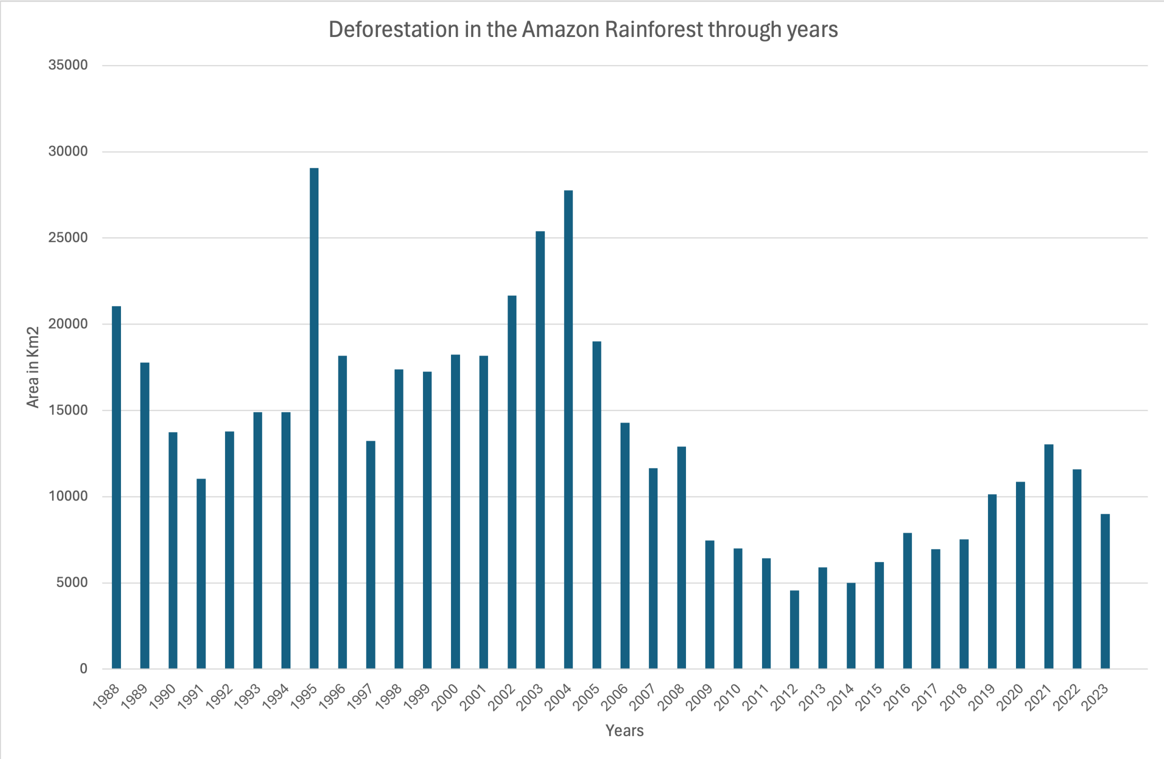

Fig. 6.1: Deforestation Evolution in the Amazon in KM2. Data from: INPE/PRODES

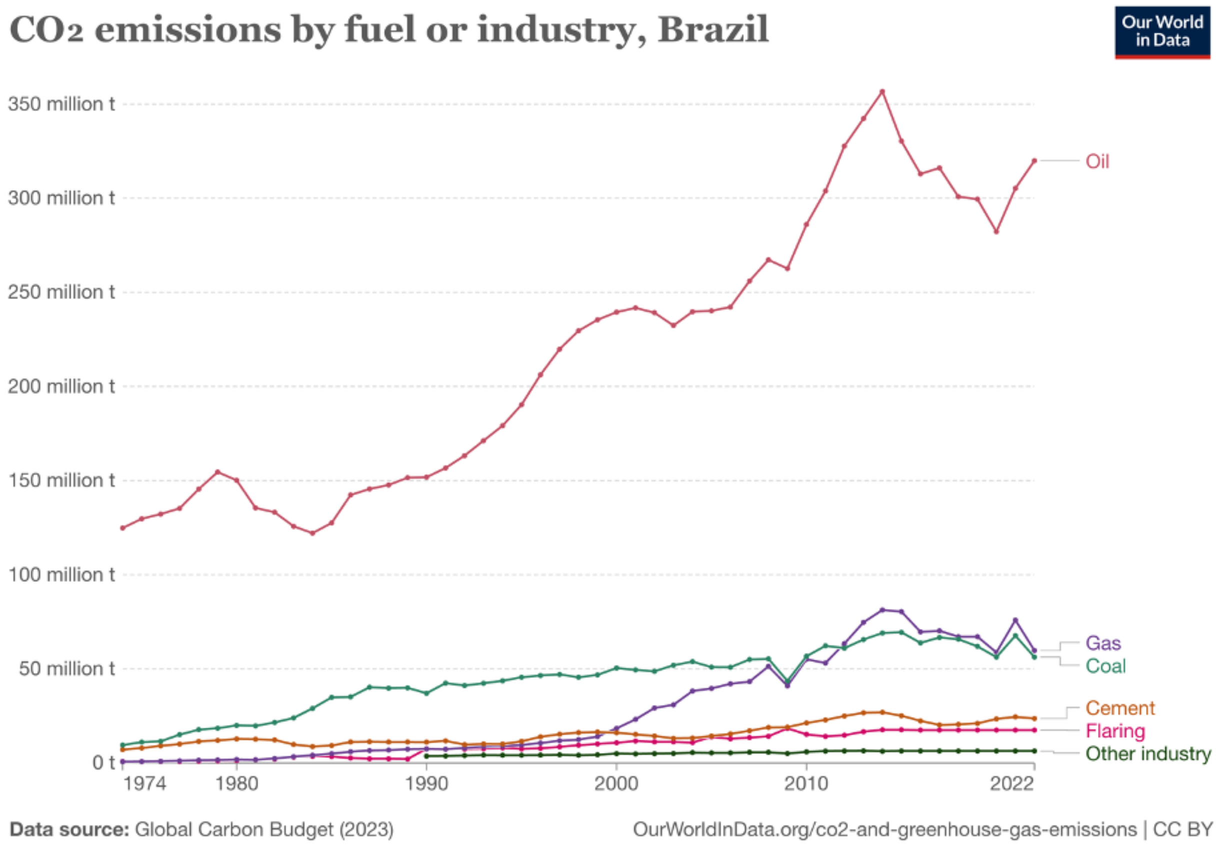

Fig. 6.2: CO2 Emissions. Source: Our World in Data

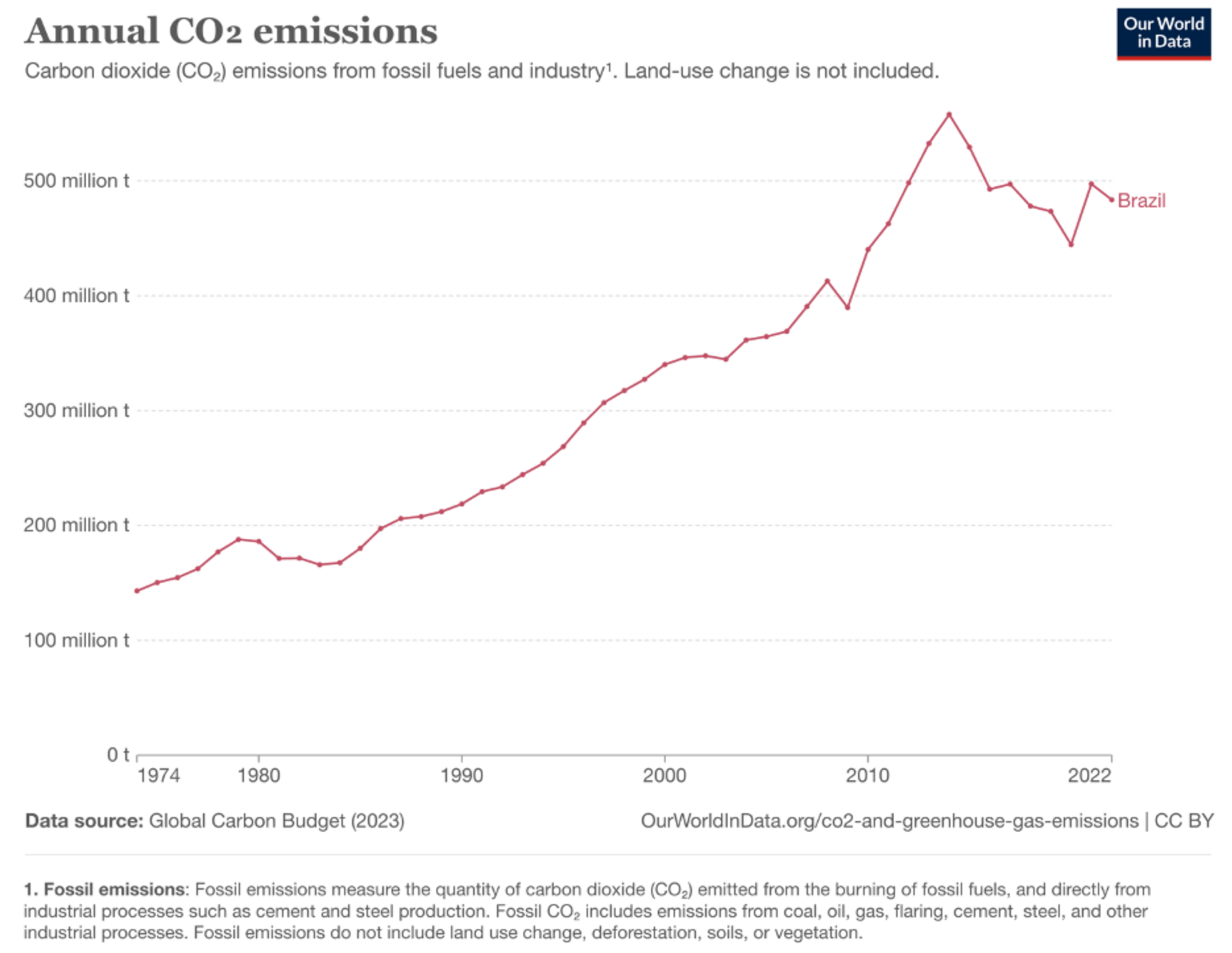

Fig. 6.3: Annual CO2 Emissions. Source: Our World in Data

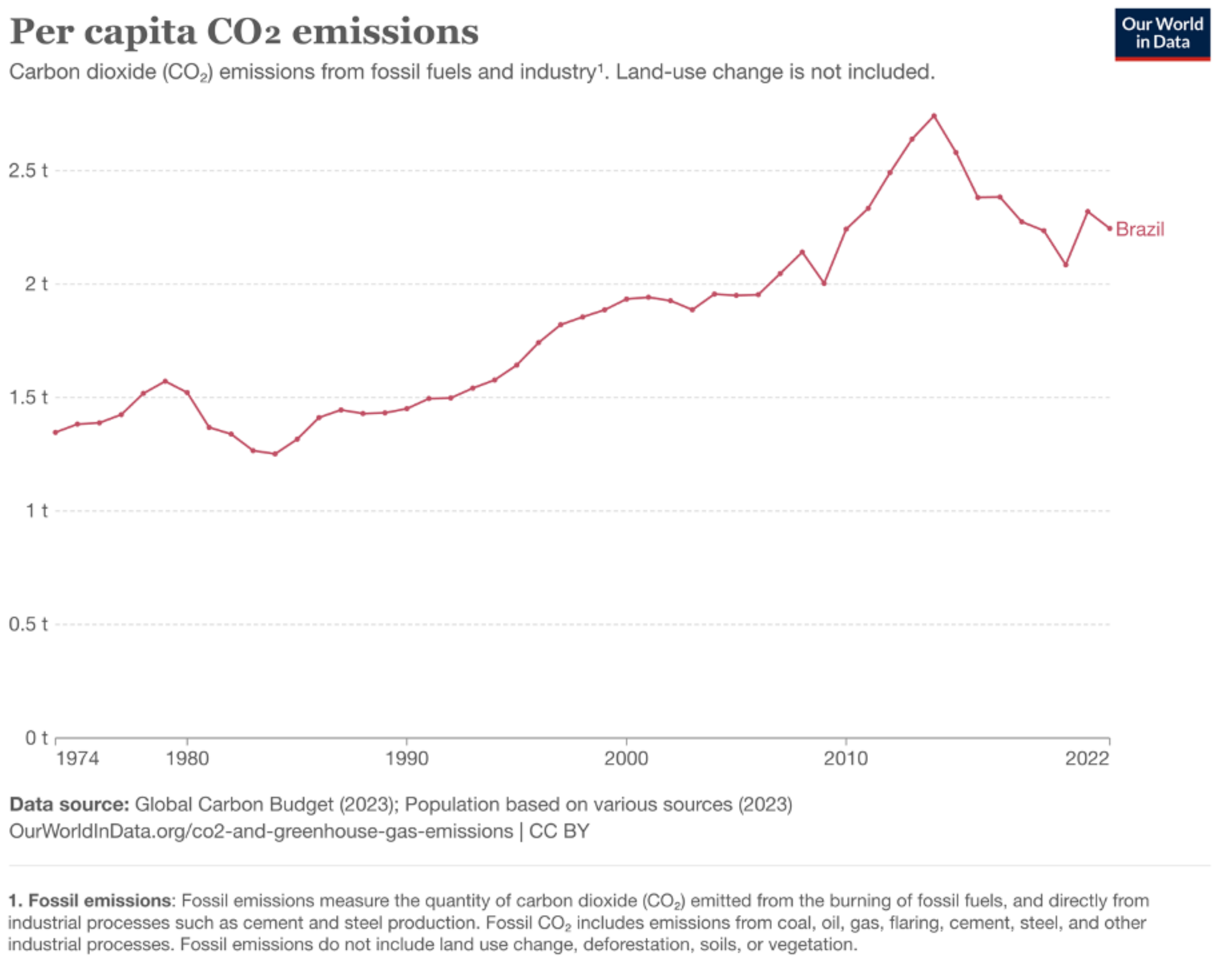

Fig. 6.4: Annual CO2 Emissions per Capita. Source: Our World in Data

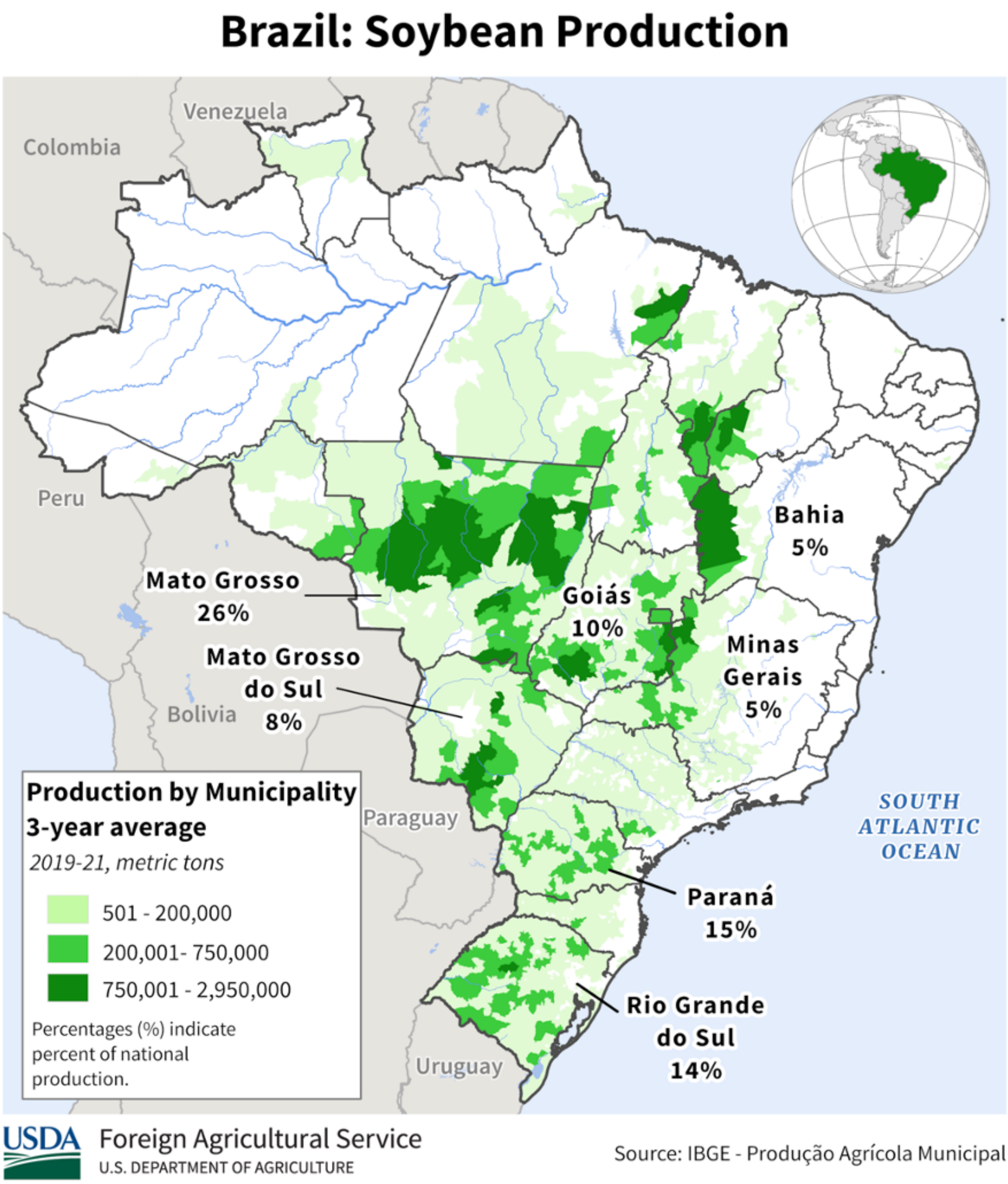

Fig. 6.5: Soybean Production in Brazil. Source: US Department of Agriculture, Data from IBGE

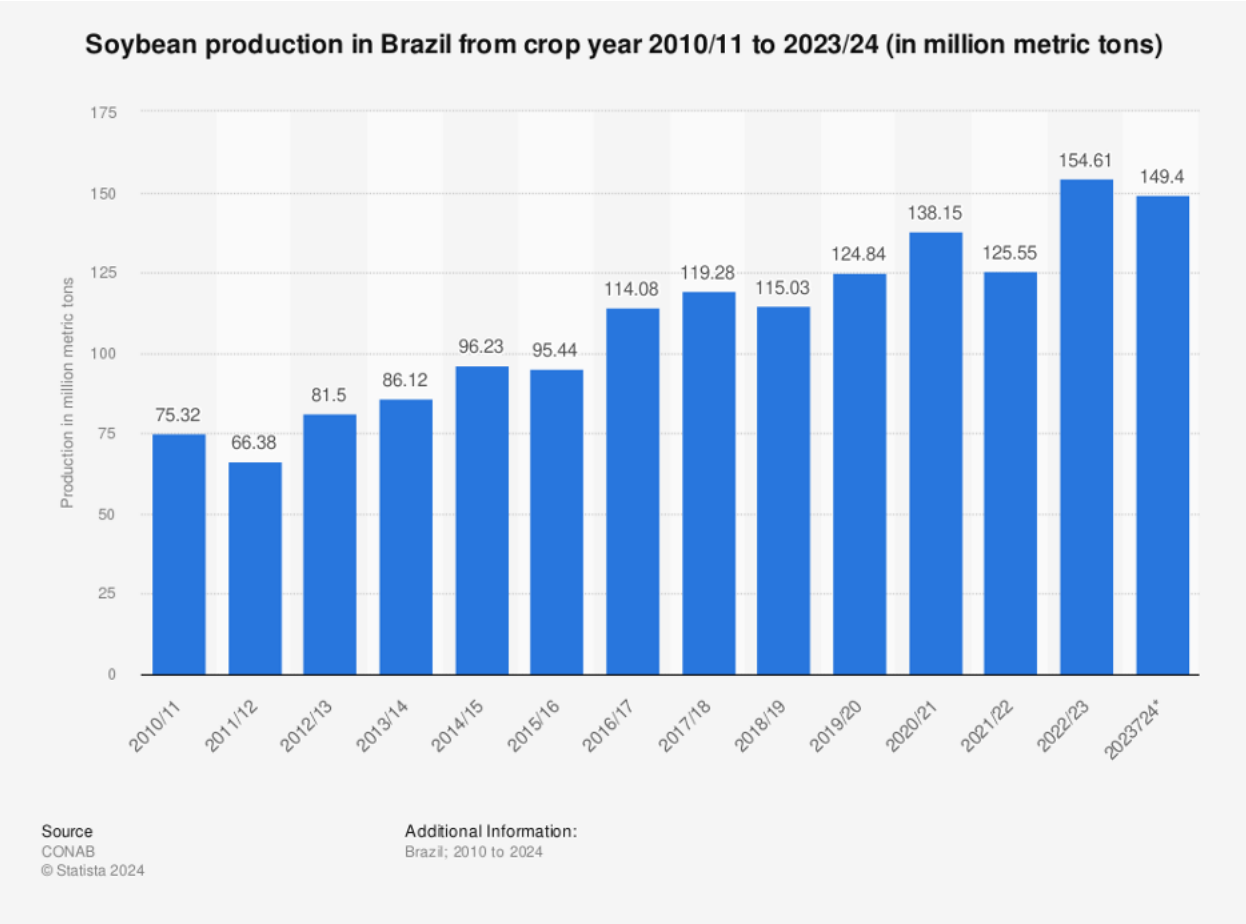

Fig. 6.6: Soybean production in Ton, Source: Statista

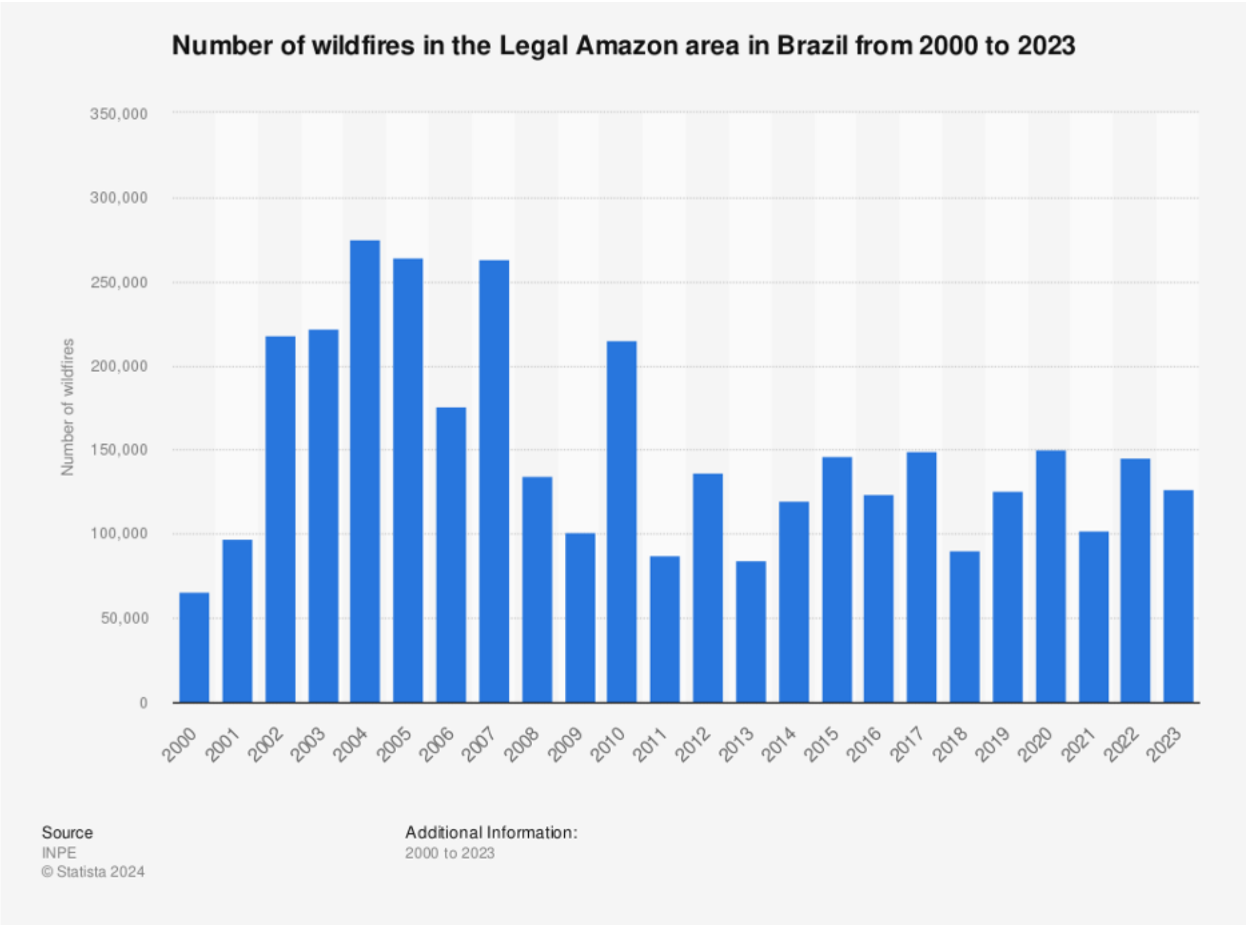

Fig. 6.7: Fires in the Amazon, Source: Statista

CHAPTER 7

Brazil: Actors, Institutions, and Interests

7.1 Double Representation Model (Institutions)

Many actors have shaped environmental politics in Brazil throughout the years. It is then essential to understand the roles of these actors and how the institutional design works, thus allowing an understanding of how the influencing process works. In this sense, Matto Mildenberger (2020) develops the idea of double representation to explain how climate policies are influenced and uses the United States as an example. The author defines climate policy as a "deliberate effort to reshape carbon pollution levels," disregarding whether they are labeled as climate policies or not, focusing only on the intention to impose costs on carbon pollution (Mildenberger 2020). The author also highlights the challenges of studying the variation in climate policies, for instance, defining what is a climate policy and what is not, given their different environmental, economic, or social approaches—furthermore, developing a conceptual framework, seeking to facilitate comparison between periods and states. Mildenberger also differentiates policies by their timing, their trajectory for enactment, the modifications suffered, or the repeal, and by the dimensions of it, analysing what was the instrument of choice, the cost levels, and the cost distributions (Mildenberger 2020).

Moreover, two instruments for policies are identified, the first being pricing policies, that is, carbon taxes and emission trading schemes, seeking to raise private costs of carbon pollution. The second is environmental performance standards, or subsidies for renewable energy and carbon capture technologies. Regarding cost levels, the variation is on the level of costs and subsidies imposed, while the distribution differs, for instance, when there are sectoral exemptions or targeted subsidies (Mildenberger 2020). The author also tackles the policy ambitions, meaning the aim of reducing carbon pollution levels by shifting the political power from carbon-dependent or intensive sectors to clean energy proponents. In summary, Mildenberger (2020) identifies that to understand variation in climate policy, timing, content, and ambition are necessary. In addition, assessing how climate reform efforts influence the power of stakeholders is crucial for effective policymaking.

Advancing toward the model of double representation, it is essential to understand that climate policy preferences are cut across the existing economic and political coalition. Hence, this creates a division between the left and right within these political groups. Moreover, according to Mildenberger (2020), this cross-cutting distribution is a distinguished feature of the climate policy conflicts across advanced economies. When checking the within cuts, it is possible to understand that the pro-climate factions often struggle to enact costly climate reforms, even if there is bipartisan or multipartisan support. These preferences reinforce status quo biases in policy-making, giving an advantage to carbon-dependent business and labor interests (Mildenberger 2020).

Regarding polluters, the carbon-intensive groups and economic interests are usually rooted and embedded within major political coalitions and interest groups, facilitating the influencing process of policymaking, regardless of the party in power (Mildenberger 2020). This can be easily illustrated with the examples drafted from the previous chapter, from 2011 until 2022, with different parties in power—Rousseff (PT – Workers' Party), Temer (MDB – Brazilian Democratic Movement), Bolsonaro (PL – Liberal Party)—carbon-intensive sectors enacted anti-climate policies. Mildenberger (2020) adds that the concept of double representation elucidates how carbon polluters can influence different stakeholders, coalitions, and political spectrums.

Furthermore, the author argues that climate policies can be enacted in two forms. Firstly, one with carbon-dependent actors playing the central role, hence exercising the double representation, and a second form without direct influence (Mildenberger 2020). Moreover, in the first scenario, the carbon-intensive interests directly influence policy design, leading to policies without carbon costs and enacted without further controversies. Second, access to carbon forces is limited, leading to costly policies that lead to conflicts in the public domain and failures to achieve climate reforms (Mildenberger 2020). Finally, the author indicates that institutional factors shape policy design as one of the pluralist or corporative systems; that is, carbon-dependent unions and businesses have guaranteed access to decision-makers to shape policy design.

Moreover, there are formal institutional links between political parties and economic interest groups; left-wing parties, unions, and labor movements have the power to pressure the government, given their influence in these parties. Meanwhile, in right-wing parties, carbon-intensive actors such as businesses have substantial power and can shape public policies. In summary, the Double Representation Theory claims that within right and left parties, there is a subdivision between pro-climate and pro-carbon players. For instance, in a left-wing coalition, unions tend to be more pro-carbon given that the interests of the workers are to keep working; the same goes for the right-wing coalitions, in which the business owner will favor carbon-intense policies.

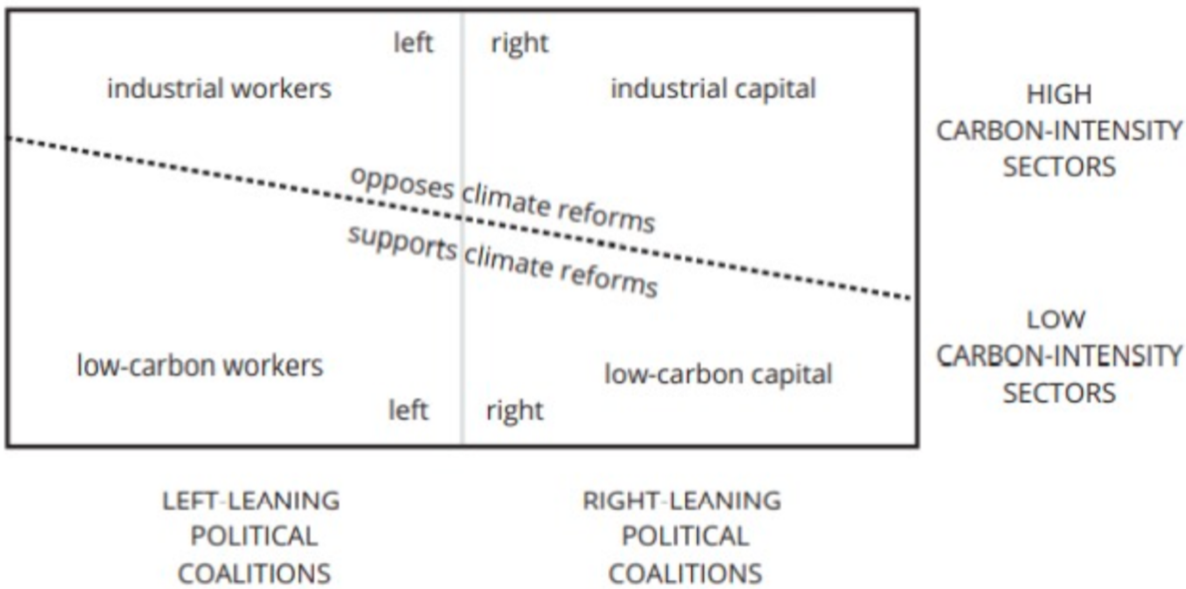

Fig. 7.1: Double Representation example (Mildenberger 2020)

Given the Double Representation Model, it is crucial to understand how actors and groups of interest act in Brazilian politics. In this sense, it will be possible to understand the trajectory of climate policies in the country, as discussed in Chapter 8.

7.2 Actors and Interests

7.2.1 Parties

In Latin American countries, including Brazil, Climate Change is not a divisive issue politically or has salience for the electorate. regardless of their political spectrum, parties often represent low-intensity standings when enacting climate policies (Ryan 2017). Moreover, as explained in the previous chapter, environmental issues were especially significant in 2010 and 2014, with the candidacy of Marina Silva. In the 2022 elections, they were a disaster during Bolsonaro's administration, although this was not a central topic tackled by the candidates. In Brazil, some parties allegedly defend environmental ideologies, such as the Green Party (Partido Verde) and the Sustainability Network (Rede Sustentabilidade) (Hochstetler and Keck, 2007). The former was founded by environmentalists, who were critical of the status quo in the country and on the traditional left in Brazil. However, it struggled to gain general appeal. For instance, the party never had a significant number of politicians elected, peaking with 13 deputies out of 513 in the legislatures of 2007-2011 and 2011-2015, and had two candidates for Presidential elections; in 2010, Marina Silva received almost 20 million of votes, representing 19% of the total votes. Whereas in 2014, Eduardo Jorge, from the Green Party, disputed against Marina, at that time in the Brazilian Socialist Party, and he got 0.61% of the total votes, while Silva received 21%, more than 22 million votes. Hence, it is possible to observe the poor performance of the Green Party in Brazilian politics. Marina Silva founded the latter, although it still faces challenges with electoral performance despite the popularity of Silva; for instance, in the presidential elections that launched Marina as the candidate, the party received only 1% of the votes in 2018, and elected 2 Federal Deputies in 2022. Thus, Climate Change is not a relevant topic for the Brazilian electorate. It is also important to emphasize that other parties engage with environmental issues in ad hoc situations based on public opinion receptivity. However, there is no systematic programmatic commitment to environmental issues by other parties. Furthermore, data shows a trend in deforestation rates and election years: during these years, the rates are often higher, thus indicating a lack of ideological environmental commitment in exchange for political gains using reduced monitoring and a lack of law enforcement.

7.2.2 Environmental Movement

The Environmental Movement in Brazil is diverse and contains urban groups aligned with a significant environmental agenda; groups are also connected to socioenvironmental justice causes that advocate for marginalized populations. One of the problems of the movement in the country is that there needs to be a shared sense of priority, leading to problems of collective action and making it difficult to shape public policy enactment actively. For instance, rural grassroots groups are in favor of extractive economies, while indigenous populations are fighting for land rights (Viola and Franchini 2017; Pereira and Viola 2022). Unlike the political parties, those groups do not have open access to policy-making; their actions are more connected to demonstrations and acts aiming to increase population awareness and create pressure. Brazil also has NGOs, such as the SOS Mata Atlântica, which advocates conserving what exists in the southern forests. Despite not influencing climate policies, the Friends of the Earth, Greenpeace, and other international groups are also present in the country.

7.2.3 Business Groups

Business groups can be divided into clusters based on their alignment with environmental and climate-related issues. One of the groups contains businesses integrated into global value chains (GVCs), for instance, large exporter agribusiness, bioenergy sectors, and conglomerates; examples of those are Shell and Vale, respectively oil and mining sectors. They respond to regulatory changes and consumer pressures over the chain and have a higher probability of supporting pro-climate initiatives (Viola and Franchini 2017; Pereira and Viola 2022). The second group is those not connected to GVCs or involved in illegal activities, such as land grabbing, logging, or mining. They oppose climate policies while significantly influencing Brazilian politics because they control local and state politics and have representatives in the Federal parliament within the caucuses. This influence usually appears through corrupt money and donations to the parties to sponsor their electoral propaganda. Moreover, the so-called Frente Parlamentar da Agropecuária (Agriculture Parliamentary and Front) has 324 out of 513 elected members in the Congress, and 50 out of 81 in the Senate. This explains the large influence business groups and illegal activity firms have over the politics in the country and why, from 2011 onwards, backlashes have happened there (Viola and Franchini 2017; Pereira and Viola 2022).

7.2.4 Military

The Brazilian military has a history of controlling both the areas of the Amazon rainforest and the Cerrado biome, as seen in the previous chapter. In this sense, projects such as the Projeto Calha Norte aimed to enhance the presence of the Brazilian State in the region, hence supporting military initiatives. As an institution of armed forces, the military does not have an official position on Climate Change; thus, there are supporters and skeptics of the cause within the organization. However, it is essential to highlight that the group has yet to take an official institutional stance on climate action. Furthermore, some areas within the military also see the action of International NGOs and countries, such as France, towards the Amazon as a threat to the national sovereignty of the country, an Amazon Paranoia. The role of the military in the government increased during Bolsonaro's administration. Nonetheless, the armed forces were not directly responsible for shaping any public policy related to Climate Change, neither supporting nor opposing it (Pereira and Viola 2022).

7.2.5 International Actors

The European Union has been a consistent progressive actor in international climate politics, influencing Brazilian climate policies through diplomatic relations, participation in initiatives such as the Amazon Fund, and through bilateral economic accords, such as the Merocosur-EU trade agreement. A relevant example appeared in 2019 when concerns about rainforest preservation emerged; in this sense, the European Union included the integrity of the Amazon as crucial for reaching a deal. The primary basis of this commercial agreement was to allow the South American countries to export commodities, such as soy, crude oil, and iron ore, to the EU. The Europeans would export industrialized goods, such as vehicles and wine (Nolte et al. 2017). Another crucial international actor is the United States, which influences Brazil through alliances between American NGOs and Democratic administrations pushing for climate policies in Brazil. It is essential to highlight that Trump, on the other hand, exercised a negative influence by withdrawing from the Paris Agreement, which led Bolsonaro to threaten on following Trump's action [1]. Finally, China, the principal trade partner in the country, has been historically conservative in international climate politics but has recently taken more progressive stances. As China is the major buyer of Brazilian commodities, pressure from Beijing would significantly influence the Rural Caucus, leading to Climate Policy Enactment (Viola, Franchini, and Ribeiro 2014; Basso and Viola 2014).

[1] "Bolsonaro Diz Que 'Pode Sair Fora' Do Acordo de Paris ," Agência Brasil, December 13, 2018, https://agenciabrasil.ebc.com.br/politica/noticia/2018-12/bolsonaro-diz-que-pode-sair-fora-do-acordo-de-paris.

Chapter 8

Brazil: Climate Extreme Events, Compliance, and History

8.1 Climate Extreme Events in Brazil

This research is being written amidst one of the most devastating climate catastrophes in Rio Grande do Sul, Brazil. The flood in the state has left a trail of destruction, causing approximately two billion U.S. Dollars in damages and affecting over three million people. Over the years, Brazil has witnessed a significant surge in climate extreme events, as evidenced by the International Disaster Database (EM-Dat). This database classifies major disasters as ten or more fatalities, over 100 affected people, a declaration of a state of emergency, or a call for international aid.

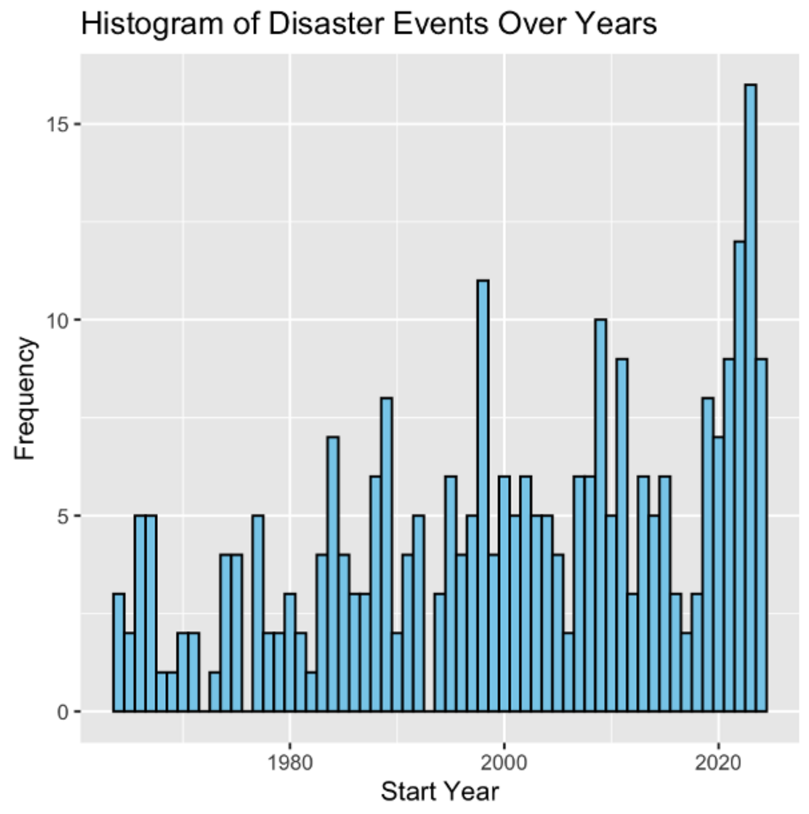

Fig. 8.1: Histogram of Disaster events through the years in Brazil

From 1964 to 2024, Brazil has experienced many climate extreme events. However, it is possible to see that these numbers increased in the past four years. Moreover, the trend for those events is to take place even more frequently in the following years with the aggravation of Climate Change and the rise in the global average temperature. Among the most common events in the country, floods, storms, mass movements (landslides), and droughts are the most common, with a particularly high occurrence of floods.

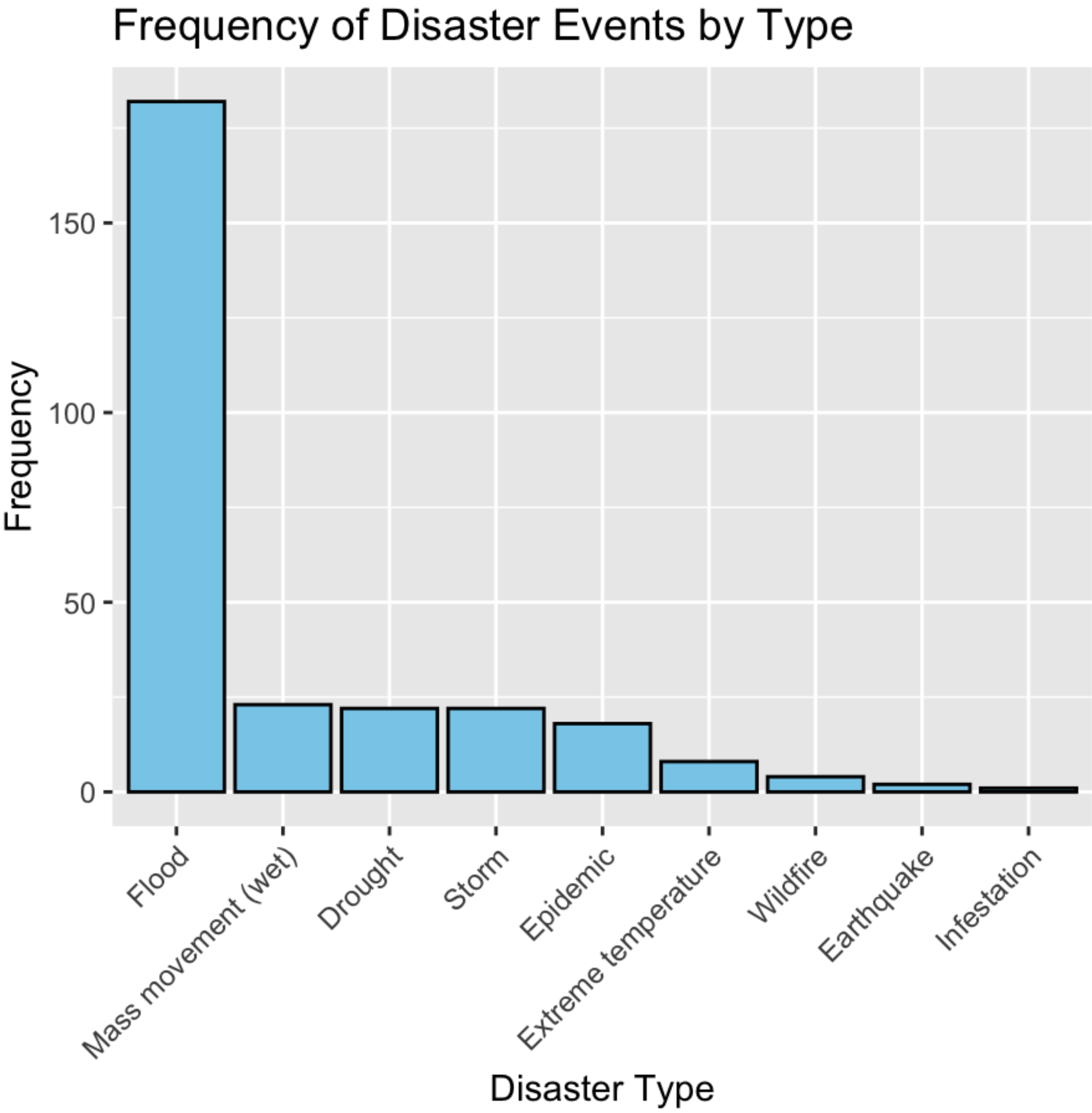

Fig. 8.2: Frequency of disaster by type in Brazil

When it comes to the number of deaths, it can be seen that the events are often not as hazardous for the population in general, but are causing more destruction than loss of human life. For instance, the death toll for these events has two peaks, one in 1974, during the military regime with widespread Meningitis in the city of São Paulo, leading to an unofficial number of 1500 deaths. The EM-data classified this as a natural disaster of biological order. It is important to emphasize that Climate Change and deforestation are two causes of widespread epidemics. However, there is no clear link between the disease outbreak and Climate Change in this case. In 2011, in the municipality of Nova Friburgo in the state of Rio de Janeiro, intense rain caused floods and landslides, given the mountainous landscape of the region, causing more than 900 deaths and a "mud sea" . The same was seen in the human provoked catastrophes in Mariana and Brumadinho, both in Minas Gerais, given the rupture of a mining dam. It is also essential to notice that many smaller events have also provoked a high number of casualties, which in the aggregate of one year ended up being a high death toll, as is possible to see in the graph.

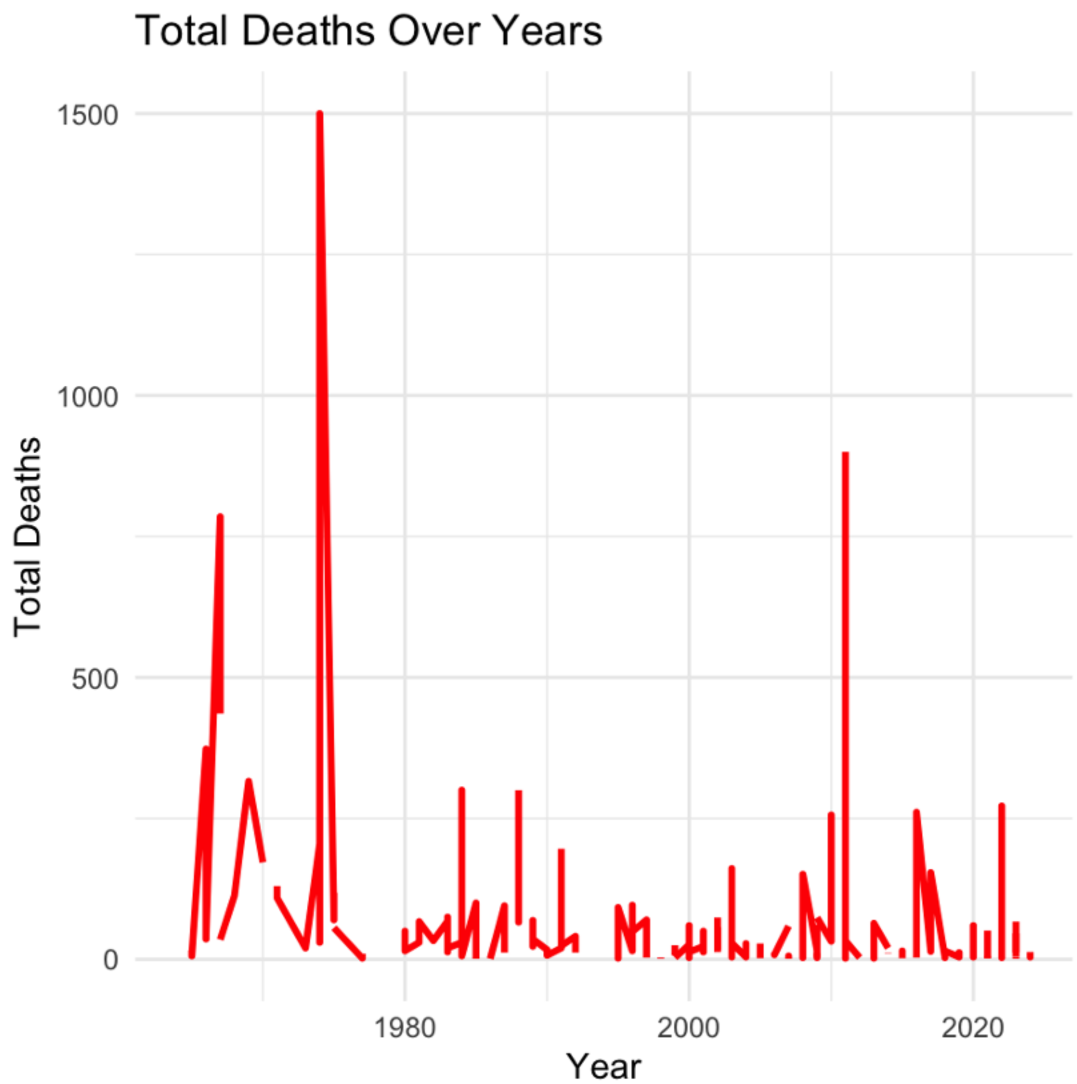

Fig. 8.3: Number of deaths consequence of disasters

Finally, when assessing the effects of climate events on deaths, it is possible to see that a higher frequency of floods leads to a high number of deaths. Still, it is also indicated that Brazil is more susceptible to floods in terms of climate events. However, based on the rough data, it is possible to observe that a significant part of these events happened in the country's southern region or the coastal area of the northeast region. Hence, there are minimal occurrences in the North and Center-West, where agriculture is more prominent.

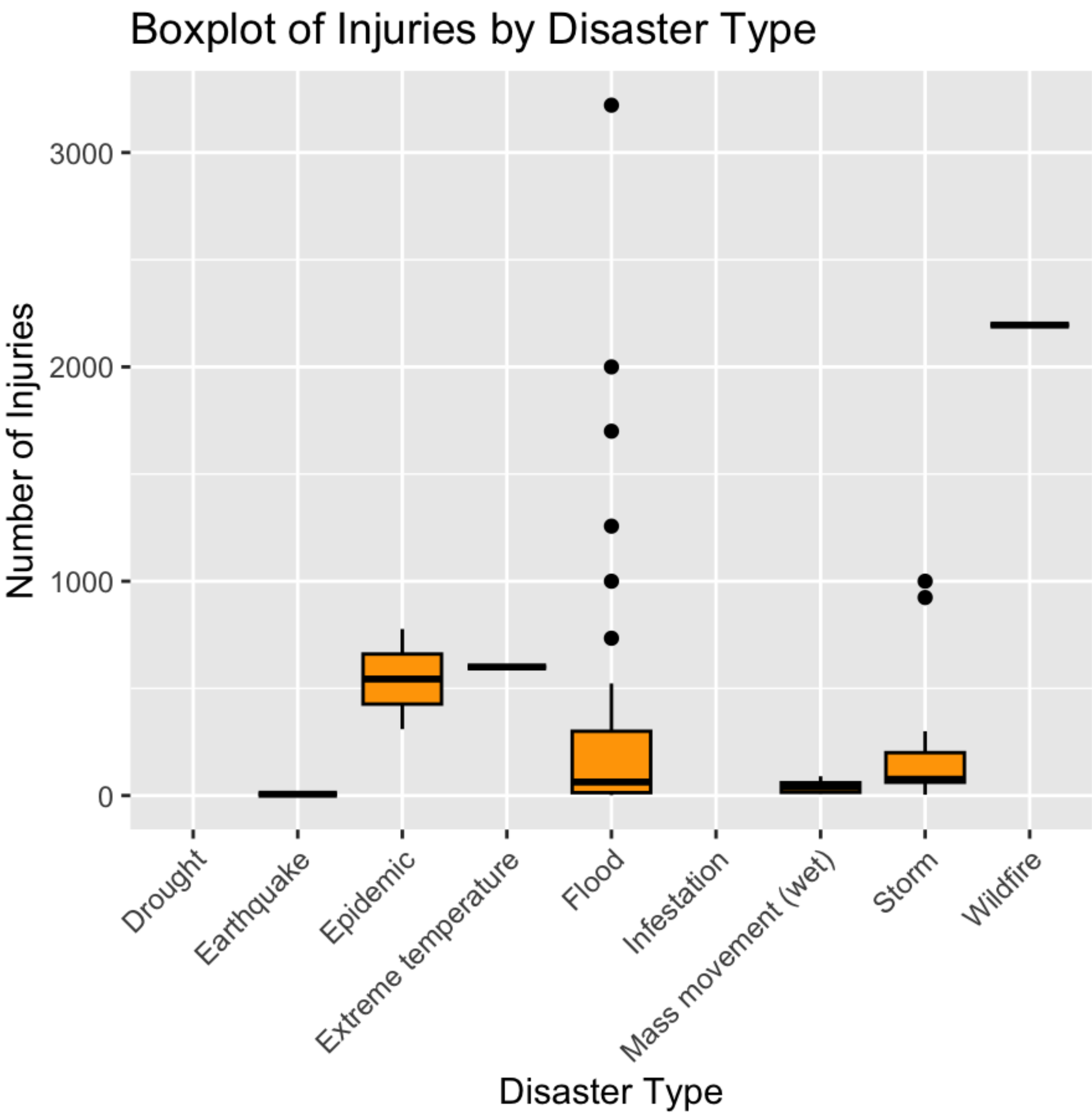

Fig. 8.4: Box Plot of injuries by disaster type

8.2 Compliance and Occurrence of Events

Brazil had a single period of high compliance with international norms for Climate Change, which happened during Lula's presidency between 2003 and 2011, as it was qualitatively assessed and explained in Chapter 6 of this research.. The compliance and leadership position is attributed to the good economic moment that the country had with the international boom of commodities and Lula's general idea of diplomacy. Thus, the role of the president actively engaging in Foreign Affairs summed up the good economic moment and the awareness of the people turned to ecological and environmental matters, led the country to have a more progressive agenda in terms of Climate Change and environmental policy. This scenario was different before 2003 and after 2011; both periods have something in common: political and economic instability. In this sense, both the government and the population did not see the climate problem as relevant, and this happens because economic issues have an immediate effect, such as unemployment and inflation. Over the period between 1991 and 2024, Brazil experienced an oscillation in the unemployment rate, which was reduced over the years. Still, with the political instability of the Dilma administration, it began to rise again, reaching 14% of unemployed people in the country; a similar situation can be seen from 1991 until 2000, with repeated years of rate increase.

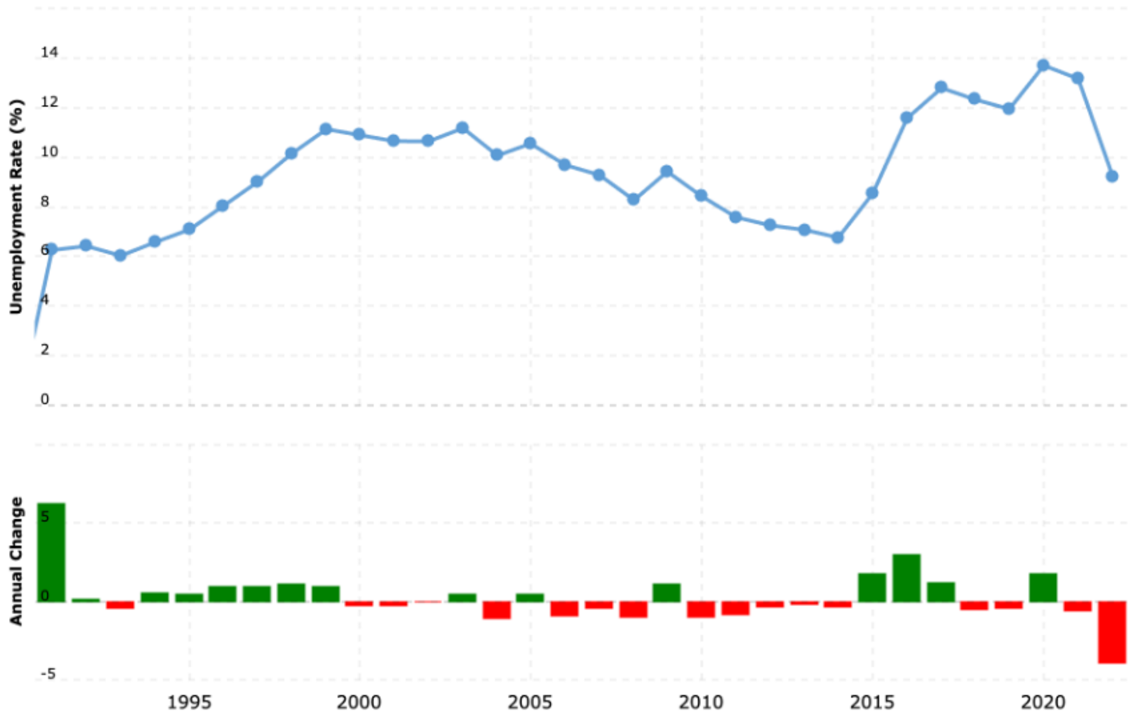

Fig. 8.5: Unemployement Rate in Brazil from 1991-2024. Source: Macrotrends

When it comes to inflation, economic problems are even more prominent, and it helps to understand why the population puts economic gains over climate policies. During the '80s and '90s, Brazil suffered a period of high inflation, having peaked with an inflation rate of 3000%. After many failed economic plans, the situation stabilized around 1996, allowing other problems to be tackled in the new millennium. In this sense, from 2000 onwards, it is possible to observe an inflation stabilization, with a slight increase during the 2010s and the decade of the 20s.

This explains why public opinion does not consider climate problems salient and why these topics are sometimes only addressed during presidential elections. However, in addition to that, it is essential to look at other information, such as soybean exports. This sector is considered the most significant GHG emission in the country, as also seen in the emissions profile explained in Chapter 6 and the relevance of the rural caucus in

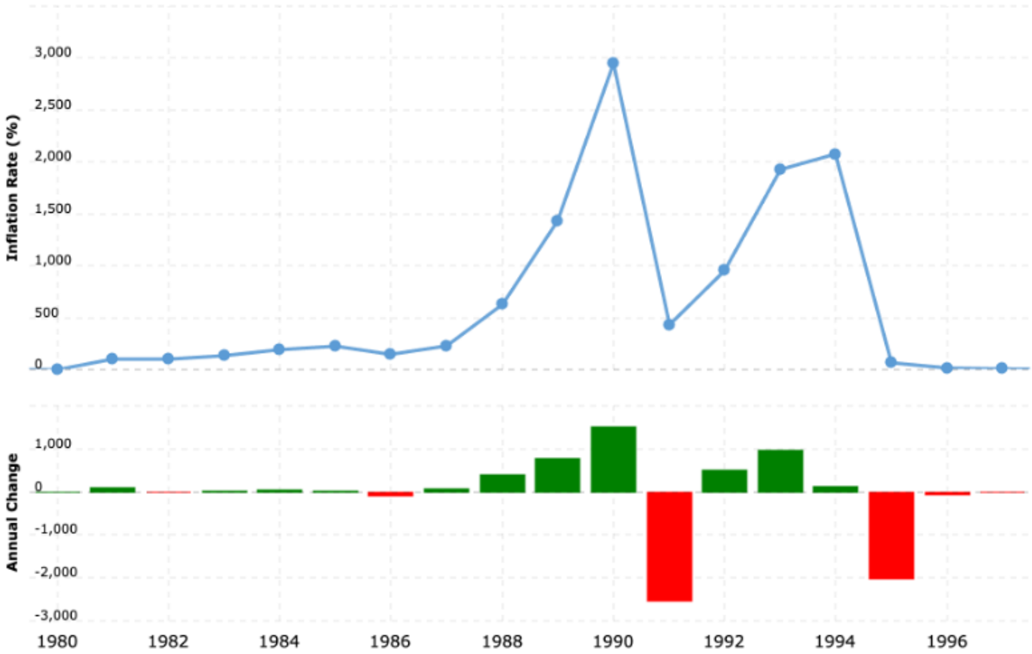

Fig. 8.6: Inflation Rate in Brazil 1980-1998. Source: Macrotrends

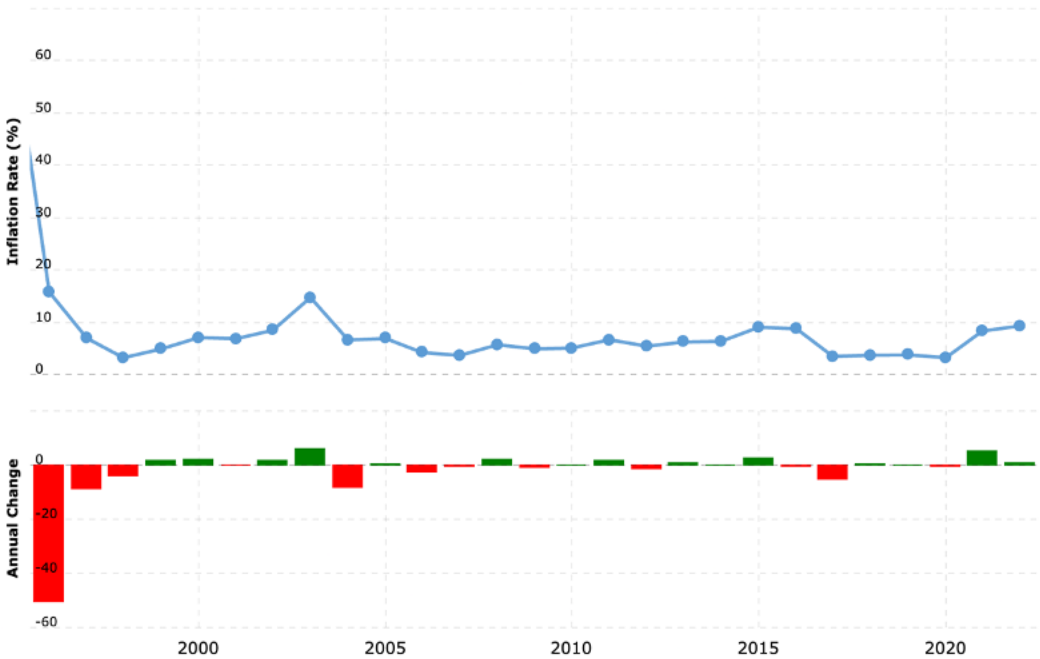

Fig. 8.7: Inflation Rate in Brazil 1999-2024. Source: Macrotrends

policymaking in Chapter 7. It is possible to observe that the exports of this commodity have been breaking records, bringing economic gain to the country. This is a consequence of the caucus's action from 2011 onwards, easing the environmental legislation and the lack of public pressure to enforce more strict rules. As for the general population, economic development comes before environmental politics, given the immediatism of the effects.

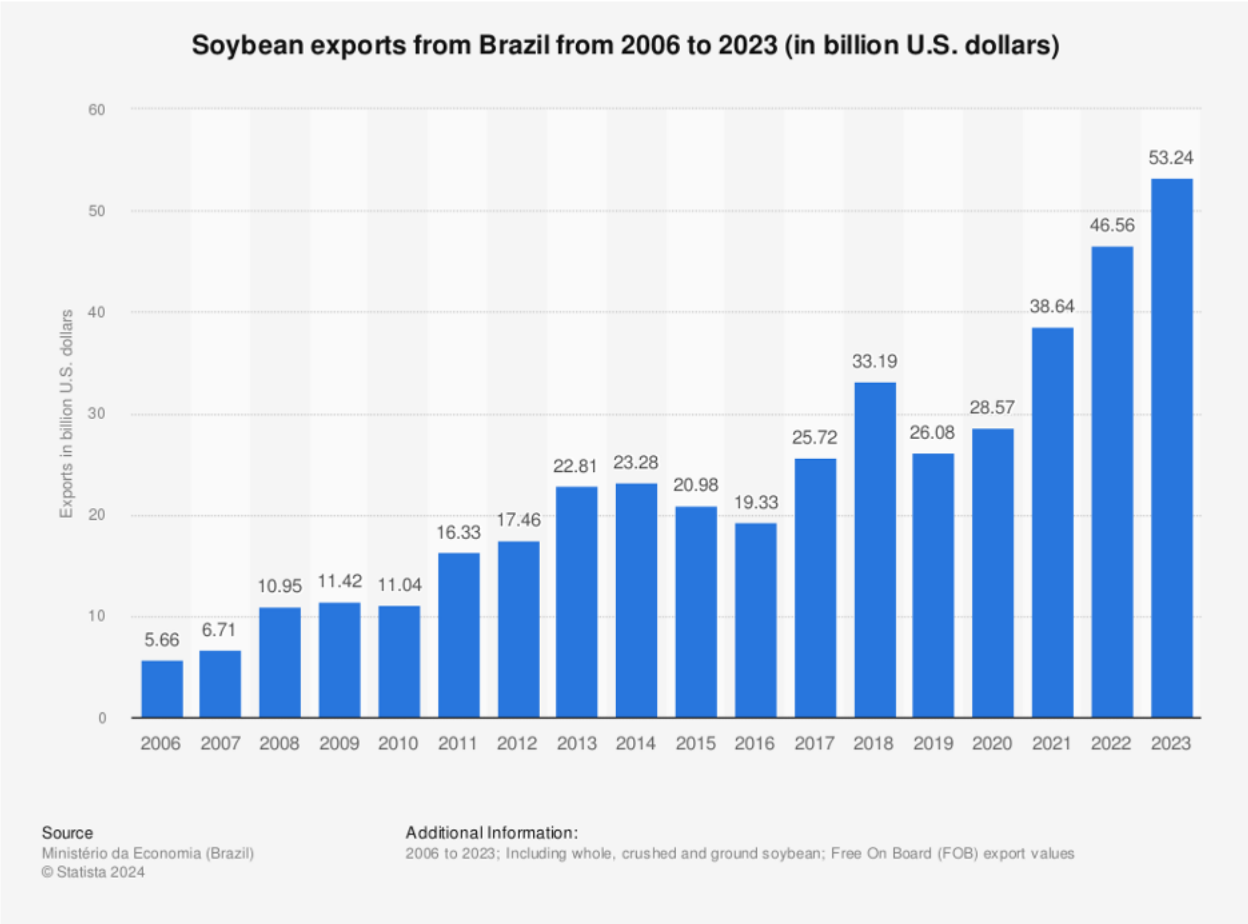

Fig. 8.8: Brazilian Soybean Exports. Source: Statista, data from the Brazilian Economics Ministery

8.3 Discussion

In Section 1 of this research, the main argument was that as Climate Change is indeed a security problem and when States are threatened by it, they will comply more with international norms and agreements to mitigate the risk as a form of self-defense. In Chapter 5, the quantitative analysis showed that there is a small effect of risk on compliance. In this sense, a higher perceived risk will lead to a slight increase in compliance through the occurrence of events. In the previous Section, after understanding the trajectory of environmental policy in Brazil and the role of many actors, it is possible to comprehend how the dynamics work in this context. Finally, in this chapter, the frequency of extreme climate events enlightens the analysis and opens space for discussion. It is widely known that the problem of Climate Change is a Collective Action Problem (Olson 1965); that is, everyone would benefit from fewer changes because the climate patterns would not be altered, and the incidence of extreme events would be reduced. Another economics concept that explains the situation well is the Tragedy of the Commons, introduced by Hardin (1968). To put it simply, it happens when actors behave in a self-centered way and deplete the finite resources of a system, hence leaving everyone worse off. In this sense, countries face a dilemma because, at the same time that solving Climate Change will be a common good, no one would give up the resources. Because they know that free riders will still use the resources and benefit of the common good despite not paying the costs of change.

Furthermore, despite the cost analysis, countries are also exposed to multiple other threats and issues, both internationally and domestically. For instance, Ukraine, during the period of war against Russia, could never advance resolutions of Climate Change mitigation, given that the country is facing a military threat. In Brazil's case, as in most other developed countries, socio-economic issues tend to speak louder and appeal more to the general population. That can be explained using the Selectorate Theory, presented by Mesquita (2003). This theory advances the logic of political survival; once in office, politicians will do what they can to remain in office. Due to this, when incumbents face social pressures, the answer must be given in a way that guarantees reelection. This explains why emissions in Brazil tend to be higher in electoral years, as mentioned before. Because emissions are still, to some extent, indicators of development or at least improvement of economic situations, it is comprehensive why Brazil, undergoing a turbulent period, politically and economically, relaxed environmental regulation. However, it is essential to remember another factor: the representation of carbon-intensive groups within the parliament. The Frente Parliamentary Agropecuária is a very powerful caucus in Congress and the Senate, representing the interests of the Carbon industry. Hence, it is possible to observe a Double Representation (Mildenberger 2020) problem in the congress. Therefore, with such significant participation of the carbon industry in Congress, they will not enact hurtful policies for their sector.

This is true, until a certain point, there are two main situations in which Environmental Policies would be enacted, even if they hurt the caucus. The first is if China, Brazil's most significant commercial partner, suddenly changes the traditional policy concerning Climate Change and starts advocating for green economies. Furthermore, that would be a situation in which the Asian country would demand strict regulations from the Brazilians as a precondition to continue trade. In this scenario, the core incentive is economic factors. However, there is another situation involving the Selectorate Theory. In this second scenario, the population in the country would acknowledge Climate Change as an existential risk and start pressuring the politicians to enact measures. This may happen with the incidence of climate extreme events being more intense and frequent, leading to more destruction and fatalities. In this situation, politicians willing to be reelected would adapt their discourses to please their Selectorate, who would advocate for harsher measures on environmental protection. Through this way, Hypothesis 2, that "Individual risk perception influences public policy on the macro level.", using the logic of Selectorate Theory (Mesquita 2003), can also be validated.

In summary, when putting together both initial sections of this research, it is possible to understand that climate threat has a minimal lagged effect on compliance. However, one must know that in general terms, it is tough to assume that if a country suffers from extreme climate events with determined frequency, it will become a leader advocating for climate policies internationally. Instead, for this to happen, several countries would have to suffer from the effects and acknowledge Climate Change as a security and existential threat. If this does not happen, what may occur is that internal problems will always prevail when confronted with climate issues. Moreover, despite the incentives for cooperating, in the end, the fear of free riders makes States pursue the self-help logic, leading to a Tragedy of the Commons situation. Thus, despite affecting compliance, climate threat analysis must always be followed by a deeper qualitative study to understand the scenarios and conditions in which each country stands. Statistically, some advances have been made over time given the climate threat, but those effects must catch up on time and minimally. Finally, political interests, groups of influence, and lobbying still dominate policy enactment, and only a worsening in the current scenario, with more immediate effects, may trigger a proper, robust response from the international community.

Chapter 9

Conclusion

This research, which delves into the crucial issue of compliance and international cooperation in the field of Climate Change and environmental policy, is framed by an international security lens. The thesis is structured into three parts; the first part establishes the groundwork with key questions, definitions, and a general methodology for the core research question, namely, “To what extent are countries more prominently threatened by Climate Change more prone to adopt and enforce environmental policies?” The second part focuses on Brazil, using the South American country as a case study. The third part brings all the elements together, providing a comprehensive discussion and conclusive remarks. Chapter 1 introduces the topic, underscores the research question and the hypothesis, and defines important concepts used throughout the research. Chapter 2 revisits the literature on climate security and environmental policies, explaining the logic of the consequences argument, the threat multiplier argument, and the concepts of war for resources and climate refugees. This chapter lays the foundation for the subsequent chapters, establishing why Climate Change should be viewed as a security issue. The paper’s contribution to the literature lies in the innovative methodological approaches employed when studying state behavior in response to Climate Change.

Chapter 3 explains the theory behind the argument and its rationale. In this context, traditional concepts of International Relations theory are presented and adapted for the climate situation. The concepts explained range from Walt’s (1987) alliance formation theories, such as Balancing and Bandwagoning, and Snyder’s (1984) Security Dilemma, to Gray’s (1971) framework of the arms race. In short, the rationale presents that Climate Change, in the object of climate extreme events, indeed poses a threat to countries and global security, so states should form alliances—therefore Balancing—in order to cooperate in the pool of mitigation. In addition, given the idea of a Security Dilemma, the harsher the impacts of the event, the harsher the response by the states. This chapter also introduces both hypotheses assessed in this research, H1: "Countries which are more threatened by Climate Change will have higher compliance to International Environmental Norms" and H2: “Individual risk perception influences public policy on the macro level.” Following Chapter 4, the idea is to explain compliance and challenges when measuring it, especially in the environmental field. In this part of the book, still in Section 1, the objective is to develop a comprehensive framework to measure compliance and use this index in the methodological part.

Chapter 5 is dedicated to testing H1 using data from three datasets, two of which are pre-existing compilations by the Quality of Government (QoG) Institute from the University of Gothenburg. A third dataset is developed based on yearly reports published by the German Watch Institute. The methodology involves using the QoG Environmental dataset to compile a metric for compliance using PCA analysis to reduce the dimensionality of the dataset. A K-Means Cluster algorithm is then used to assign groups of compliance, and scores from 0 to 10 are manually assigned based on the countries in specific clusters. The next step involves running regressions using Fixed and Random Effects on average and lagged data. The results indicate a positive causal relationship between the Gini index and compliance scores, suggesting that higher income inequality is associated with higher compliance with international environmental norms.

The findings of the research reveal mixed results for CO2 emissions, however, majorly a higher compliance is indeed related to the decrease of emissions. Furthermore, GDP per capita shows insignificant results in compliance scores. This supports the hypothesis that countries facing more significant threats from Climate Change demonstrate higher compliance with international environmental norms. However, while the overall effect of ecological threat on compliance supports the hypothesis, its strength is insignificant, suggesting that other factors may also play a role in shaping compliance behavior.

Moving to Section 2 of the book, Chapter 6 dives deep into Brazil's historical position. Studying the basic background information of the country, such as Land use, land-use change, and forestry (LULUCF), driven mainly by deforestation in the Amazon, which have been significant sources of emissions. In addition, it is highlighted that the Ministry of Environment has oscillated between pro-sustainability and conservative approaches. Moreover, before the 1990s, the encouragement of land speculation and weak enforcement of environmental regulations made Brazil significantly contribute to environmental degradation during this period. From 1990 to 1995, high deforestation and growth in tensions between economic development and environmental conservation were seen, despite the Earth Summit of 1992, in which Brazil was the host. During Cardoso's administration, Brazil faced higher crop outputs and increased emissions from land use and agriculture sectors. Moreover, given the international criticism for deforestation in the Amazon, the government opted to harshen the legal deforestation rules; Brazil also participated in the Kyoto Conference of 1997.

During Lula (2003-2010), significant progress was made in building institutional capacity through domestic policies to address Climate Change. Furthermore, while being led by figures like Marina Silva and Carlos Minc, Brazil transitioned from a "climate villain" to a leadership role among developing countries by efficiently controlling emissions and reducing deforestation rates. The government also established the Amazon Fund to finance conservation efforts, and incentivized compliance with environmental norms through access to credit—moreover, laws such as the Climate Law were enacted during this period, setting targets for 2020. However, emissions reductions were offset by spikes in emissions from other sectors, such as energy and agriculture, driven by expansion in fossil fuel consumption and agricultural activities.

In summary, Lula's presidency enhanced Brazil's international standing in climate negotiations and access to funding for forest conservation, but also faced pressure for policy changes from various stakeholders, including environmental NGOs and corporate coalitions. During Rousseff's period (2011- 2016), a reduction in ecological topics occurred, and the growing influence of the rural caucus in parliament pressured for less environmentally strict actions. A new Forest Law was enacted in 2012, allowing more devastation of natural areas and canceling fines for environmental crimes before 2008. In summary, emissions increased during Rousseff's tenure, driven by high deforestation rates and increased fossil fuel usage, despite some sectoral mitigation plans like the Low Carbon Agriculture Plan (Plano ABC).

During Temer's tenure, environmental policies took a backseat, with laws favoring landowners, cancellation of fines for environmental crimes, and reduced budgets for ecological institutions. The period is marked by budget cuts and a pro-agribusiness stance hindering progress on climate and forest protection efforts. While in the international arena, Brazil's leadership in climate negotiations eroded, with conservative positions hindering progress and eroding the country's reputation as a climate player. As for Bolsonaro, a significant shift towards anti-environmental policies took place, with appointments and actions aimed at dismantling environmental protection institutions and relaxing regulations. Bolsonaro's administration faced criticism for climate denial, budget cuts to environmental agencies, and efforts to exploit the Amazon for economic gain. Thus, the period observed increases in deforestation, fires, and emissions. Finally, the new Lula government signaled a shift towards progressive environmental policies, with the replacement of anti-environmental officials and a focus on conservation efforts. This can be expressed through the signs of reduction of deforestation and the return of international climate diplomacy, with Brazil again attending the Conference of the Parties (COP).

Following this, Chapter 7 explains the Double Representation Model, proposed by Matto Mildenberger, which describes how climate policy preferences intersect with existing economic and political coalitions. In this sense, it explains how climate policy preferences cut across traditional political divides in Brazil, hence making carbon-intensive industries exert significant influence over decision-makers, regardless of the party in power, shaping policy outcomes. The chapter also explores the stakeholders and their interests, for instance, the lack of control of the Green Party, and how data suggests a trend of increased deforestation rates during election years, indicating a lack of ideological environmental commitment in favor of political gains—the limited paper of the environmental movement, and the action of business groups. For instance, the Agriculture Parliamentary Front, with many members in Congress, represents the influence of agribusiness interests on policymaking. It also explains the military's role and how international players shape the decisions; for instance, China is the most significant commercial partner, and the European Union settled environmental commitment clauses to close the deal of free trade agreements.

Finally, Chapter 8, in Section 3, uses the International Disaster Database (EM-DAT) to consider the occurrence of extreme climate events. This shows how, over time, Brazil has experienced an increase in extreme climate events. It also ignites the discussion of the policy shifting in Brazil and the findings of Chapter 5. Hence, the main argument posited in Section 1 is that Climate Change represents a security threat to states, which motivates them to comply with international norms and agreements as a form of self-defense. It also brings more economic approaches, such as the Collective Action Problem and Tragedy of the Commons discussions, to link all the findings. Thus, while climate threats have a minimal lagged effect on compliance, deeper qualitative analysis is necessary to understand the specific scenarios in which countries prioritize environmental policies. Political interests, lobbying, and domestic priorities often overshadow climate concerns, but worsening the current scenario with more immediate effects may trigger a more robust response from the international community.

However, this research needs to be completed, as many limitations exist and further research is still necessary. For instance, assigning compliance scores may require more precision, and measuring compliance qualitatively over time would provide a more accurate metric. In addition to that, other factors influencing compliance behavior still need to be fully explored. As for the second section, the core limitation is the use of only historical perspective, without quantitative analysis, such as speech analysis, which would help identify patterns of discussions and the modus operands of the Rural Caucus. Another limitation is the time frame studied, which could be enhanced considering all countries, as this research cuts poor countries from the analysis. Another general limitation is that it only addresses the case of Brazil; in this sense, for future research, scholars could employ similar methods and assess politics from different countries across the globe.

In an extra note, the author thinks that despite the quantitative results demonstrated in this research showing that some improvement has happened over the years, this improvement is not enough. Countries may even acknowledge climate change as a security problem, or as a problem at all, however, in the end to achieve a high standard of green economy and produce wealth in the same amount as carbon intensive forces do it takes a lot of regulation, to create incentives, and investment, from public and private parties. If one thinks carefully, carbon intensive sectors and means of production exist since the Industrial Revolution, while talks on green economy and climate change are relatively new. In this sense, it is clearly more reliable to go back in the discussion between development and ecology, it is a trade-off. Because, by one hand in order to achieve a developed status it is important to produce wealth, and the cheapest means to produce wealth is using carbon intensive technologies that have existed and evolved for more than centuries. By the other hand, underdeveloped countries have no chance on developing greener technologies for a series of reasons. Among those, it is important to highlight, the lack of money to invest, and the urgency of other themes over environmental policies.

Ultimately, it will always come back to environmental issues going on the background while "real" and more "serious" problems are more salient in society. Climate Extreme events are getting more frequent and serious, as it is showcased by the floods in Rio Grande do Sul in April 2024, or the extreme temperature that has been hitting Europe over summer. However, this is only a moment problem, and no politician will raise the issue when it comes to getting reelected. No policies will be enables, because on the verge of several crashes of stock markets, as it happened in Japan in August 2024, economy and money matter more. It is understandable that it is beyond the selfishness of investors and politicians, obviously in order to develop technology to mitigate or adapt climate change, investment is beyond necessary. Moreover, the conditions for investment to exist are clear, a good economic moment. This is true for developed countries, but the climate change problem is not an even problem. Because some regions will suffer more than others, and resources are not evenly distributed across the globe. Countries such as China, the United States and European countries have more economic resources to deploy and develop technology. Moreover, if the situation becomes irreversible at some point and adaptation is the only way out, those countries have power to implement policies that will save themselves. Meanwhile, low income countries will suffer from a problem that was not even created by them, since they do not even have industries, and will pay the price of not having enough resources to adapt the new conditions.

It is clear that the energy transition is coming slower than it should, given both geopolitical challenges, such as the war in Ukraine and Economic problems, following the consequences of the COVID emergency, leading to the lack of continuous investments by countries to tackle the problem. In the end, Climate change is not only a security problem, it is a problem that transcend any sphere and cannot be labeled as simply one thing. It is a worldwide problem and needs worldwide action to be tackled.

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Apendix

Raul Bassi

2024-04-30

#Setting up Python ambient

Exploratory Analysis QoG-Env Data

```
df = pd.read_csv("https://raw.githubusercontent.com/rauls3/R-Projects/main/preliminarydata.csv", sep=';
df.drop(df[df.year < 2010].index, inplace=True) #As the analysis will take place from 2011 onwards, we 
df['country_year'] = df['cname'].astype(str).str.cat(df['year'].astype(str)) #Here I create a new varia
```

```
dfn = df.rename(columns={'ccl_lpp': 'laws_adopted_per_year', 'ccl_mitlpp': 'mitigation_laws', 'ccl_nexe
       'ccl_nlp': 'cumulative_number_of_laws', 'ccl_nmitlp': 'cumulative_mitigation_laws', 'iead_eif1':
       'iead_inforce': 'in_force_all', 'iead_inforce_noterm': 'in_force_except_terminated', 'iead_rat':
       'iead_sig': 'signatures', 'iead_term': 'terminated', 'iead_withdraw1': 'withdraws',
       'em_envmin': 'envinromental_ministry',
       'slaws_mit_ex_lt': 'exec_policies_last3yrs',
       'slaws_mit_leg_lt': 'leg_policies_last3yrs', 'slaws_mit_lt': 'gov_policies_last3yrs'})

#Here I rename the variables for a better understanding of what is going on
```

```
dfn
```

```
##                cname  ccode  ...  gov_policies_last3yrs       country_year
## 64       Afghanistan    4.0  ...                    NaN    Afghanistan2010
## 65       Afghanistan    4.0  ...                    NaN    Afghanistan2011
## 66       Afghanistan    4.0  ...                    NaN    Afghanistan2012
## 67       Afghanistan    4.0  ...                    NaN    Afghanistan2013
## 68       Afghanistan    4.0  ...                    NaN    Afghanistan2014
## ...              ...    ...  ...                    ...                ...
## 15220  South Vietnam    NaN  ...                    NaN  South Vietnam2016
## 15221  South Vietnam    NaN  ...                    NaN  South Vietnam2017
## 15222  South Vietnam    NaN  ...                    NaN  South Vietnam2018
## 15223  South Vietnam    NaN  ...                    NaN  South Vietnam2019
## 15224  South Vietnam    NaN  ...                    NaN  South Vietnam2020
##
## [2233 rows x 99 columns]
```

```
dfn.info() #Here we check the variables as well missing values
```

```
## <class 'pandas.core.frame.DataFrame'>
```

```
## Index: 2233 entries, 64 to 15224
## Data columns (total 99 columns):
##  #   Column                          Non-Null Count  Dtype
## ---  ------                          --------------  -----
##  0   cname                           2233 non-null   object
##  1   ccode                           2200 non-null   float64
##  2   year                            2233 non-null   int64
##  3   cname_qog                       2233 non-null   object
##  4   ccci_coop                       0 non-null      object
##  5   ccci_em                         0 non-null      object
##  6   ccci_fin                        0 non-null      object
##  7   ccci_kyoto                      0 non-null      object
##  8   ccci_rep                        0 non-null      object
##  9   ccci_unfccc                     0 non-null      object
##  10  ccl_exepp                       2035 non-null   float64
##  11  ccl_leglp                       2035 non-null   float64
##  12  laws_adopted_per_year           2035 non-null   float64
##  13  mitigation_laws                 2035 non-null   float64
##  14  cumulative_number_of_laws_exec  2035 non-null   float64
##  15  number_of_laws                  2035 non-null   float64
##  16  cumulative_number_of_laws       2035 non-null   float64
##  17  cumulative_mitigation_laws      2035 non-null   float64
##  18  edgar_co                        1104 non-null   object
##  19  edgar_co2gdp                    1768 non-null   object
##  20  edgar_co2pc                     1768 non-null   object
##  21  edgar_co2t                      1768 non-null   object
##  22  edgar_pm25                      1122 non-null   object
##  23  edgar_so2                       1104 non-null   object
##  24  edi_edi                         70 non-null     object
##  25  edi_gee                         70 non-null     object
##  26  envinromental_ministry          177 non-null    float64
##  27  engo_nengo                      0 non-null      float64
##  28  epi_agr                         180 non-null    object
##  29  epi_air                         180 non-null    object
##  30  epi_ape                         180 non-null    object
##  31  epi_bca                         2024 non-null   object
##  32  epi_bdh                         180 non-null    object
##  33  epi_bhv                         2121 non-null   object
##  34  epi_cch                         180 non-null    object
##  35  epi_cda                         2057 non-null   object
##  36  epi_cha                         2057 non-null   object
##  37  epi_ghp                         2132 non-null   object
##  38  epi_gib                         2066 non-null   object
##  39  epi_grl                         1923 non-null   object
##  40  epi_h2o                         180 non-null    object
##  41  epi_had                         2121 non-null   object
##  42  epi_hmt                         180 non-null    object
##  43  epi_lcb                         1868 non-null   object
##  44  epi_mpa                         1606 non-null   object
##  45  epi_msw                         2121 non-null   object
##  46  epi_mti                         1452 non-null   object
##  47  epi_noa                         2057 non-null   object
##  48  epi_nxa                         2024 non-null   object
##  49  epi_ozd                         2121 non-null   object
```

```
##  50  epi_par                        2121 non-null   object
##  51  epi_pbd                        2121 non-null   object
##  52  epi_pmd                        2121 non-null   object
##  53  epi_sda                        2024 non-null   object
##  54  epi_shi                        1780 non-null   object
##  55  epi_snm                        2077 non-null   object
##  56  epi_spi                        1716 non-null   object
##  57  epi_tbg                        2132 non-null   object
##  58  epi_tbn                        2132 non-null   object
##  59  epi_tcl                        1967 non-null   object
##  60  epi_usd                        2121 non-null   object
##  61  epi_uwd                        2121 non-null   object
##  62  epi_wmg                        180 non-null    object
##  63  epi_wrs                        180 non-null    object
##  64  epi_wtl                        1813 non-null   object
##  65  epi_wwt                        2101 non-null   object
##  66  enforced                       1928 non-null   float64
##  67  enforced2                      1928 non-null   float64
##  68  iead_eif3                      1928 non-null   float64
##  69  in_force_all                   1928 non-null   float64
##  70  in_force_except_terminated     1928 non-null   float64
##  71  ratifications                  1928 non-null   float64
##  72  signatures                     1928 non-null   float64
##  73  terminated                     1928 non-null   float64
##  74  withdraws                      1928 non-null   float64
##  75  iead_withdraw2                 1928 non-null   float64
##  76  nrmi_nrpi                      970 non-null    object
##  77  oecd_cctr_gdp                  801 non-null    object
##  78  oecd_cctr_tot                  847 non-null    object
##  79  oecd_eampg                     190 non-null    object
##  80  oecd_epea                      182 non-null    object
##  81  oecd_eps                       153 non-null    object
##  82  oecd_etr_gdp                   851 non-null    object
##  83  oecd_etr_tot                   849 non-null    object
##  84  oecd_pm25ex15p                 1454 non-null   object
##  85  oecd_pm25ex25p                 1454 non-null   object
##  86  oecd_polagdpg                  190 non-null    object
##  87  sgi_en                         246 non-null    object
##  88  sgi_enen                       246 non-null    object
##  89  sgi_enge                       246 non-null    object
##  90  sgi_epe                        246 non-null    float64
##  91  sgi_ger                        246 non-null    float64
##  92  slaws_mit_ex_l3                931 non-null    float64
##  93  exec_policies_last3yrs         931 non-null    float64
##  94  slaws_mit_l3                   931 non-null    float64
##  95  slaws_mit_leg_l3               931 non-null    float64
##  96  leg_policies_last3yrs          931 non-null    float64
##  97  gov_policies_last3yrs          931 non-null    float64
##  98  country_year                   2233 non-null   object
## dtypes: float64(29), int64(1), object(69)
## memory usage: 1.7+ MB
```

```
dfn.isnull().sum().head(40)
```

```
## cname                              0
## ccode                             33
## year                               0
## cname_qog                          0
## ccci_coop                       2233
## ccci_em                         2233
## ccci_fin                        2233
## ccci_kyoto                      2233
## ccci_rep                        2233
## ccci_unfccc                     2233
## ccl_exepp                        198
## ccl_leglp                        198
## laws_adopted_per_year            198
## mitigation_laws                  198
## cumulative_number_of_laws_exec   198
## number_of_laws                   198
## cumulative_number_of_laws        198
## cumulative_mitigation_laws       198
## edgar_co                        1129
## edgar_co2gdp                     465
## edgar_co2pc                      465
## edgar_co2t                       465
## edgar_pm25                      1111
## edgar_so2                       1129
## edi_edi                         2163
## edi_gee                         2163
## envinromental_ministry          2056
## engo_nengo                      2233
## epi_agr                         2053
## epi_air                         2053
## epi_ape                         2053
## epi_bca                          209
## epi_bdh                         2053
## epi_bhv                          112
## epi_cch                         2053
## epi_cda                          176
## epi_cha                          176
## epi_ghp                          101
## epi_gib                          167
## epi_grl                          310
## dtype: int64
```

```
dfn.ccode.tail(64)
```

```
## 14750    891.0
## 14751    891.0
## 14752    891.0
## 14753    891.0
## 14754    891.0
##           ...
## 15220      NaN
## 15221      NaN
## 15222      NaN
## 15223      NaN
```

```
## 15224      NaN
## Name: ccode, Length: 64, dtype: float64
```

```
# Ccode has missing values because:
# "Numeric country code based on the International Organization for Standardization (ISO). Please be ad
```

```
dfn.columns
```

```
## Index(['cname', 'ccode', 'year', 'cname_qog', 'ccci_coop', 'ccci_em',
##        'ccci_fin', 'ccci_kyoto', 'ccci_rep', 'ccci_unfccc', 'ccl_exepp',
##        'ccl_leglp', 'laws_adopted_per_year', 'mitigation_laws',
##        'cumulative_number_of_laws_exec', 'number_of_laws',
##        'cumulative_number_of_laws', 'cumulative_mitigation_laws', 'edgar_co',
##        'edgar_co2gdp', 'edgar_co2pc', 'edgar_co2t', 'edgar_pm25', 'edgar_so2',
##        'edi_edi', 'edi_gee', 'envinromental_ministry', 'engo_nengo', 'epi_agr',
##        'epi_air', 'epi_ape', 'epi_bca', 'epi_bdh', 'epi_bhv', 'epi_cch',
##        'epi_cda', 'epi_cha', 'epi_ghp', 'epi_gib', 'epi_grl', 'epi_h2o',
##        'epi_had', 'epi_hmt', 'epi_lcb', 'epi_mpa', 'epi_msw', 'epi_mti',
##        'epi_noa', 'epi_nxa', 'epi_ozd', 'epi_par', 'epi_pbd', 'epi_pmd',
##        'epi_sda', 'epi_shi', 'epi_snm', 'epi_spi', 'epi_tbg', 'epi_tbn',
##        'epi_tcl', 'epi_usd', 'epi_uwd', 'epi_wmg', 'epi_wrs', 'epi_wtl',
##        'epi_wwt', 'enforced', 'enforced2', 'iead_eif3', 'in_force_all',
##        'in_force_except_terminated', 'ratifications', 'signatures',
##        'terminated', 'withdraws', 'iead_withdraw2', 'nrmi_nrpi',
##        'oecd_cctr_gdp', 'oecd_cctr_tot', 'oecd_eampg', 'oecd_epea', 'oecd_eps',
##        'oecd_etr_gdp', 'oecd_etr_tot', 'oecd_pm25ex15p', 'oecd_pm25ex25p',
##        'oecd_polagdpg', 'sgi_en', 'sgi_enen', 'sgi_enge', 'sgi_epe', 'sgi_ger',
##        'slaws_mit_ex_l3', 'exec_policies_last3yrs', 'slaws_mit_l3',
##        'slaws_mit_leg_l3', 'leg_policies_last3yrs', 'gov_policies_last3yrs',
##        'country_year'],
##       dtype='object')
```

```
# Here I will plot 3 tables containing all the informations of every variable


numerical_features1 = ['laws_adopted_per_year', 'mitigation_laws',
       'cumulative_number_of_laws_exec', 'number_of_laws',
       'cumulative_number_of_laws', 'cumulative_mitigation_laws','envinromental_ministry']

numerical_features2 = ['enforced', 'enforced2', 'in_force_all',
       'in_force_except_terminated', 'ratifications', 'signatures',
       'terminated', 'withdraws']

numerical_features3 = ['slaws_mit_ex_l3', 'exec_policies_last3yrs', 'slaws_mit_l3',
       'slaws_mit_leg_l3', 'leg_policies_last3yrs', 'gov_policies_last3yrs']



dfn[numerical_features1].describe().round(2)
```

```
##        laws_adopted_per_year  ...  envinromental_ministry
## count                2035.00  ...                  177.00
## mean                    0.72  ...                    0.73
```

```
## std                    1.08  ...                  0.44
## min                    0.00  ...                  0.00
## 25%                    0.00  ...                  0.00
## 50%                    0.00  ...                  1.00
## 75%                    1.00  ...                  1.00
## max                    9.00  ...                  1.00
##
## [8 rows x 7 columns]
```

```
dfn[numerical_features2].describe().round(2)
```

```
##         enforced  enforced2  in_force_all  ...  signatures  terminated  withdraws
## count    1928.00    1928.00       1928.00  ...     1928.00     1928.00    1928.00
## mean        7.11       0.04        214.04  ...        0.55        0.39       0.13
## std         5.41       0.22         83.43  ...        0.83        0.78       1.57
## min         0.00       0.00         16.00  ...        0.00        0.00       0.00
## 25%         3.00       0.00        159.00  ...        0.00        0.00       0.00
## 50%         6.00       0.00        213.00  ...        0.00        0.00       0.00
## 75%        10.00       0.00        261.00  ...        1.00        1.00       0.00
## max        94.00       2.00        517.00  ...        6.00        4.00      67.00
##
## [8 rows x 8 columns]
```

```
dfn[numerical_features3].describe().round(2)
```

```
##         slaws_mit_ex_l3  ...  gov_policies_last3yrs
## count            931.00  ...                 931.00
## mean               0.87  ...                   6.03
## std                1.11  ...                   5.21
## min                0.00  ...                   0.00
## 25%                0.00  ...                   2.00
## 50%                1.00  ...                   5.00
## 75%                1.00  ...                   8.00
## max                7.00  ...                  37.00
##
## [8 rows x 6 columns]
```

```
numerical_features = ['laws_adopted_per_year', 'mitigation_laws',
       'cumulative_number_of_laws_exec', 'number_of_laws',
       'cumulative_number_of_laws', 'cumulative_mitigation_laws','envinromental_ministry',
       'enforced', 'enforced2', 'in_force_all',
       'in_force_except_terminated', 'ratifications', 'signatures',
       'terminated', 'withdraws',
       'slaws_mit_ex_l3', 'exec_policies_last3yrs', 'slaws_mit_l3',
       'slaws_mit_leg_l3', 'leg_policies_last3yrs', 'gov_policies_last3yrs']
```

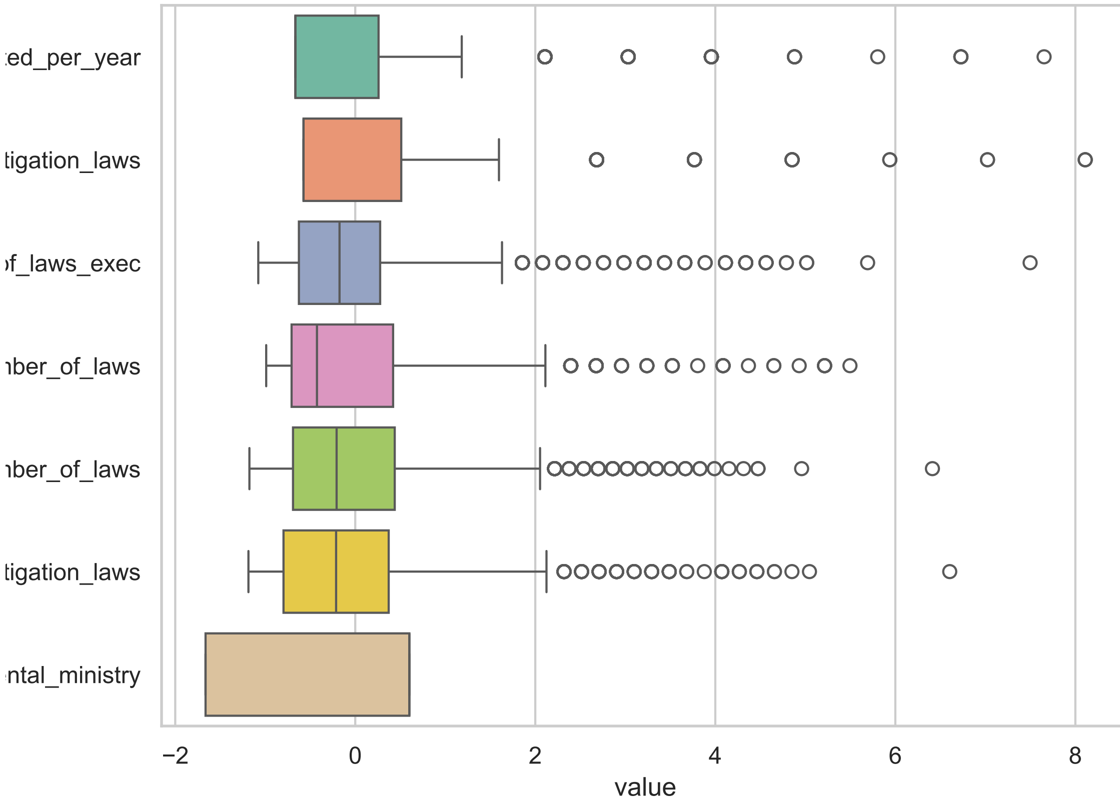
```
dfn[numerical_features].info()
```

```
## <class 'pandas.core.frame.DataFrame'>
## Index: 2233 entries, 64 to 15224
## Data columns (total 21 columns):
```

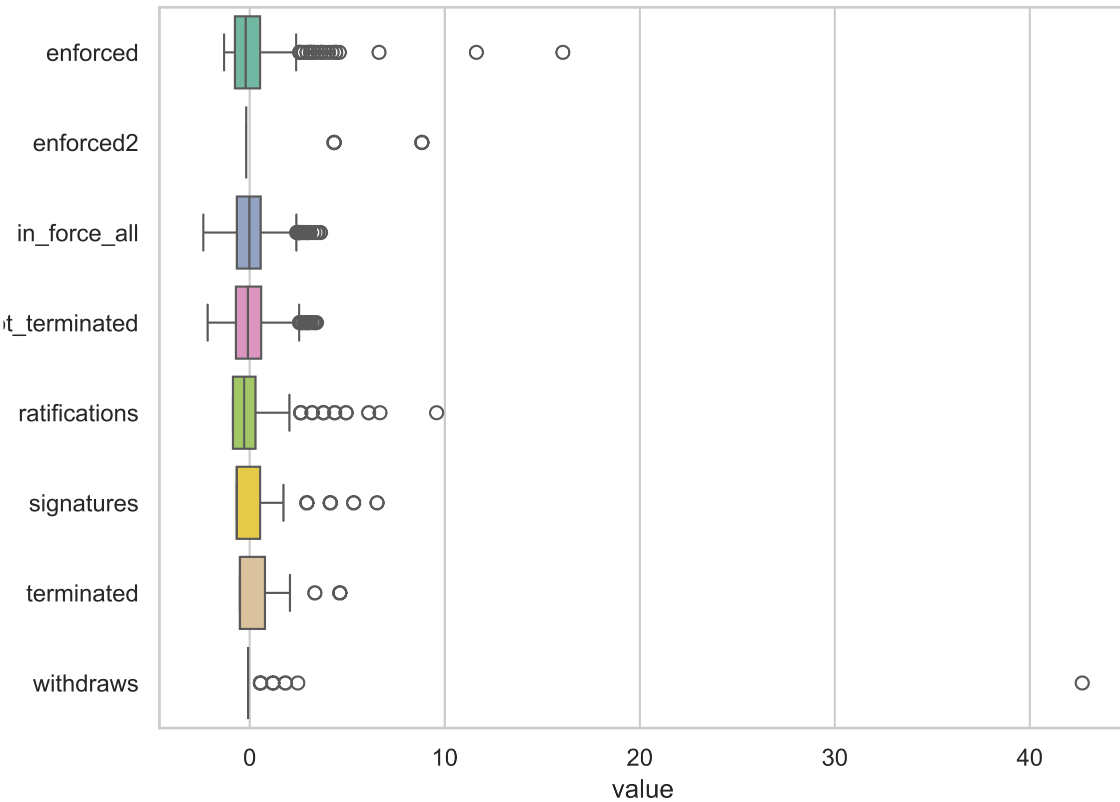
```
##  #   Column                          Non-Null Count  Dtype
## ---  ------                          --------------  -----
##  0   laws_adopted_per_year           2035 non-null   float64
##  1   mitigation_laws                 2035 non-null   float64
##  2   cumulative_number_of_laws_exec  2035 non-null   float64
##  3   number_of_laws                  2035 non-null   float64
##  4   cumulative_number_of_laws       2035 non-null   float64
##  5   cumulative_mitigation_laws      2035 non-null   float64
##  6   envinromental_ministry          177 non-null    float64
##  7   enforced                        1928 non-null   float64
##  8   enforced2                       1928 non-null   float64
##  9   in_force_all                    1928 non-null   float64
##  10  in_force_except_terminated      1928 non-null   float64
##  11  ratifications                   1928 non-null   float64
##  12  signatures                      1928 non-null   float64
##  13  terminated                      1928 non-null   float64
##  14  withdraws                       1928 non-null   float64
##  15  slaws_mit_ex_l3                 931 non-null    float64
##  16  exec_policies_last3yrs          931 non-null    float64
##  17  slaws_mit_l3                    931 non-null    float64
##  18  slaws_mit_leg_l3                931 non-null    float64
##  19  leg_policies_last3yrs           931 non-null    float64
##  20  gov_policies_last3yrs           931 non-null    float64
## dtypes: float64(21)
## memory usage: 383.8 KB
```

```
#These are the variables, we will have to deal with missing values
```

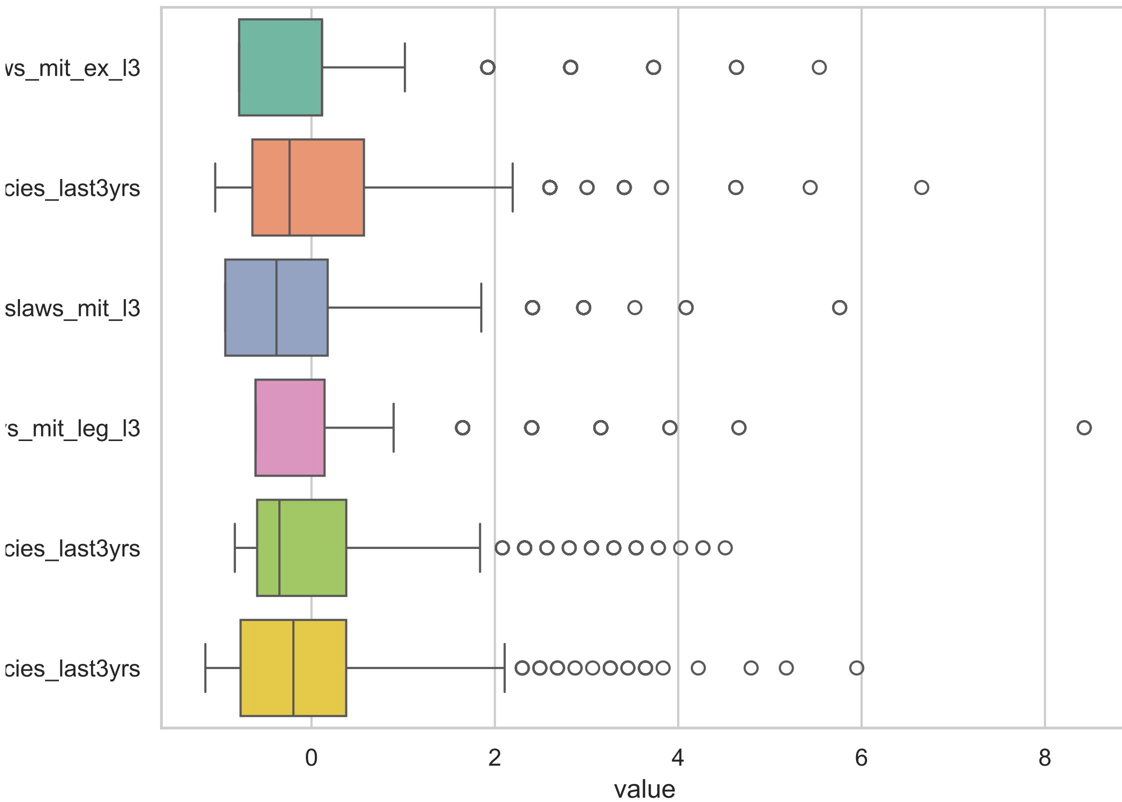
```
df_scaled = scale(dfn[numerical_features1])
df2 = pd.DataFrame(df_scaled, columns=numerical_features1)
df2['country_year'] = pd.Series(dfn['country_year'], index=dfn.index)
df3 = pd.melt(df2, id_vars='country_year', value_vars=df2[numerical_features1])
plt.figure(figsize=(8,6))
sns.set(style="whitegrid")
sns.boxplot(y='variable',x='value', data=df3, palette="Set2")
plt.show()
```



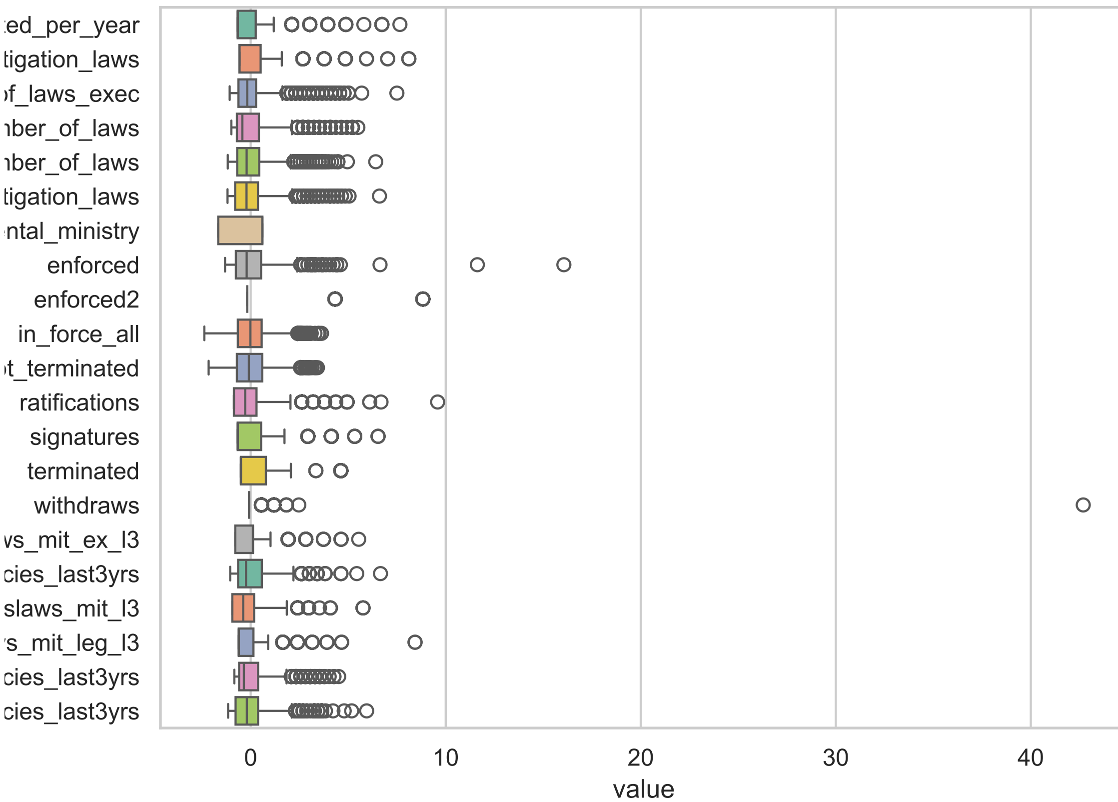

```
df_scaled = scale(dfn[numerical_features2])
df2 = pd.DataFrame(df_scaled, columns=numerical_features2)
df2['country_year'] = pd.Series(dfn['country_year'], index=dfn.index)
df3 = pd.melt(df2, id_vars='country_year', value_vars=df2[numerical_features2])
plt.figure(figsize=(8,6))
sns.set(style="whitegrid")
sns.boxplot(y='variable',x='value', data=df3, palette="Set2")
plt.show()
```




```
df_scaled = scale(dfn[numerical_features3])
df2 = pd.DataFrame(df_scaled, columns=numerical_features3)
df2['country_year'] = pd.Series(dfn['country_year'], index=dfn.index)
df3 = pd.melt(df2, id_vars='country_year', value_vars=df2[numerical_features3])
plt.figure(figsize=(8,6))
sns.set(style="whitegrid")
sns.boxplot(y='variable',x='value', data=df3, palette="Set2")
plt.show()
```

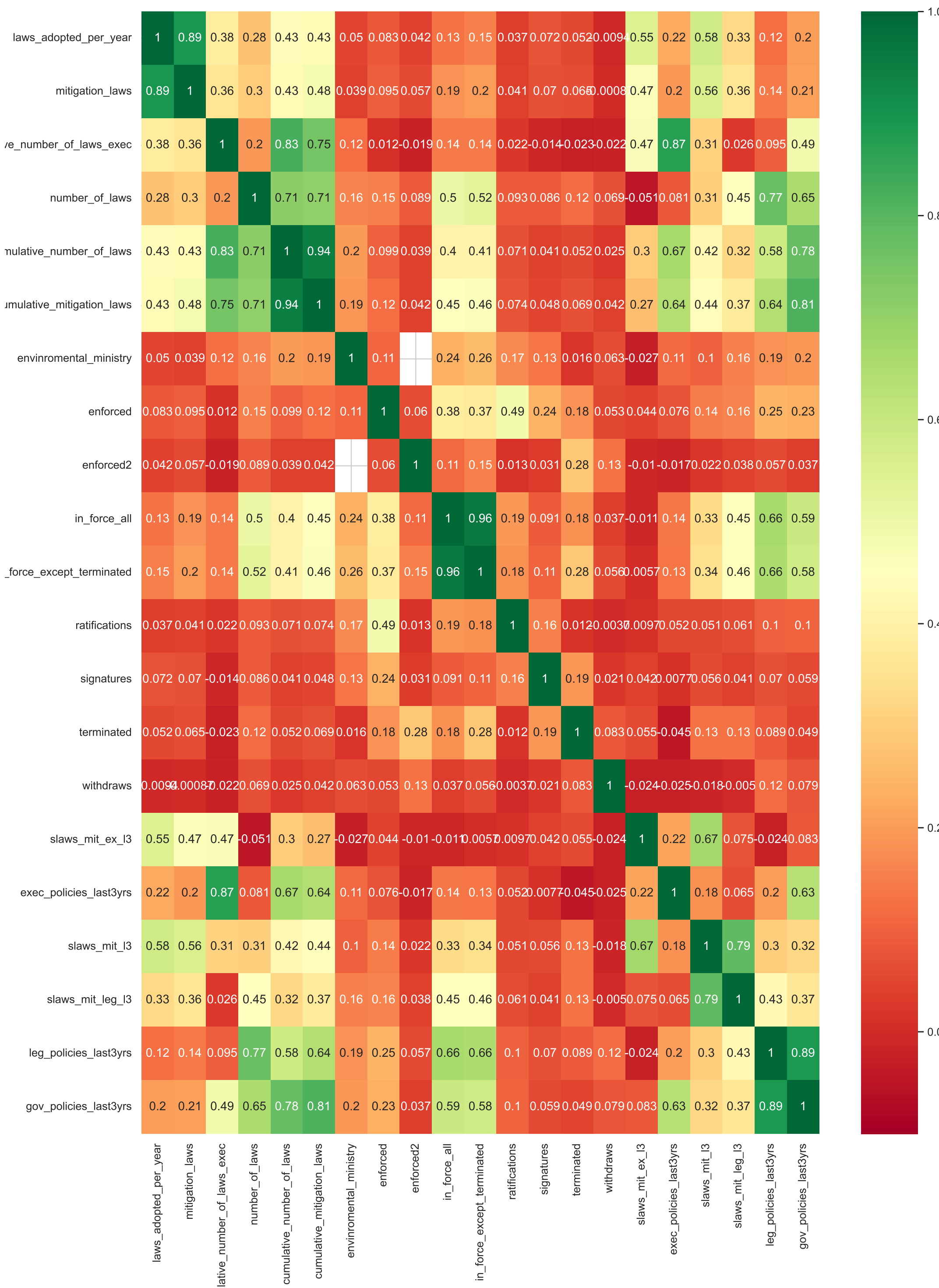



```
df_scaled = scale(dfn[numerical_features])
df2 = pd.DataFrame(df_scaled, columns=numerical_features)
df2['country_year'] = pd.Series(dfn['country_year'], index=dfn.index)
df3 = pd.melt(df2, id_vars='country_year', value_vars=df2[numerical_features])
plt.figure(figsize=(8,6))
sns.set(style="whitegrid")
sns.boxplot(y='variable',x='value', data=df3, palette="Set2")
plt.show()
```



From these graphics we can spot that some data have a lot of outliers that will have to be taken care of

```
plt.figure(figsize=(15,20))
sns.set(style="whitegrid")
sns.heatmap(df2[numerical_features].corr(method='pearson'), vmin=-.1, vmax=1,  annot=True, cmap='RdYlGn
plt.show()
```



The correlation matrix show strong correlation between some variables, which might incur in homogeneity problems

```
df2.info()
```

```
## <class 'pandas.core.frame.DataFrame'>
## RangeIndex: 2233 entries, 0 to 2232
## Data columns (total 22 columns):
##  #   Column                          Non-Null Count  Dtype
## ---  ------                          --------------  -----
##  0   laws_adopted_per_year           2035 non-null   float64
##  1   mitigation_laws                 2035 non-null   float64
##  2   cumulative_number_of_laws_exec  2035 non-null   float64
##  3   number_of_laws                  2035 non-null   float64
##  4   cumulative_number_of_laws       2035 non-null   float64
##  5   cumulative_mitigation_laws      2035 non-null   float64
##  6   envinromental_ministry          177 non-null    float64
##  7   enforced                        1928 non-null   float64
##  8   enforced2                       1928 non-null   float64
##  9   in_force_all                    1928 non-null   float64
##  10  in_force_except_terminated      1928 non-null   float64
##  11  ratifications                   1928 non-null   float64
##  12  signatures                      1928 non-null   float64
##  13  terminated                      1928 non-null   float64
##  14  withdraws                       1928 non-null   float64
##  15  slaws_mit_ex_l3                 931 non-null    float64
##  16  exec_policies_last3yrs          931 non-null    float64
##  17  slaws_mit_l3                    931 non-null    float64
##  18  slaws_mit_leg_l3                931 non-null    float64
##  19  leg_policies_last3yrs           931 non-null    float64
##  20  gov_policies_last3yrs           931 non-null    float64
##  21  country_year                    319 non-null    object
## dtypes: float64(21), object(1)
## memory usage: 383.9+ KB
```

Dealing with missing data

```
df4 = (df2.isnull().sum() / len(df2)) * 100
df4 = df4.drop(df4[df4 == 0].index).sort_values(ascending=False)[:30]
missing_data = pd.DataFrame({'Missing Ratio' :df4})
missing_data.head(25)
```

```
##                                 Missing Ratio
## envinromental_ministry              92.073444
## country_year                        85.714286
## gov_policies_last3yrs               58.307210
## leg_policies_last3yrs               58.307210
## slaws_mit_leg_l3                    58.307210
## slaws_mit_l3                        58.307210
## exec_policies_last3yrs              58.307210
## slaws_mit_ex_l3                     58.307210
## signatures                          13.658755
```

```
## withdraws                            13.658755
## terminated                           13.658755
## ratifications                        13.658755
## in_force_except_terminated           13.658755
## in_force_all                         13.658755
## enforced2                            13.658755
## enforced                             13.658755
## mitigation_laws                       8.866995
## cumulative_mitigation_laws            8.866995
## cumulative_number_of_laws             8.866995
## number_of_laws                        8.866995
## cumulative_number_of_laws_exec        8.866995
## laws_adopted_per_year                 8.866995
```

Feature Engineering

```python
#I am going to replace the missing values either by the mean of the country or by zero, depending on th

# All IEAD will be replaced by 0 because missing values here mean that nothing happened in that year
df2["withdraws"] = df2["withdraws"].fillna(0)
df2["terminated"] = df2["terminated"].fillna(0)
df2["in_force_all"] = df2["in_force_all"].fillna(0)
df2["in_force_except_terminated"] = df2["in_force_except_terminated"].fillna(0)
df2["ratifications"] = df2["ratifications"].fillna(0)
df2["signatures"] = df2["signatures"].fillna(0)
df2["enforced"] = df2["enforced"].fillna(0)
df2["enforced2"] = df2["enforced2"].fillna(0)

# All ccl will be replaced by 0, as well
df2["mitigation_laws"] = df2["mitigation_laws"].fillna(0)
df2["cumulative_mitigation_laws"] = df2["cumulative_mitigation_laws"].fillna(0)
df2["cumulative_number_of_laws"] = df2["cumulative_number_of_laws"].fillna(0)
df2["number_of_laws"] = df2["number_of_laws"].fillna(0)
df2["laws_adopted_per_year"] = df2["laws_adopted_per_year"].fillna(0)
df2["cumulative_number_of_laws_exec"] = df2["cumulative_number_of_laws_exec"].fillna(0)

#For Slaws I will replace by the general average
df2['slaws_mit_ex_l3'].fillna(int(df2['slaws_mit_ex_l3'].mean()), inplace=True)
```

```
## <string>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through cha
## The behavior will change in pandas 3.0. This inplace method will never work because the intermediate
##
## For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inp
```

```python
df2['exec_policies_last3yrs'].fillna(int(df2['exec_policies_last3yrs'].mean()), inplace=True)
```

```
## <string>:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through cha
## The behavior will change in pandas 3.0. This inplace method will never work because the intermediate
##
## For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inp
```

```
df2['slaws_mit_l3'].fillna(int(df2['slaws_mit_l3'].mean()), inplace=True)
df2['slaws_mit_leg_l3'].fillna(int(df2['slaws_mit_leg_l3'].mean()), inplace=True)
df2['leg_policies_last3yrs'].fillna(int(df2['leg_policies_last3yrs'].mean()), inplace=True)
df2['gov_policies_last3yrs'].fillna(int(df2['gov_policies_last3yrs'].mean()), inplace=True)

#Same for EM
df2['envinromental_ministry'].fillna(int(df2['envinromental_ministry'].mean()), inplace=True)
```

```
dfnn = df2
dfnn
```

```
##       laws_adopted_per_year  ...  country_year
## 0                 -0.665355  ...           NaN
## 1                  1.183105  ...           NaN
## 2                  0.258875  ...           NaN
## 3                  0.258875  ...           NaN
## 4                  1.183105  ...           NaN
## ...                     ...  ...           ...
## 2228               0.000000  ...           NaN
## 2229               0.000000  ...           NaN
## 2230               0.000000  ...           NaN
## 2231               0.000000  ...           NaN
## 2232               0.000000  ...           NaN
##
## [2233 rows x 22 columns]
```

```
#Missing Data count (again)
df4 = (df2.isnull().sum() / len(df2)) * 100
df4 = df4.drop(df4[df4 == 0].index).sort_values(ascending=False)[:30]
missing_data = pd.DataFrame({'Missing Ratio' :df4})
missing_data.head(20)
```

```
##               Missing Ratio
## country_year      85.714286
```

Principal Component Analysis

```
scaler = StandardScaler()
segmentation_std = scaler.fit_transform(df2[numerical_features])
```

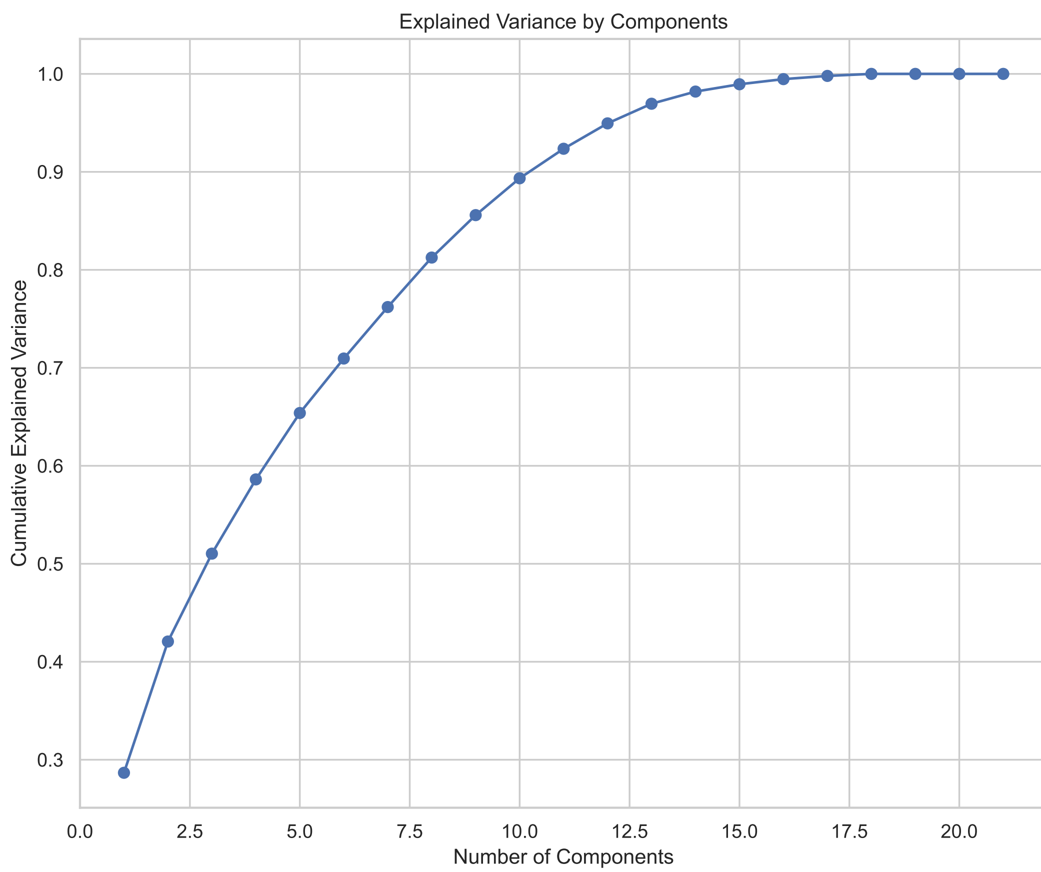
```
pca = PCA()
#Here is just a test as seen in https://365datascience.com/tutorials/python-tutorials/pca-k-means/
pca.fit(df2[numerical_features])
```

```
## PCA()
```

```
pca.explained_variance_ratio_
```

```
## array([2.86692852e-01, 1.33970722e-01, 8.96907998e-02, 7.57754196e-02,
##        6.77603821e-02, 5.55955002e-02, 5.25434153e-02, 5.05098889e-02,
##        4.33190917e-02, 3.76062044e-02, 3.01250820e-02, 2.59161987e-02,
##        2.00359077e-02, 1.24136834e-02, 7.46282463e-03, 5.24242089e-03,
##        3.27521939e-03, 2.06438762e-03, 1.14910354e-32, 6.36239229e-33,
##        3.76368574e-33])
```

```
plt.figure(figsize = (10,8))
plt.plot(range(1,22), pca.explained_variance_ratio_.cumsum(), marker = 'o')
plt.title('Explained Variance by Components')
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
```




```
pca = PCA(n_components = 8)
```

```
pca.fit(df2[numerical_features])
```

```
## PCA(n_components=8)
```

```
pca.transform(df2[numerical_features])
```

```
## array([[-2.67447201e+00,  1.34833152e+00, -2.25606793e-01, ...,
##          4.05603476e-01,  2.35340606e-01,  7.27274608e-01],
##        [-1.59484853e+00,  2.60870608e+00,  6.88381551e-01, ...,
##          4.57141453e-01,  2.30976697e-01,  6.47804210e-02],
##        [-1.99805519e+00,  2.07540085e+00, -3.42181871e-01, ...,
##          2.98232967e-01,  4.48576147e-01,  2.89409351e-01],
##        ...,
##        [ 3.99531483e-17, -1.98260179e-17,  4.30840188e-18, ...,
##          1.65274890e-17, -4.95412470e-18, -7.15302834e-18],
##        [ 3.99531483e-17, -1.98260179e-17,  4.30840188e-18, ...,
##          1.65274890e-17, -4.95412470e-18, -7.15302834e-18],
##        [ 3.99531483e-17, -1.98260179e-17,  4.30840188e-18, ...,
##          1.65274890e-17, -4.95412470e-18, -7.15302834e-18]])
```

```
score_pca = pca.transform(df2[numerical_features])
```

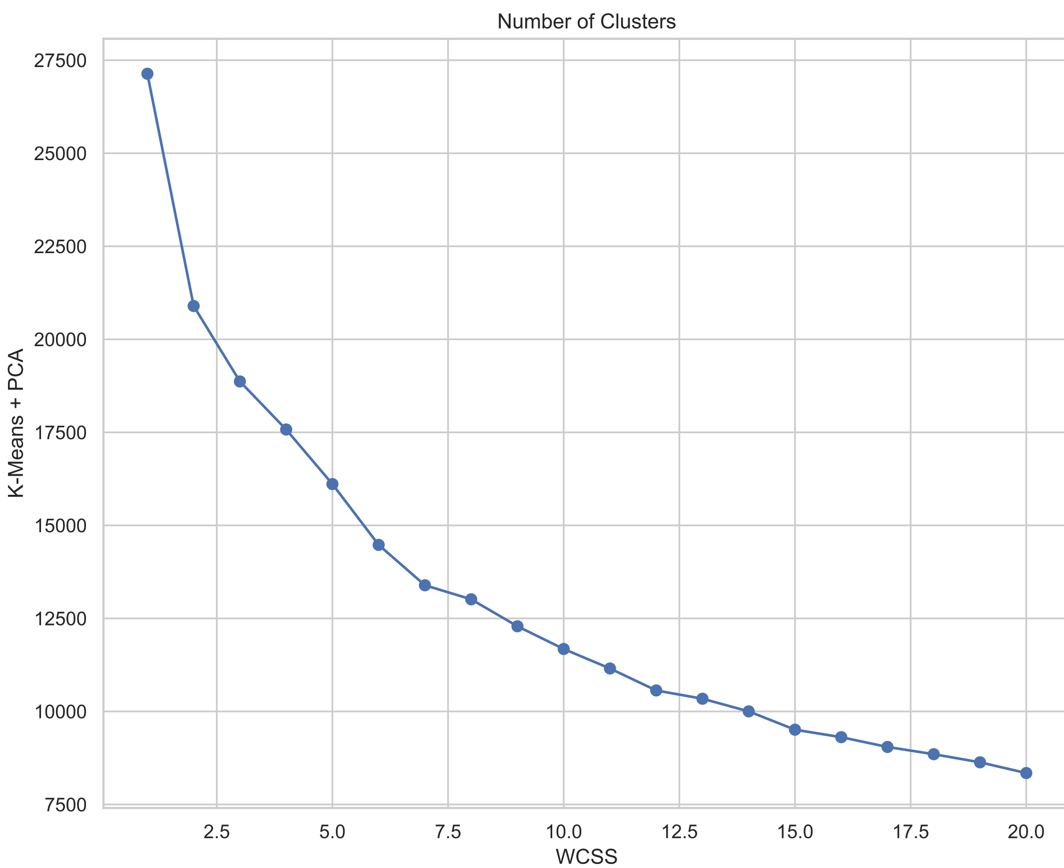
K-Means

```
wcss = []
for i in range (1,21):
    kmeans_pca = KMeans(n_clusters = i, init = 'k-means++', random_state = 69)
    kmeans_pca.fit(score_pca)
    wcss.append(kmeans_pca.inertia_)
```

```
## KMeans(n_clusters=1, random_state=69)
## KMeans(n_clusters=2, random_state=69)
## KMeans(n_clusters=3, random_state=69)
## KMeans(n_clusters=4, random_state=69)
## KMeans(n_clusters=5, random_state=69)
## KMeans(n_clusters=6, random_state=69)
## KMeans(n_clusters=7, random_state=69)
## KMeans(random_state=69)
## KMeans(n_clusters=9, random_state=69)
## KMeans(n_clusters=10, random_state=69)
## KMeans(n_clusters=11, random_state=69)
## KMeans(n_clusters=12, random_state=69)
## KMeans(n_clusters=13, random_state=69)
## KMeans(n_clusters=14, random_state=69)
## KMeans(n_clusters=15, random_state=69)
## KMeans(n_clusters=16, random_state=69)
## KMeans(n_clusters=17, random_state=69)
## KMeans(n_clusters=18, random_state=69)
## KMeans(n_clusters=19, random_state=69)
## KMeans(n_clusters=20, random_state=69)
```

```
plt.figure(figsize = (10,8))
plt.plot(range(1,21), wcss, marker = 'o')
plt.title('Number of Clusters')
```

```
plt.xlabel('WCSS')
plt.ylabel('K-Means + PCA')
```




```
kmeans_pca = KMeans(n_clusters = 6, init = 'k-means++', random_state = 69)
```

```
kmeans_pca.fit(score_pca)
```

```
## KMeans(n_clusters=6, random_state=69)
```

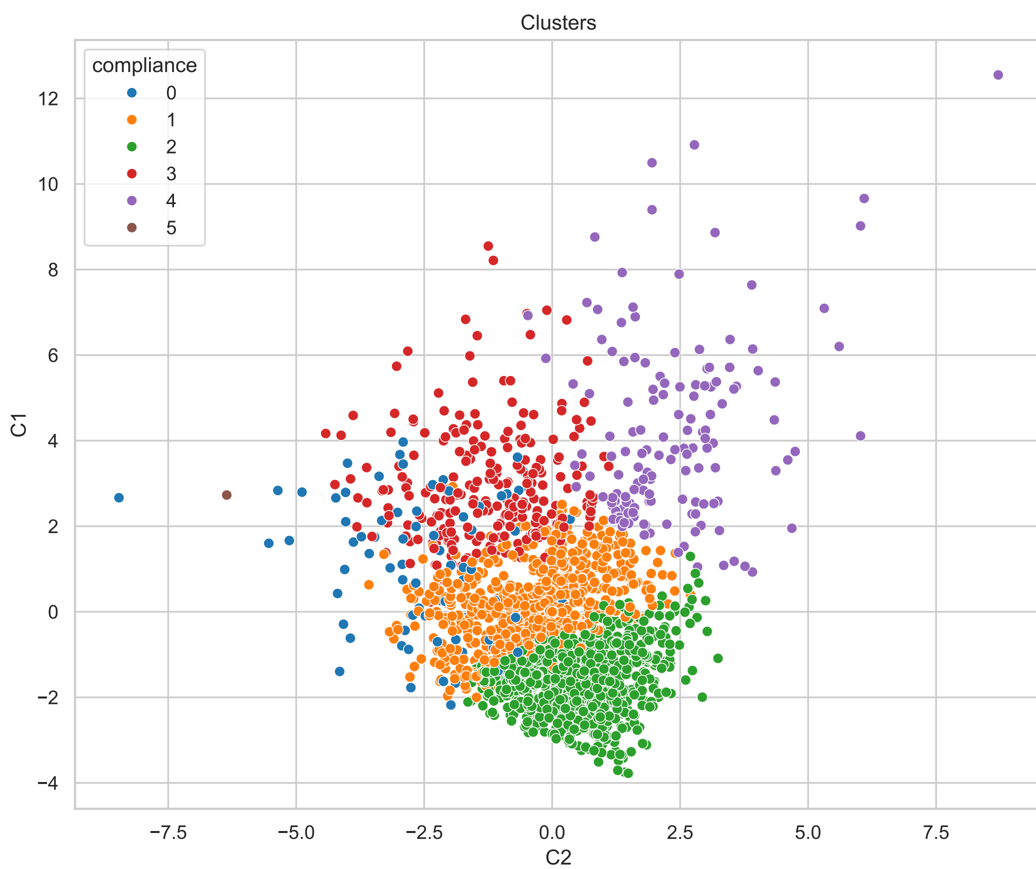
```
df10 = pd.concat([df2.reset_index(drop=True), pd.DataFrame(score_pca)], axis=1)
df10.columns.values[-8: ] = ['C1', 'C2', 'C3','C4','C5','C6','C7', 'C8']
df10['compliance'] = kmeans_pca.labels_

y3 = kmeans_pca.labels_
```

```
df10
```

```
##      laws_adopted_per_year  mitigation_laws  ...            C8  compliance
## 0                -0.665355        -0.574495  ...  7.272746e-01           2
```

```
## 1                   1.183105         0.511018  ...  6.478042e-02          2
## 2                   0.258875        -0.574495  ...  2.894094e-01          2
## 3                   0.258875        -0.574495  ...  7.867443e-01          1
## 4                   1.183105        -0.574495  ...  3.123885e-01          2
## ...                      ...              ...  ...           ...        ...
## 2228                0.000000         0.000000  ... -7.153028e-18          1
## 2229                0.000000         0.000000  ... -7.153028e-18          1
## 2230                0.000000         0.000000  ... -7.153028e-18          1
## 2231                0.000000         0.000000  ... -7.153028e-18          1
## 2232                0.000000         0.000000  ... -7.153028e-18          1
##
## [2233 rows x 31 columns]
```

```
custom_palette = sns.color_palette("tab10", 6)
x_axis = df10['C2']
y_axis = df10['C1']
plt.figure(figsize=(10,8))
sns.scatterplot(x=x_axis, y=y_axis, hue=df10['compliance'], palette=custom_palette)
plt.title('Clusters')
plt.show()
```



```
dfn['compliance'] = y3
```

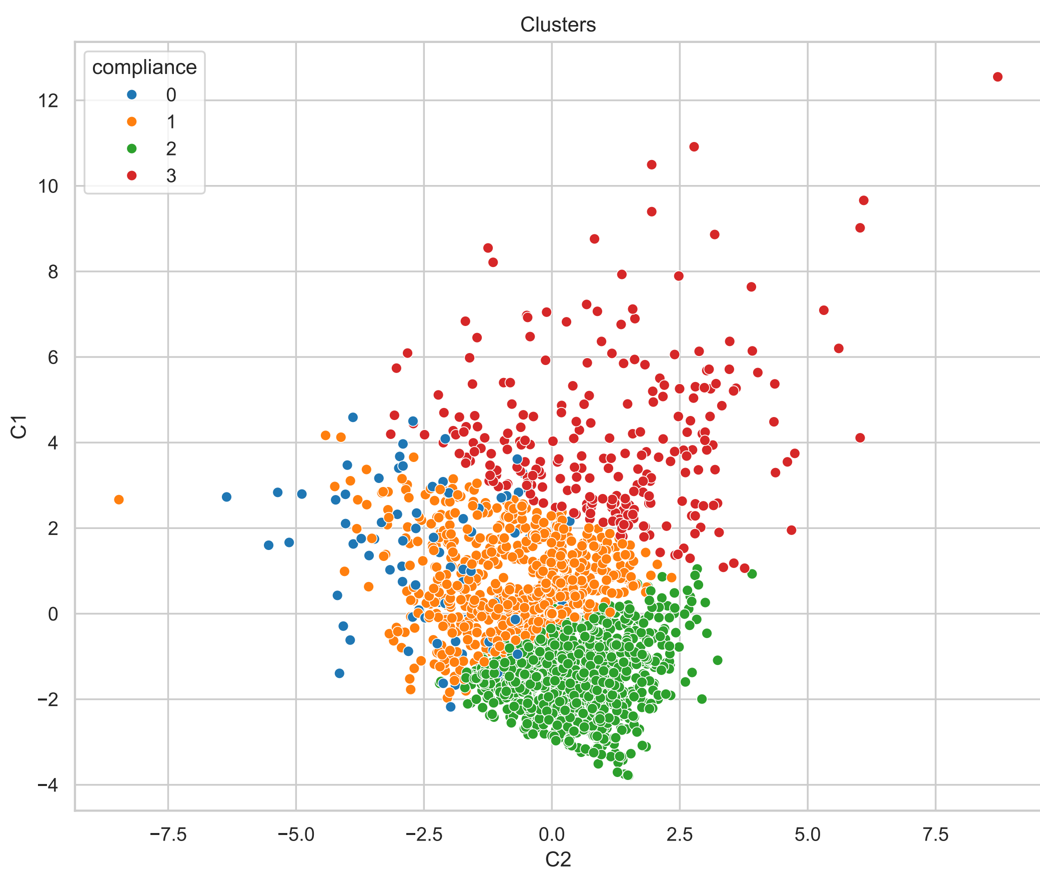
```
kmeans_pca1 = KMeans(n_clusters = 4, init = 'k-means++', random_state = 69)
```

```
kmeans_pca1.fit(score_pca)
```

```
## KMeans(n_clusters=4, random_state=69)
```

```
df11 = pd.concat([df2.reset_index(drop=True), pd.DataFrame(score_pca)], axis=1)
df11.columns.values[-8: ] = ['C1', 'C2', 'C3','C4','C5','C6','C7', 'C8']
df11['compliance'] = kmeans_pca1.labels_

y4 = kmeans_pca1.labels_
```

```
custom_palette1 = sns.color_palette("tab10", 4)
x_axis = df11['C2']
y_axis = df11['C1']
plt.figure(figsize=(10,8))
sns.scatterplot(x=x_axis, y=y_axis, hue=df11['compliance'], palette=custom_palette)
plt.title('Clusters')
plt.show()
```



```
dfn['compliance1'] = y4
```

```
features = ['cname', 'year', 'cname_qog', 'compliance', 'compliance1']
```

```
compliance_data = dfn[features]
```

Second Apporach

Now I will try another approach, for a third measurement of compliance

```
dataframe = pd.read_csv("https://raw.githubusercontent.com/rauls3/R-Projects/main/preliminarydata.csv",
dataframe.drop(dataframe[dataframe.year < 2010].index, inplace=True)
dataframe['country_year'] = dataframe['cname'].astype(str).str.cat(dataframe['year'].astype(str))

dataframen = dataframe.rename(columns={'ccl_lpp': 'laws_adopted_per_year', 'ccl_mitlpp': 'mitigation_law
       'ccl_nlp': 'cumulative_number_of_laws', 'ccl_nmitlp': 'cumulative_mitigation_laws', 'iead_eif1':
       'iead_inforce': 'in_force_all', 'iead_inforce_noterm': 'in_force_except_terminated', 'iead_rat':
       'iead_sig': 'signatures', 'iead_term': 'terminated', 'iead_withdraw1': 'withdraws',
       'em_envmin': 'envinromental_ministry',
       'slaws_mit_ex_lt': 'exec_policies_last3yrs',
       'slaws_mit_leg_lt': 'leg_policies_last3yrs', 'slaws_mit_lt': 'gov_policies_last3yrs'})

numerical_features = ['laws_adopted_per_year', 'mitigation_laws',
       'cumulative_number_of_laws_exec', 'number_of_laws',
       'cumulative_number_of_laws', 'cumulative_mitigation_laws','envinromental_ministry',
       'enforced', 'enforced2', 'in_force_all',
       'in_force_except_terminated', 'ratifications', 'signatures',
       'terminated', 'withdraws',
       'slaws_mit_ex_l3', 'exec_policies_last3yrs', 'slaws_mit_l3',
       'slaws_mit_leg_l3', 'leg_policies_last3yrs', 'gov_policies_last3yrs']

dataframen[numerical_features].describe().round(2)
```

```
##        laws_adopted_per_year  ...  gov_policies_last3yrs
## count                2035.00  ...                 931.00
## mean                    0.72  ...                   6.03
## std                     1.08  ...                   5.21
## min                     0.00  ...                   0.00
## 25%                     0.00  ...                   2.00
## 50%                     0.00  ...                   5.00
## 75%                     1.00  ...                   8.00
## max                     9.00  ...                  37.00
##
## [8 rows x 21 columns]
```

```
dataframen[numerical_features].info()
```

```
## <class 'pandas.core.frame.DataFrame'>
## Index: 2233 entries, 64 to 15224
## Data columns (total 21 columns):
```

```
## #   Column                          Non-Null Count  Dtype
## --- ------                          --------------  -----
##  0   laws_adopted_per_year           2035 non-null   float64
##  1   mitigation_laws                 2035 non-null   float64
##  2   cumulative_number_of_laws_exec  2035 non-null   float64
##  3   number_of_laws                  2035 non-null   float64
##  4   cumulative_number_of_laws       2035 non-null   float64
##  5   cumulative_mitigation_laws      2035 non-null   float64
##  6   envinromental_ministry          177 non-null    float64
##  7   enforced                        1928 non-null   float64
##  8   enforced2                       1928 non-null   float64
##  9   in_force_all                    1928 non-null   float64
##  10  in_force_except_terminated      1928 non-null   float64
##  11  ratifications                   1928 non-null   float64
##  12  signatures                      1928 non-null   float64
##  13  terminated                      1928 non-null   float64
##  14  withdraws                       1928 non-null   float64
##  15  slaws_mit_ex_l3                 931 non-null    float64
##  16  exec_policies_last3yrs          931 non-null    float64
##  17  slaws_mit_l3                    931 non-null    float64
##  18  slaws_mit_leg_l3                931 non-null    float64
##  19  leg_policies_last3yrs           931 non-null    float64
##  20  gov_policies_last3yrs           931 non-null    float64
## dtypes: float64(21)
## memory usage: 383.8 KB
```

```
dataframe_scaled = scale(dataframen[numerical_features])
dataframe2 = pd.DataFrame(dataframe_scaled, columns=numerical_features)

#Missing Data
dataframe4 = (dataframe2.isnull().sum() / len(dataframe2)) * 100
dataframe4 = dataframe4.drop(dataframe4[dataframe4 == 0].index).sort_values(ascending=False)[:30]
missing_data = pd.DataFrame({'Missing Ratio' :dataframe4})
missing_data.head(25)
```

```
##                                 Missing Ratio
## envinromental_ministry              92.073444
## gov_policies_last3yrs               58.307210
## leg_policies_last3yrs               58.307210
## slaws_mit_leg_l3                    58.307210
## slaws_mit_l3                        58.307210
## exec_policies_last3yrs              58.307210
## slaws_mit_ex_l3                     58.307210
## ratifications                       13.658755
## withdraws                           13.658755
## terminated                          13.658755
## signatures                          13.658755
## in_force_except_terminated          13.658755
## in_force_all                        13.658755
## enforced2                           13.658755
## enforced                            13.658755
## mitigation_laws                      8.866995
## cumulative_mitigation_laws           8.866995
## cumulative_number_of_laws            8.866995
```

```
## number_of_laws                        8.866995
## cumulative_number_of_laws_exec        8.866995
## laws_adopted_per_year                 8.866995
```

```
# All IEAD will be replaced by 0 because missing values here mean that nothing happened in that year
##dataframe2["iead_withdraw2"] = dataframe2["iead_withdraw2"].fillna(0)
dataframe2["withdraws"] = dataframe2["withdraws"].fillna(0)
dataframe2["terminated"] = dataframe2["terminated"].fillna(0)
dataframe2["in_force_all"] = dataframe2["in_force_all"].fillna(0)
dataframe2["in_force_except_terminated"] = dataframe2["in_force_except_terminated"].fillna(0)
dataframe2["ratifications"] = dataframe2["ratifications"].fillna(0)
dataframe2["signatures"] = dataframe2["signatures"].fillna(0)
dataframe2["enforced"] = dataframe2["enforced"].fillna(0)
dataframe2["enforced2"] = dataframe2["enforced2"].fillna(0)
##dataframe2["iead_eif3"] = dataframe2["iead_eif3"].fillna(0)

# All ccl will be replaced by 0, as well
dataframe2["mitigation_laws"] = dataframe2["mitigation_laws"].fillna(0)
dataframe2["cumulative_mitigation_laws"] = dataframe2["cumulative_mitigation_laws"].fillna(0)
dataframe2["cumulative_number_of_laws"] = dataframe2["cumulative_number_of_laws"].fillna(0)
dataframe2["number_of_laws"] = dataframe2["number_of_laws"].fillna(0)
dataframe2["laws_adopted_per_year"] = dataframe2["laws_adopted_per_year"].fillna(0)
dataframe2["cumulative_number_of_laws_exec"] = dataframe2["cumulative_number_of_laws_exec"].fillna(0)

#For Slaws I will replace by the general average
dataframe2['slaws_mit_ex_l3'].fillna(int(dataframe2['slaws_mit_ex_l3'].mean()), inplace=True)
```

```
## <string>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through cha
## The behavior will change in pandas 3.0. This inplace method will never work because the intermediate
##
## For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inp
```

```
dataframe2['exec_policies_last3yrs'].fillna(int(dataframe2['exec_policies_last3yrs'].mean()), inplace=Tr
```

```
## <string>:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through cha
## The behavior will change in pandas 3.0. This inplace method will never work because the intermediate
##
## For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inp
```

```
dataframe2['slaws_mit_l3'].fillna(int(dataframe2['slaws_mit_l3'].mean()), inplace=True)
dataframe2['slaws_mit_leg_l3'].fillna(int(dataframe2['slaws_mit_leg_l3'].mean()), inplace=True)
dataframe2['leg_policies_last3yrs'].fillna(int(dataframe2['leg_policies_last3yrs'].mean()), inplace=True
dataframe2['gov_policies_last3yrs'].fillna(int(dataframe2['gov_policies_last3yrs'].mean()), inplace=True

#Same for EM
dataframe2['envinromental_ministry'].fillna(int(dataframe2['envinromental_ministry'].mean()), inplace=Tr
```

```
#Missing Data count (again)
dataframe4 = (dataframe2.isnull().sum() / len(dataframe2)) * 100
dataframe4 = dataframe4.drop(dataframe4[dataframe4 == 0].index).sort_values(ascending=False)[:30]
missing_data = pd.DataFrame({'Missing Ratio' :dataframe4})
missing_data.head(20)
```

```
## Empty DataFrame
## Columns: [Missing Ratio]
## Index: []
```

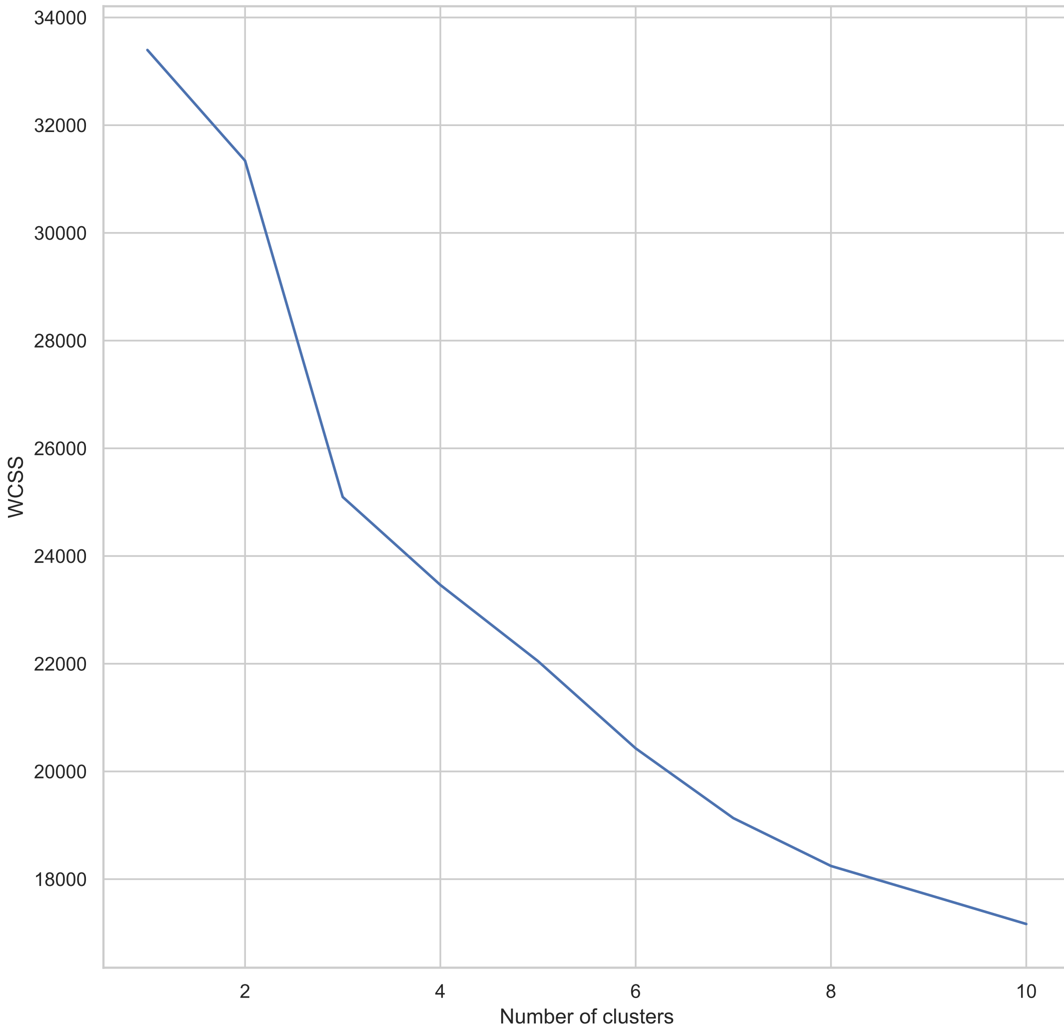
```
x = dataframe2[numerical_features]
print(x)
```

```
##       laws_adopted_per_year  ...  gov_policies_last3yrs
## 0                 -0.665355  ...                    0.0
## 1                  1.183105  ...                    0.0
## 2                  0.258875  ...                    0.0
## 3                  0.258875  ...                    0.0
## 4                  1.183105  ...                    0.0
## ...                     ...  ...                    ...
## 2228               0.000000  ...                    0.0
## 2229               0.000000  ...                    0.0
## 2230               0.000000  ...                    0.0
## 2231               0.000000  ...                    0.0
## 2232               0.000000  ...                    0.0
##
## [2233 rows x 21 columns]
```

```
wcss = []
for i in range(1,11):
  model = KMeans(n_clusters = i, init = "k-means++")
  model.fit(x)
  wcss.append(model.inertia_)
```

```
## KMeans(n_clusters=1)
## KMeans(n_clusters=2)
## KMeans(n_clusters=3)
## KMeans(n_clusters=4)
## KMeans(n_clusters=5)
## KMeans(n_clusters=6)
## KMeans(n_clusters=7)
## KMeans()
## KMeans(n_clusters=9)
## KMeans(n_clusters=10)
```

```
plt.figure(figsize=(10,10))
plt.plot(range(1,11), wcss)
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



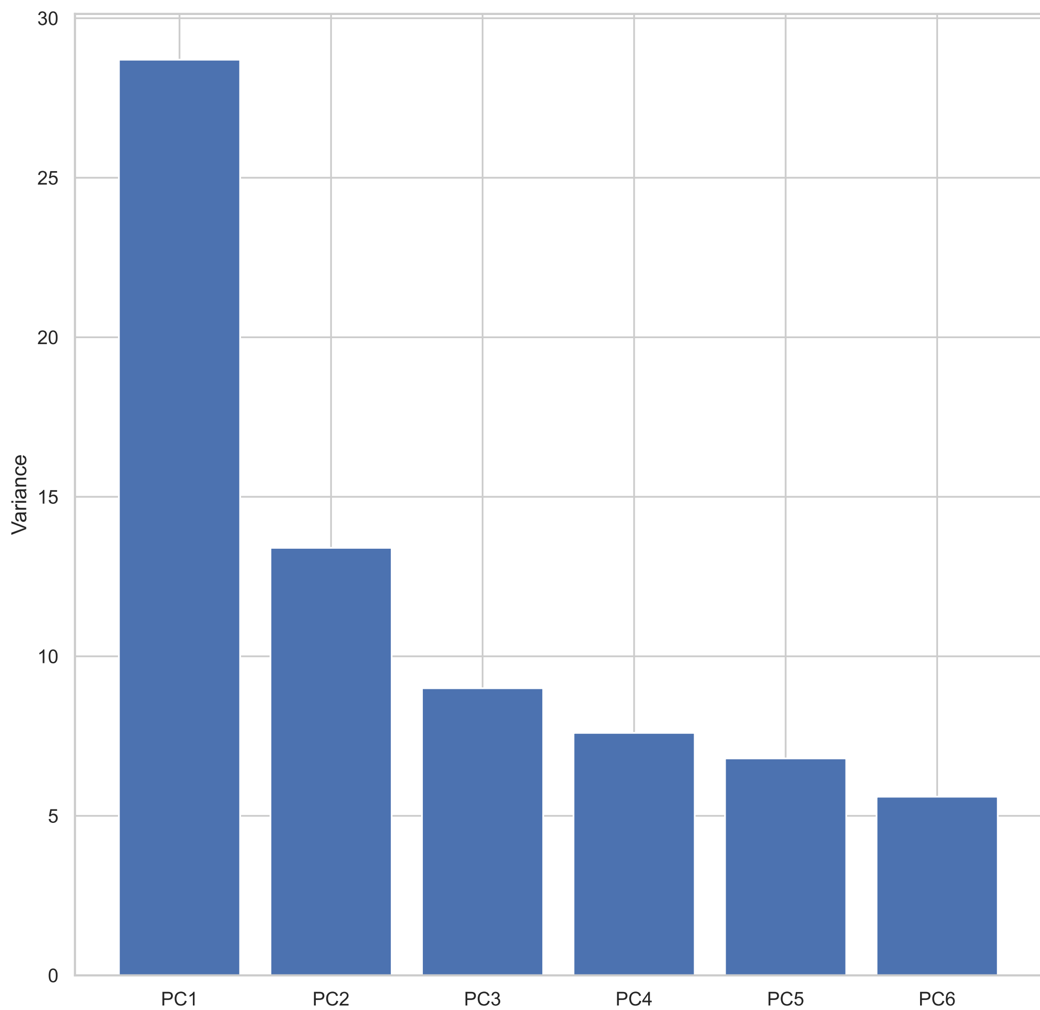

```
pca = PCA(6)
```

```
data = pca.fit_transform(x)
```

```
plt.figure(figsize=(10,10))
var = np.round(pca.explained_variance_ratio_*100, decimals = 1)
lbls = ['PC'+ str(x) for x in range(1,len(var)+1)]
plt.bar(x=range(1,len(var)+1), height = var, tick_label = lbls)
```

```
## <BarContainer object of 6 artists>
```

```
plt.ylabel('Variance')
plt.show()
```



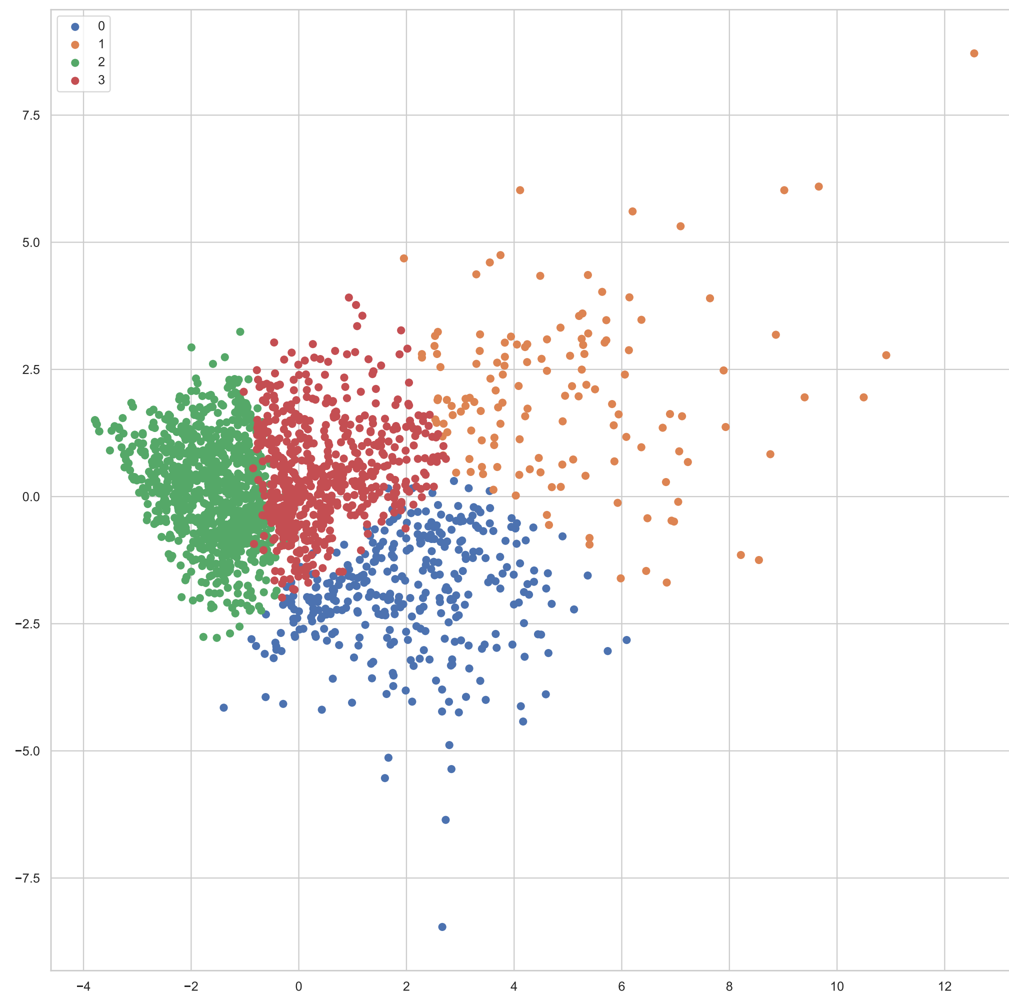

```
model1 = KMeans(n_clusters = 4, init = "k-means++", random_state= 169)
label = model1.fit_predict(data)
print(label)
```

```
## [2 2 2 ... 3 3 3]
```

```
model2 = KMeans(n_clusters = 6, init = "k-means++", random_state=169)
y2 = model2.fit_predict(x)
```

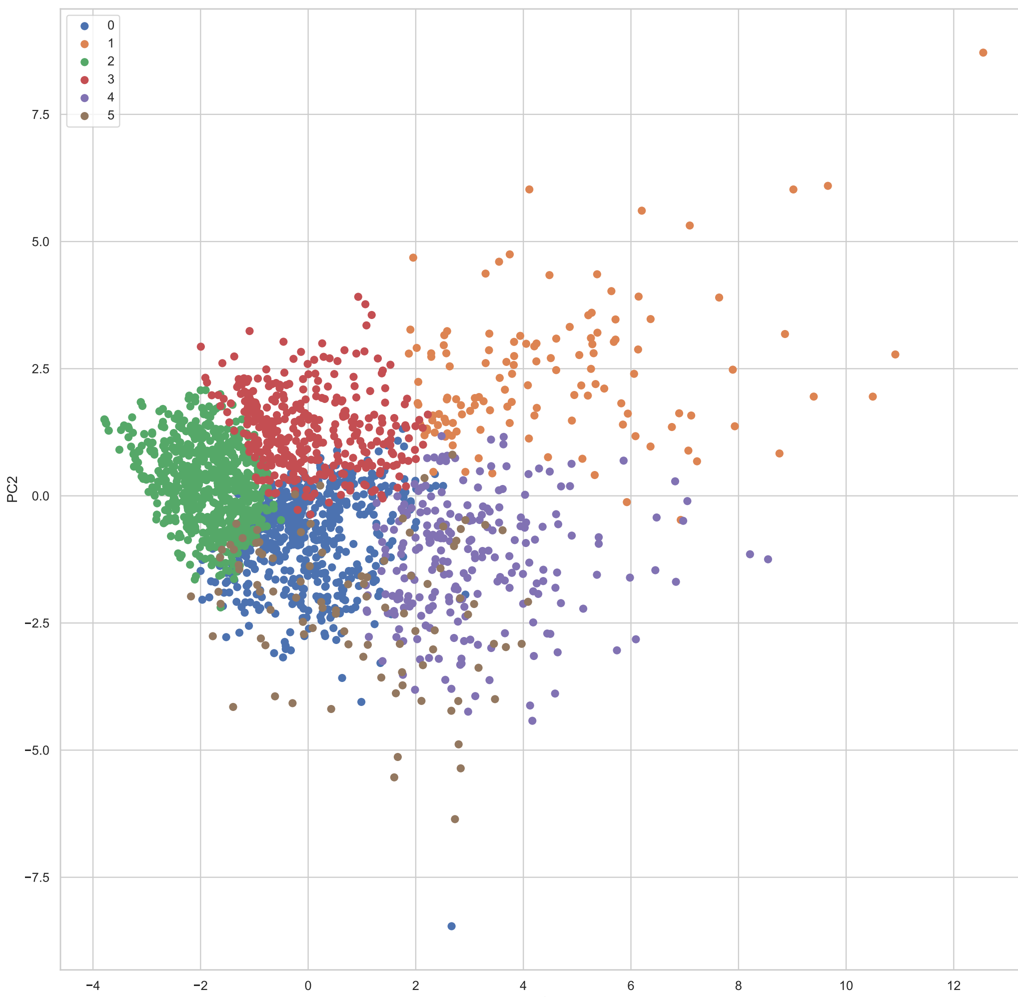
```
model3 = KMeans(n_clusters = 3, init = "k-means++", random_state=169)
y4 = model3.fit_predict(x)
```

```
plt.figure(figsize=(15,15))
uniq = np.unique(label)
for i in uniq:
  plt.scatter(data[label == i , 0] , data[label == i , 1] , label = i)

plt.legend()
plt.show()
```

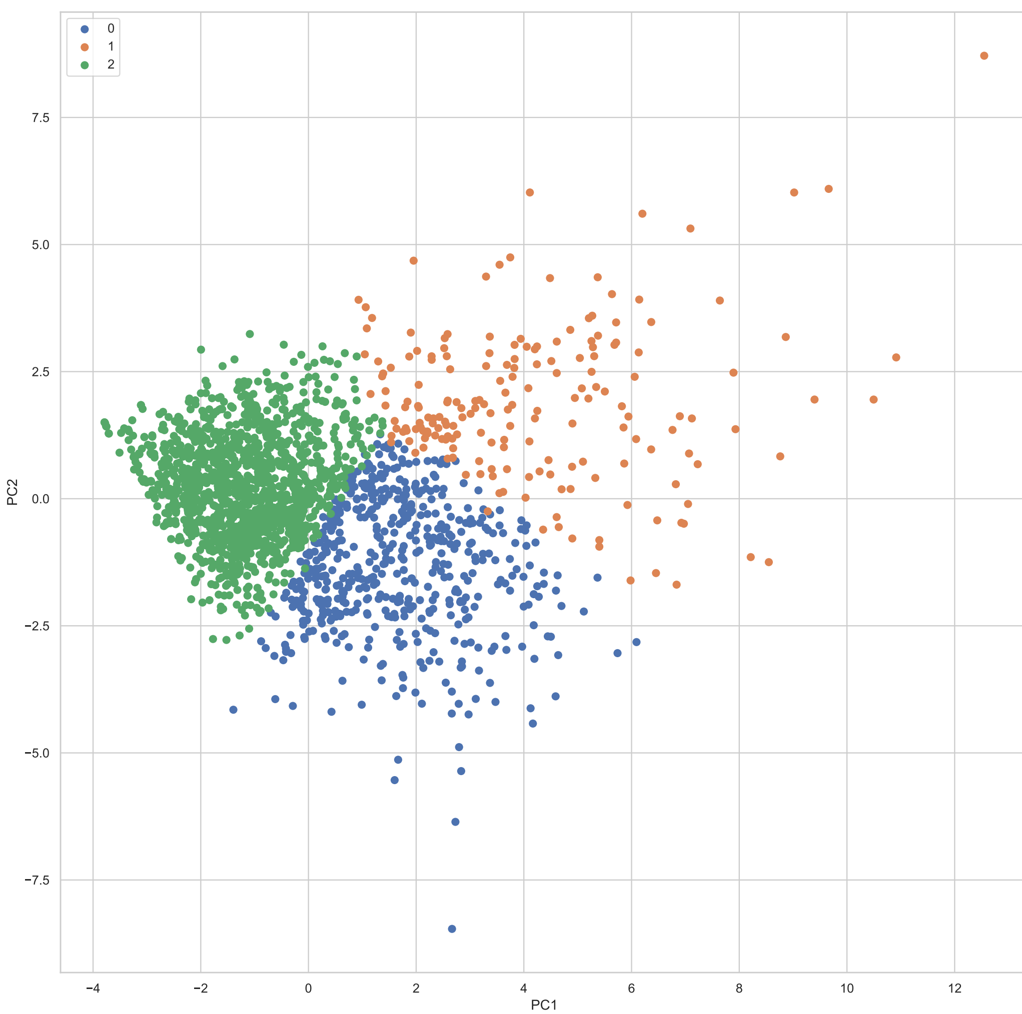


```
label2 = model2.fit_predict(data)
label3 = model3.fit_predict(data)
```

```
plt.figure(figsize=(15,15))
uniq = np.unique(label2)
for i in uniq:
  plt.scatter(data[label2 == i , 0] , data[label2 == i , 1] , label = i)
plt.xlabel([])
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend()
plt.show()
```

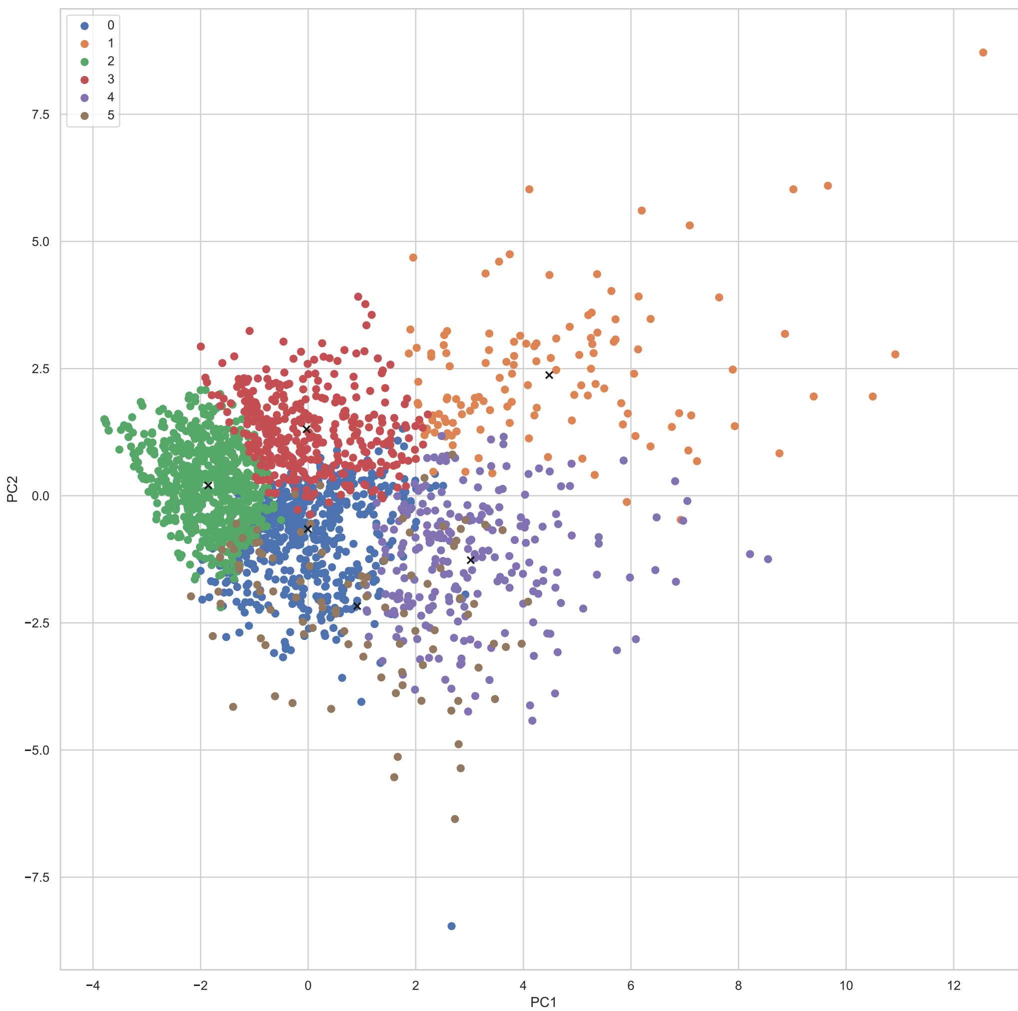


```
plt.figure(figsize=(15,15))
uniq = np.unique(label3)
for i in uniq:
  plt.scatter(data[label3 == i , 0] , data[label3 == i , 1] , label = i)
plt.xlabel([])
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend()
plt.show()
```




```
centers = np.array(model2.cluster_centers_)
```

```
plt.figure(figsize=(15,15))
uniq = np.unique(label2)

for i in uniq:
  plt.scatter(data[label2 == i , 0] , data[label2 == i , 1] , label = i)
plt.xlabel([])
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.scatter(centers[:,0], centers[:,1], marker="x", color='k')
plt.legend()
plt.show()
```



```
dataframe2['compliance2'] = y4
dataframe['compliance2'] = y4
```

```
features = ['cname', 'year', 'cname_qog', 'compliance2']
dataframenew = dataframe[features]
```

```
compliance = pd.merge(dataframenew, compliance_data, on=['cname', 'year', 'cname_qog'])
```

```
compliance.to_csv('/Users/raulbassi/Desktop/tcc/compliance.csv')
```

Setting up R ambient

Exploratory Analysis Risk dataset

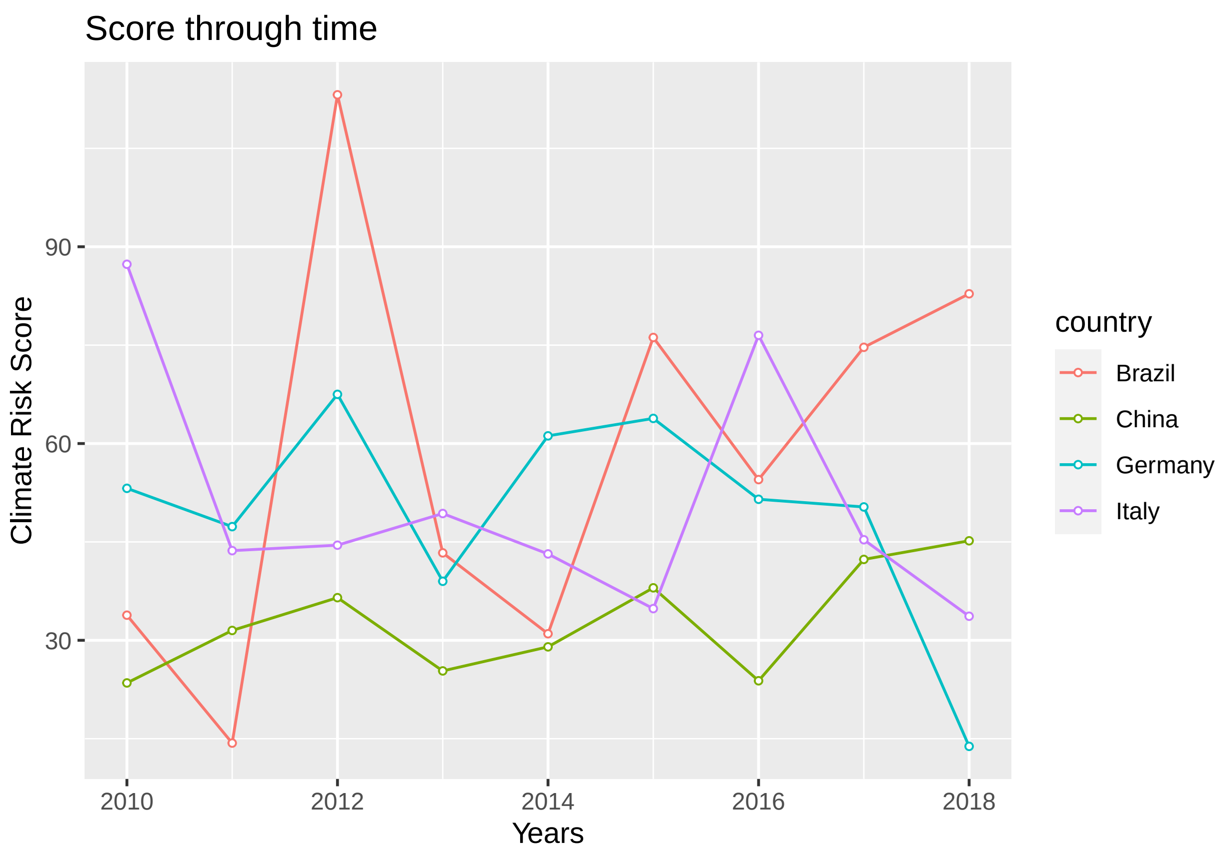
```
gwi <- read_excel("~/Desktop/tcc/TCC/GWI.xlsx",
    col_types = c("text", "numeric", "numeric"))
```

Here I will plot some graphics showing a few countries performance across the years collected.

```
v1 <- c("Brazil", "Germany", "China", "Italy")
plo <- filter(gwi, country %in% v1)

plot1 <- ggplot(data=plo, aes(x=year, y=score, group = country, colour = country)) +
    geom_line(se = FALSE) +
    geom_point( size=1, shape=21, fill="white") +
  labs(title = "Score through time",
       x = "Years",
       y = "Climate Risk Score")
```

```
## Warning in geom_line(se = FALSE): Ignoring unknown parameters: ‘se‘
```

```
plot1
```

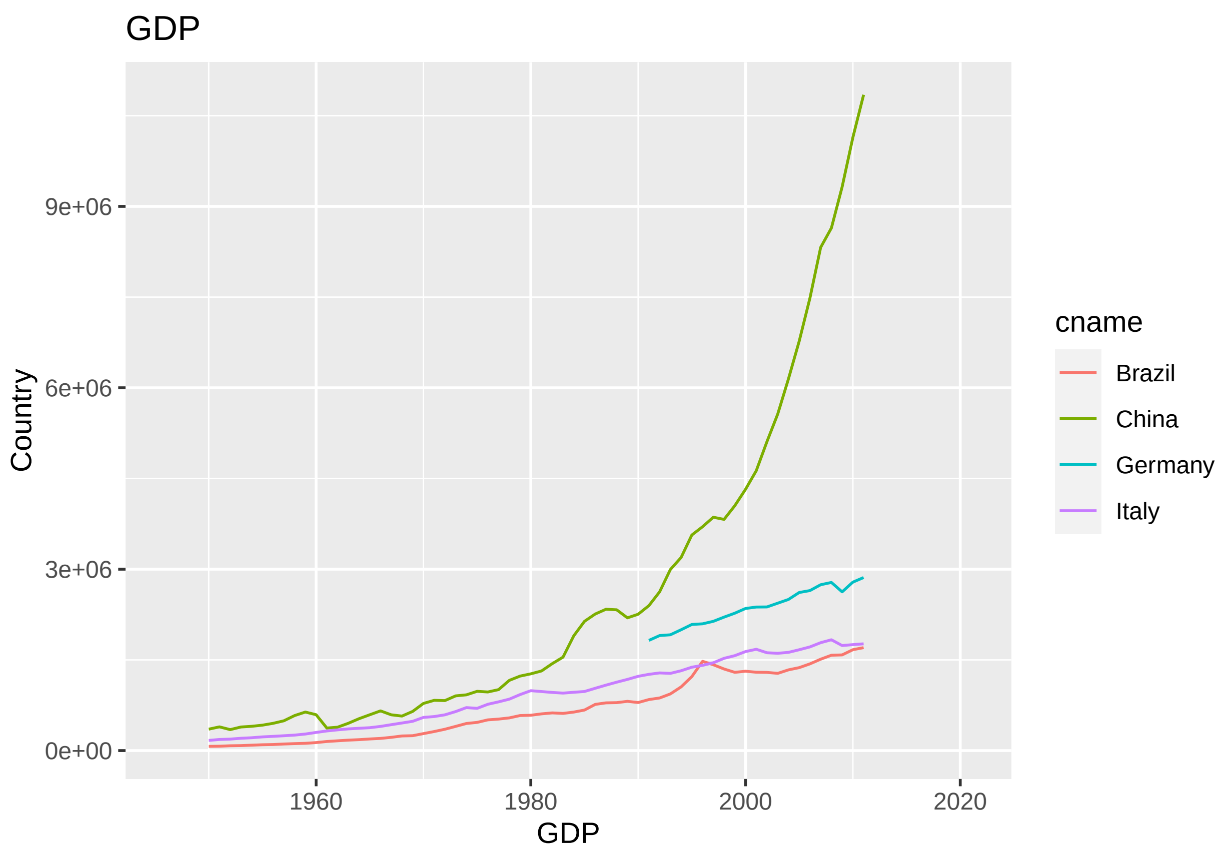



```
colnames(gwi)[which(names(gwi) == "country")] <- "cname_qog"
gwi$country_year <- paste(gwi$cname_qog, gwi$year)
```

Exploratory Analysis QoG Basic Dataset

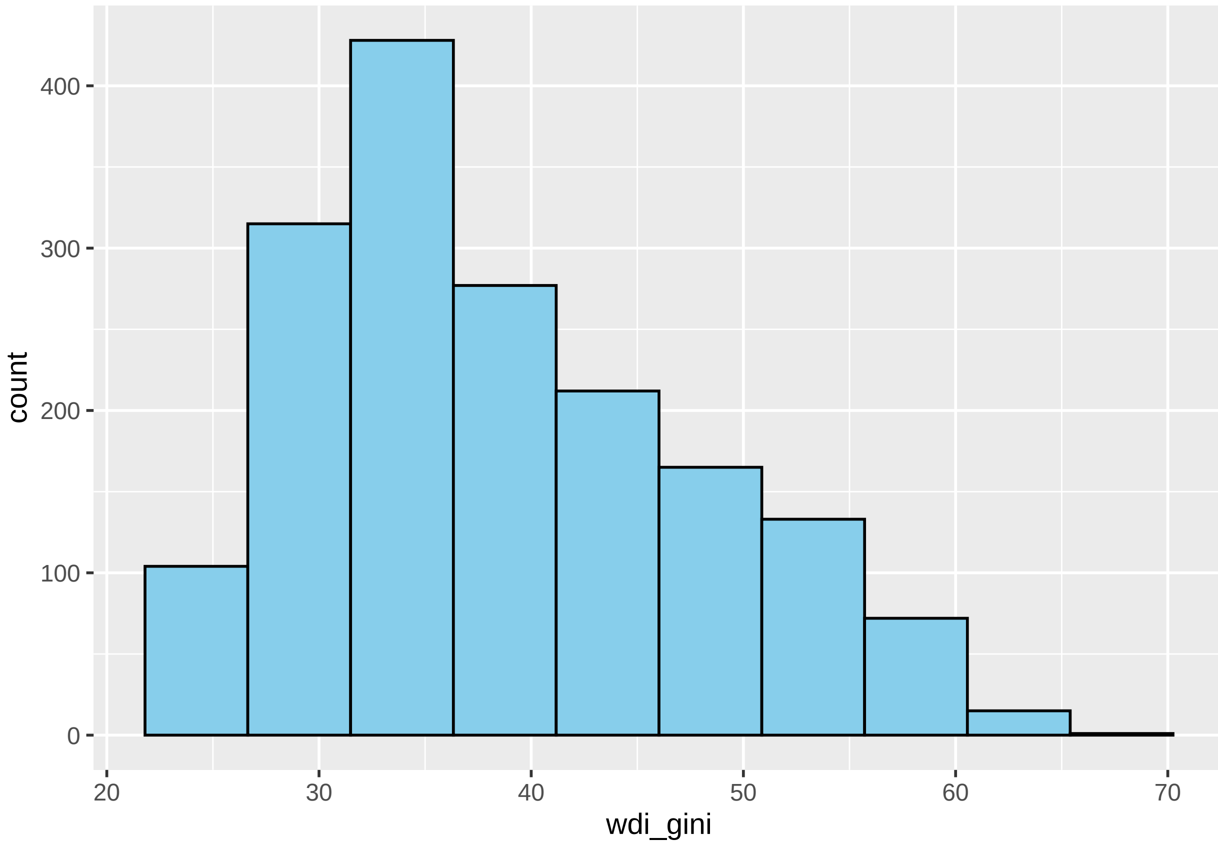
```
basic <- read.csv("~/Desktop/tcc/TCC/qog_bas_cs_jan22.csv")
eco <- basic[c(2, 3, 5, 105, 107, 110, 196, 236)]
plo1 <- filter(eco, cname_qog %in% v1)


plot2 <- ggplot(data=plo1, aes(x=year, y=gle_gdp, group = cname, colour = cname)) +
    geom_line() +
  labs(title = "GDP",
       x = "GDP",
       y = "Country")
plot2
```

```
## Warning: Removed 52 rows containing missing values (‘geom_line()‘).
```



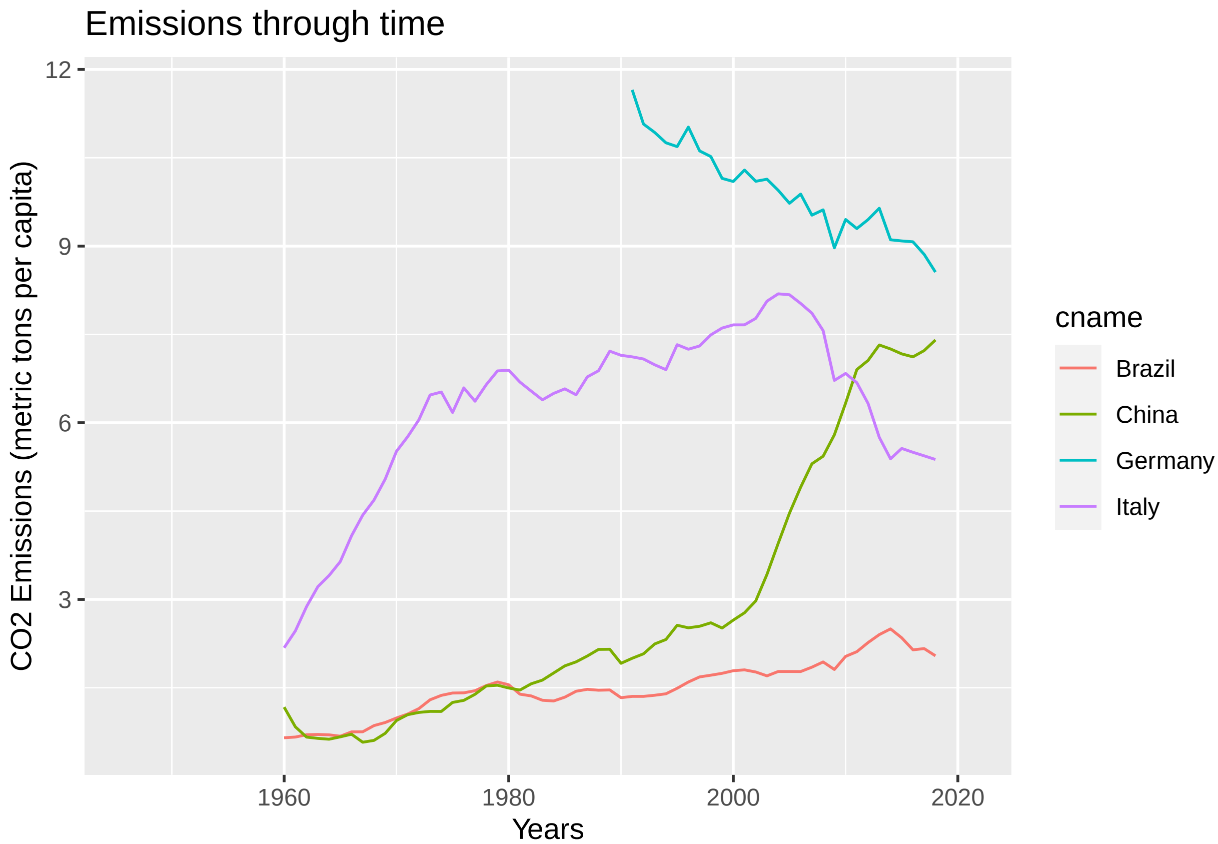

```
p<-ggplot(eco, aes(x=wdi_gini)) +
  geom_histogram(color="black", fill="skyblue", bins = 10)
p
```

```
## Warning: Removed 13446 rows containing non-finite values (`stat_bin()`).
```




```
plot3 <- ggplot(data=plo1, aes(x=year, y=wdi_co2, group = cname, colour = cname)) +
    geom_line() +
  labs(title = "Emissions through time",
       x = "Years",
       y = "CO2 Emissions (metric tons per capita)")
plot3
```

```
## Warning: Removed 54 rows containing missing values (`geom_line()`).
```



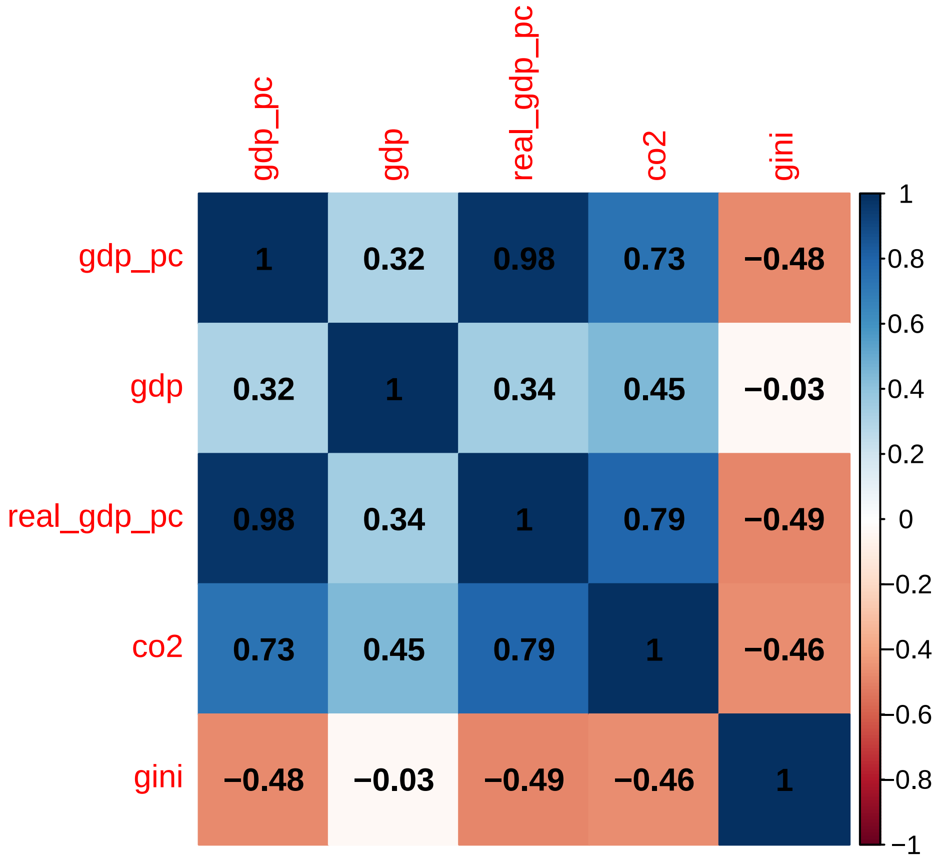

```r
names(eco)[names(eco) == "gle_cgdpc"] <- "gdp_pc"
names(eco)[names(eco) == "gle_gdp"] <- "gdp"
names(eco)[names(eco) == "gle_rgdpc"] <- "real_gdp_pc"
names(eco)[names(eco) == "wdi_co2"] <- "co2"
names(eco)[names(eco) == "wdi_gini"] <- "gini"
head(eco)
```

```
##         cname year   cname_qog gdp_pc     gdp real_gdp_pc co2 gini
## 1 Afghanistan 1946 Afghanistan     NA      NA          NA  NA   NA
## 2 Afghanistan 1947 Afghanistan     NA      NA          NA  NA   NA
## 3 Afghanistan 1948 Afghanistan     NA      NA          NA  NA   NA
## 4 Afghanistan 1949 Afghanistan     NA      NA          NA  NA   NA
## 5 Afghanistan 1950 Afghanistan 130.82 7995.78      892.59  NA   NA
## 6 Afghanistan 1951 Afghanistan 141.98 8216.95      903.66  NA   NA
```

```r
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```r
ceco <- eco[c(4,5,6,7,8)]
corre <- cor(na.omit(ceco))
corrplot(corre, method="color", addCoef.col = "black")
```




```
corre
```

```
##                  gdp_pc         gdp real_gdp_pc        co2        gini
## gdp_pc        1.0000000  0.31838651   0.9797967  0.7301052 -0.47614797
## gdp           0.3183865  1.00000000   0.3445516  0.4492780 -0.03060245
## real_gdp_pc   0.9797967  0.34455161   1.0000000  0.7930990 -0.48838456
## co2           0.7301052  0.44927799   0.7930990  1.0000000 -0.46470973
## gini         -0.4761480 -0.03060245  -0.4883846 -0.4647097  1.00000000
```

Dealing with the missing data

```
econew <- eco
econew <- econew %>%
  group_by(cname_qog) %>%
  mutate(gini = ifelse(is.na(gini), mean(gini, na.rm = TRUE), gini))

econew <- econew %>%
  group_by(cname_qog) %>%
  mutate(gdp = ifelse(is.na(gdp), mean(gdp, na.rm = TRUE), gdp))

econew <- econew %>%
  group_by(cname_qog) %>%
  mutate(gdp_pc = ifelse(is.na(gdp_pc), mean(gdp_pc, na.rm = TRUE), gdp_pc))
```

```
econew <- econew %>%
  group_by(cname_qog) %>%
  mutate(real_gdp_pc = ifelse(is.na(real_gdp_pc), mean(real_gdp_pc, na.rm = TRUE), real_gdp_pc))

econew <- econew %>%
  group_by(cname_qog) %>%
  mutate(co2 = ifelse(is.na(co2), mean(co2, na.rm = TRUE), co2))
```

```
# Count NA values for all columns
na_count_all <- colSums(is.na(econew))

# Print the count of NA values for each column
print(na_count_all)
```

```
##       cname        year   cname_qog      gdp_pc         gdp real_gdp_pc
##           0           0           0          86          86          86
##         co2        gini
##         727        2886
```

Loading the Compliance dataset from Python to R environment

```
compliance <- read.csv("~/Desktop/tcc/compliance.csv")
```

Assigning Values to each compliance category based on qualitative analysis

```
table(compliance$cname_qog, compliance$compliance)
```

```
##
##                                   0  1  2  3  4  5
##   Afghanistan                     0  4  6  0  1  0
##   Albania                         0  4  7  0  0  0
##   Algeria                         0  9  1  0  1  0
##   Andorra                         0  1  7  0  3  0
##   Angola                          0  5  3  0  3  0
##   Antigua and Barbuda             0  7  4  0  0  0
##   Argentina                       0  4  0  7  0  0
##   Armenia                         0  3  8  0  0  0
##   Australia                       1  2  0  8  0  0
##   Austria                         1  6  0  4  0  0
##   Azerbaijan                      0  2  9  0  0  0
##   Bahamas                         0  0 11  0  0  0
##   Bahrain                         0  2  9  0  0  0
##   Bangladesh                      0  7  3  0  1  0
##   Barbados                        0  0 11  0  0  0
##   Belarus                         0 10  0  0  1  0
##   Belgium                         1  1  0  9  0  0
##   Belize                          5  0  6  0  0  0
##   Benin                           1  3  7  0  0  0
```

```
##    Bhutan                         0  1 10  0  0  0
##    Bolivia                        0  9  2  0  0  0
##    Bosnia and Herzegovina         0  3  8  0  0  0
##    Botswana                       0  0 11  0  0  0
##    Brazil                         1  1  0  2  7  0
##    Brunei                         0  2  9  0  0  0
##    Bulgaria                       0  2  0  9  0  0
##    Burkina Faso                   0  4  7  0  0  0
##    Burundi                        0  0 11  0  0  0
##    Cambodia                       1  1  2  0  7  0
##    Cameroon                       1  2  8  0  0  0
##    Canada                         2  6  0  0  3  0
##    Cape Verde                     0  3  8  0  0  0
##    Central African Republic       0  1 10  0  0  0
##    Chad                           0  0 11  0  0  0
##    Chile                          0  2  0  0  9  0
##    China                          1  9  1  0  0  0
##    Colombia                       1  3  1  0  6  0
##    Comoros                        0  0 11  0  0  0
##    Congo                          1  8  2  0  0  0
##    Congo, Democratic Republic     0  1 10  0  0  0
##    Costa Rica                     0  5  2  0  4  0
##    Cote d'Ivoire                  1  8  1  0  1  0
##    Croatia                        0  3  0  8  0  0
##    Cuba                           0  8  3  0  0  0
##    Cyprus (1975-)                 1  9  1  0  0  0
##    Czech Republic                 1  9  0  1  0  0
##    Czechoslovakia                 0 11  0  0  0  0
##    Denmark                        1  1  0  9  0  0
##    Djibouti                       0  4  7  0  0  0
##    Dominica                       5  2  4  0  0  0
##    Dominican Republic             0 10  1  0  0  0
##    Ecuador                        5  5  1  0  0  0
##    Egypt                          1  2  8  0  0  0
##    El Salvador                    0  6  5  0  0  0
##    Equatorial Guinea              0  1 10  0  0  0
##    Eritrea                        0  1 10  0  0  0
##    Estonia                        0  9  2  0  0  0
##    Eswatini (former Swaziland)    0  0 11  0  0  0
##    Ethiopia (1993-)               0  2  9  0  0  0
##    Fiji                           0  2  9  0  0  0
##    Finland                        1  1  0  9  0  0
##    France (1963-)                 1  0  0  8  2  0
##    Gabon                          1  7  3  0  0  0
##    Gambia                         0  5  6  0  0  0
##    Georgia                        0  5  6  0  0  0
##    Germany                        0  0  0 10  1  0
##    Germany, East                  0 11  0  0  0  0
##    Ghana                          1 10  0  0  0  0
##    Greece                         0  0  0  9  1  1
##    Grenada                        0  1 10  0  0  0
##    Guatemala                      1  8  2  0  0  0
##    Guinea                         0  2  9  0  0  0
##    Guinea-Bissau                  0  0 11  0  0  0
```

```
##    Guyana                          0  1 10  0  0  0
##    Haiti                           0  0 11  0  0  0
##    Honduras                        0 10  1  0  0  0
##    Hungary                         0  4  0  7  0  0
##    Iceland                         5  4  2  0  0  0
##    India                           1  7  0  0  3  0
##    Indonesia                       0  0  0  0 11  0
##    Iran                            0 10  1  0  0  0
##    Iraq                            0  2  9  0  0  0
##    Ireland                         1  0  0  9  1  0
##    Israel                          0  3  0  0  8  0
##    Italy                           0  0  0  8  3  0
##    Jamaica                         0  1 10  0  0  0
##    Japan                           1  1  0  7  2  0
##    Jordan                          0  4  7  0  0  0
##    Kazakhstan                      0 10  0  1  0  0
##    Kenya                           0  7  2  0  2  0
##    Kiribati                        0  6  5  0  0  0
##    Korea, North                    0  1 10  0  0  0
##    Korea, South                    0  0  0 11  0  0
##    Kuwait                          0  8  3  0  0  0
##    Kyrgyzstan                      0  2  9  0  0  0
##    Laos                            0  1 10  0  0  0
##    Latvia                          0  6  5  0  0  0
##    Lebanon                         0  2  9  0  0  0
##    Lesotho                         0  1 10  0  0  0
##    Liberia                         0  8  3  0  0  0
##    Libya                           0  0 11  0  0  0
##    Liechtenstein                   0  1 10  0  0  0
##    Lithuania                       0  9  2  0  0  0
##    Luxembourg                      1  3  0  6  1  0
##    Madagascar                      0  5  6  0  0  0
##    Malawi                          0  3  8  0  0  0
##    Malaysia (1966-)                0  8  3  0  0  0
##    Maldives                        0  4  7  0  0  0
##    Mali                            0  1  3  0  7  0
##    Malta                           0  9  2  0  0  0
##    Marshall Islands                0  2  9  0  0  0
##    Mauritania                      0  6  5  0  0  0
##    Mauritius                       0  2  9  0  0  0
##    Mexico                          1  3  1  5  1  0
##    Micronesia                      0  0 11  0  0  0
##    Moldova                         0  7  3  0  1  0
##    Monaco                          0  2  9  0  0  0
##    Mongolia                        0 10  1  0  0  0
##    Montenegro                      0 11  0  0  0  0
##    Morocco                         0  5  0  6  0  0
##    Mozambique                      0 10  1  0  0  0
##    Myanmar                         0  6  5  0  0  0
##    Namibia                         0  5  6  0  0  0
##    Nauru                           0  0 11  0  0  0
##    Nepal                           0  1  8  0  2  0
##    Netherlands                     5  0  0  4  2  0
##    New Zealand                     5  5  0  1  0  0
```

```
##   Nicaragua                     0 11  0  0  0  0
##   Niger                         0  0 11  0  0  0
##   Nigeria                       0  6  5  0  0  0
##   North Macedonia               0  2  9  0  0  0
##   Norway                        4  0  0  7  0  0
##   Oman                          0  4  7  0  0  0
##   Pakistan (1971-)              0  8  2  0  1  0
##   Palau                         1  7  3  0  0  0
##   Panama                        5  2  1  2  1  0
##   Papua New Guinea              0  6  5  0  0  0
##   Paraguay                      0  5  6  0  0  0
##   Peru                          1  5  0  5  0  0
##   Philippines                   0  0  0  0 11  0
##   Poland                        1  2  0  8  0  0
##   Portugal                      1  0  0  7  3  0
##   Qatar                         0  1 10  0  0  0
##   Romania                       1  1  0  9  0  0
##   Russia                        3  8  0  0  0  0
##   Rwanda                        0  2  9  0  0  0
##   Samoa                         0  8  3  0  0  0
##   San Marino                    0  0 11  0  0  0
##   Sao Tome and Principe         0  1 10  0  0  0
##   Saudi Arabia                  0  0 11  0  0  0
##   Senegal                       0  8  0  0  3  0
##   Serbia                        0 10  1  0  0  0
##   Serbia and Montenegro         0 11  0  0  0  0
##   Seychelles                    0  3  8  0  0  0
##   Sierra Leone                  0  3  8  0  0  0
##   Singapore                     0  8  3  0  0  0
##   Slovakia                      0  1  0  8  2  0
##   Slovenia                      1  9  0  1  0  0
##   Solomon Islands               5  2  4  0  0  0
##   Somalia                       0  2  9  0  0  0
##   South Africa                  1  9  0  1  0  0
##   South Sudan                   0  3  8  0  0  0
##   Spain                         0  0  0  2  9  0
##   Sri Lanka                     0  8  3  0  0  0
##   St Kitts and Nevis            0  3  8  0  0  0
##   St Lucia                      0  3  8  0  0  0
##   St Vincent and the Grenadines 0  4  7  0  0  0
##   Sudan (-2011)                 0  0  2  0  0  0
##   Sudan (2012-)                 0  1  8  0  0  0
##   Suriname                      1  1  9  0  0  0
##   Sweden                        5  0  0  5  1  0
##   Switzerland                   1  7  0  3  0  0
##   Syria                         0  6  5  0  0  0
##   Taiwan                        0  4  7  0  0  0
##   Tajikistan                    0  3  8  0  0  0
##   Tanzania                      0  8  3  0  0  0
##   Thailand                      0  3  5  0  3  0
##   Tibet                         0 11  0  0  0  0
##   Timor-Leste                   0  1 10  0  0  0
##   Togo                          1  9  1  0  0  0
##   Tonga                         0  8  3  0  0  0
```

```
##   Trinidad and Tobago            0  6  5  0  0  0
##   Tunisia                        0  4  7  0  0  0
##   Turkey                         0  7  0  4  0  0
##   Turkmenistan                   0  0 11  0  0  0
##   Tuvalu                         0  5  6  0  0  0
##   Uganda                         0  2  9  0  0  0
##   Ukraine                        0  7  0  3  1  0
##   United Arab Emirates           0  2  9  0  0  0
##   United Kingdom                 0  0  0  9  2  0
##   United States                  1  4  0  6  0  0
##   Uruguay                        5  3  0  3  0  0
##   USSR                           0 11  0  0  0  0
##   Uzbekistan                     0  1 10  0  0  0
##   Vanuatu                        0  7  4  0  0  0
##   Venezuela                      1  2  8  0  0  0
##   Vietnam                        0  0  2  0  9  0
##   Vietnam, North                 0 11  0  0  0  0
##   Vietnam, South                 0 11  0  0  0  0
##   Yemen                          0  1 10  0  0  0
##   Yemen, South                   0 11  0  0  0  0
##   Yugoslavia                     0 11  0  0  0  0
##   Zambia                         0  3  6  0  2  0
##   Zimbabwe                       0  2  9  0  0  0
```

```r
table(compliance$cname_qog, compliance$compliance1)
```

```
##
##                                  0  1  2  3
##   Afghanistan                    0  2  9  0
##   Albania                        0  3  8  0
##   Algeria                        0  9  1  1
##   Andorra                        0  0  9  2
##   Angola                         0  4  3  4
##   Antigua and Barbuda            0  6  5  0
##   Argentina                      0  7  0  4
##   Armenia                        0  1 10  0
##   Australia                      1  7  0  3
##   Austria                        1  8  0  2
##   Azerbaijan                     0  2  9  0
##   Bahamas                        0  0 11  0
##   Bahrain                        0  2  9  0
##   Bangladesh                     0  7  3  1
##   Barbados                       0  0 11  0
##   Belarus                        0  9  0  2
##   Belgium                        1  9  0  1
##   Belize                         5  0  6  0
##   Benin                          0  3  8  0
##   Bhutan                         0  1 10  0
##   Bolivia                        0  8  3  0
##   Bosnia and Herzegovina         0  2  9  0
##   Botswana                       0  0 11  0
##   Brazil                         1  1  0  9
##   Brunei                         0  0 11  0
##   Bulgaria                       0 10  0  1
```

```
##    Burkina Faso                  0  2  9  0
##    Burundi                       0  0 11  0
##    Cambodia                      1  1  2  7
##    Cameroon                      1  0 10  0
##    Canada                        2  6  0  3
##    Cape Verde                    0  0 11  0
##    Central African Republic      0  1 10  0
##    Chad                          0  0 11  0
##    Chile                         0  2  0  9
##    China                         1  9  1  0
##    Colombia                      1  3  1  6
##    Comoros                       0  0 11  0
##    Congo                         1  7  3  0
##    Congo, Democratic Republic    0  0 11  0
##    Costa Rica                    0  3  4  4
##    Cote d'Ivoire                 1  7  1  2
##    Croatia                       0  6  0  5
##    Cuba                          0  4  7  0
##    Cyprus (1975-)                1  7  3  0
##    Czech Republic                0 10  1  0
##    Czechoslovakia                0 11  0  0
##    Denmark                       1 10  0  0
##    Djibouti                      0  3  8  0
##    Dominica                      5  2  4  0
##    Dominican Republic            0  8  3  0
##    Ecuador                       5  4  2  0
##    Egypt                         1  2  8  0
##    El Salvador                   0  5  6  0
##    Equatorial Guinea             0  0 11  0
##    Eritrea                       0  1 10  0
##    Estonia                       0  7  4  0
##    Eswatini (former Swaziland)   0  0 11  0
##    Ethiopia (1993-)              0  1 10  0
##    Fiji                          0  2  9  0
##    Finland                       1 10  0  0
##    France (1963-)                1  5  0  5
##    Gabon                         1  4  6  0
##    Gambia                        0  2  9  0
##    Georgia                       0  4  7  0
##    Germany                       1  1  0  9
##    Germany, East                 0 11  0  0
##    Ghana                         1  9  1  0
##    Greece                        2  5  0  4
##    Grenada                       0  0 11  0
##    Guatemala                     1  6  4  0
##    Guinea                        0  0 11  0
##    Guinea-Bissau                 0  0 11  0
##    Guyana                        0  1 10  0
##    Haiti                         0  0 11  0
##    Honduras                      0  9  2  0
##    Hungary                       0  9  0  2
##    Iceland                       5  4  2  0
##    India                         1  5  0  5
##    Indonesia                     0  0  0 11
```

```
##    Iran                            0 10  1  0
##    Iraq                            0  1 10  0
##    Ireland                         1  3  0  7
##    Israel                          0  3  0  8
##    Italy                           0  0  0 11
##    Jamaica                         0  0 11  0
##    Japan                           1  4  0  6
##    Jordan                          0  1 10  0
##    Kazakhstan                      0 11  0  0
##    Kenya                           0  6  3  2
##    Kiribati                        0  4  7  0
##    Korea, North                    0  0 11  0
##    Korea, South                    1  0  0 10
##    Kuwait                          0  4  7  0
##    Kyrgyzstan                      0  1 10  0
##    Laos                            0  0 11  0
##    Latvia                          0  5  6  0
##    Lebanon                         0  2  9  0
##    Lesotho                         0  0 11  0
##    Liberia                         0  5  6  0
##    Libya                           0  0 11  0
##    Liechtenstein                   0  1 10  0
##    Lithuania                       0  7  4  0
##    Luxembourg                      1  9  0  1
##    Madagascar                      0  4  7  0
##    Malawi                          0  3  8  0
##    Malaysia (1966-)                0  6  5  0
##    Maldives                        0  2  9  0
##    Mali                            0  0  4  7
##    Malta                           0  8  3  0
##    Marshall Islands                0  1 10  0
##    Mauritania                      0  1 10  0
##    Mauritius                       0  1 10  0
##    Mexico                          1  7  1  2
##    Micronesia                      0  0 11  0
##    Moldova                         0  5  5  1
##    Monaco                          0  0 11  0
##    Mongolia                        0 10  1  0
##    Montenegro                      0 10  1  0
##    Morocco                         0 11  0  0
##    Mozambique                      0  7  4  0
##    Myanmar                         0  4  6  1
##    Namibia                         0  3  8  0
##    Nauru                           0  0 11  0
##    Nepal                           0  0  8  3
##    Netherlands                     5  4  0  2
##    New Zealand                     5  5  1  0
##    Nicaragua                       0  9  2  0
##    Niger                           0  0 11  0
##    Nigeria                         0  5  6  0
##    North Macedonia                 0  1 10  0
##    Norway                          4  6  0  1
##    Oman                            0  1 10  0
##    Pakistan (1971-)                0  6  3  2
```

```
## Palau                          0  8  3  0
## Panama                         5  4  1  1
## Papua New Guinea               0  4  7  0
## Paraguay                       0  3  8  0
## Peru                           1  8  0  2
## Philippines                    0  0  0 11
## Poland                         1  6  0  4
## Portugal                       1  0  0 10
## Qatar                          0  1 10  0
## Romania                        1  5  0  5
## Russia                         2  9  0  0
## Rwanda                         0  1 10  0
## Samoa                          0  7  4  0
## San Marino                     0  0 11  0
## Sao Tome and Principe          0  1 10  0
## Saudi Arabia                   0  0 11  0
## Senegal                        0  8  0  3
## Serbia                         0  9  2  0
## Serbia and Montenegro          0 11  0  0
## Seychelles                     0  0 11  0
## Sierra Leone                   0  1 10  0
## Singapore                      0  7  4  0
## Slovakia                       0  4  0  7
## Slovenia                       0 10  1  0
## Solomon Islands                5  0  6  0
## Somalia                        0  2  9  0
## South Africa                   1  9  0  1
## South Sudan                    0  2  9  0
## Spain                          0  0  0 11
## Sri Lanka                      0  7  4  0
## St Kitts and Nevis             0  1 10  0
## St Lucia                       0  1 10  0
## St Vincent and the Grenadines  0  2  9  0
## Sudan (-2011)                  0  0  2  0
## Sudan (2012-)                  0  1  8  0
## Suriname                       1  0 10  0
## Sweden                         5  5  0  1
## Switzerland                    1 10  0  0
## Syria                          0  3  8  0
## Taiwan                         0  1 10  0
## Tajikistan                     0  2  9  0
## Tanzania                       0  8  3  0
## Thailand                       0  3  5  3
## Tibet                          0 11  0  0
## Timor-Leste                    0  0 11  0
## Togo                           1  9  1  0
## Tonga                          0  6  5  0
## Trinidad and Tobago            0  2  9  0
## Tunisia                        0  3  8  0
## Turkey                         0 11  0  0
## Turkmenistan                   0  0 11  0
## Tuvalu                         0  3  8  0
## Uganda                         0  2  9  0
## Ukraine                        0  9  0  2
```

```
##    United Arab Emirates           0  1 10  0
##    United Kingdom                 1  0  0 10
##    United States                  1  9  0  1
##    Uruguay                        5  6  0  0
##    USSR                           0 11  0  0
##    Uzbekistan                     0  0 11  0
##    Vanuatu                        0  5  6  0
##    Venezuela                      1  0 10  0
##    Vietnam                        0  0  2  9
##    Vietnam, North                 0 11  0  0
##    Vietnam, South                 0 11  0  0
##    Yemen                          0  0 11  0
##    Yemen, South                   0 11  0  0
##    Yugoslavia                     0 11  0  0
##    Zambia                         0  1  8  2
##    Zimbabwe                       0  2  9  0
```

```r
table(compliance$cname_qog, compliance$compliance2)
```

```
##
##                                   0  1  2
##    Afghanistan                    1 10  0
##    Albania                        0 11  0
##    Algeria                        1  9  1
##    Andorra                        3  8  0
##    Angola                         7  3  1
##    Antigua and Barbuda            0 11  0
##    Argentina                      1  1  9
##    Armenia                        0 11  0
##    Australia                      1  0 10
##    Austria                        1  3  7
##    Azerbaijan                     0 11  0
##    Bahamas                        0 11  0
##    Bahrain                        0 11  0
##    Bangladesh                     1 10  0
##    Barbados                       0 11  0
##    Belarus                        2  3  6
##    Belgium                        0  0 11
##    Belize                         0 10  1
##    Benin                          0 10  1
##    Bhutan                         0 10  1
##    Bolivia                        1 10  0
##    Bosnia and Herzegovina         0 11  0
##    Botswana                       0 11  0
##    Brazil                         9  0  2
##    Brunei                         0 11  0
##    Bulgaria                       0  0 11
##    Burkina Faso                   0 11  0
##    Burundi                        0 11  0
##    Cambodia                       8  3  0
##    Cameroon                       0 11  0
##    Canada                         3  3  5
##    Cape Verde                     0 11  0
##    Central African Republic       0 11  0
```

```
##   Chad                          0 11  0
##   Chile                         9  0  2
##   China                         0  5  6
##   Colombia                      7  3  1
##   Comoros                       0 11  0
##   Congo                         0  9  2
##   Congo, Democratic Republic    0 11  0
##   Costa Rica                    5  6  0
##   Cote d'Ivoire                 3  3  5
##   Croatia                       0  0 11
##   Cuba                          0 11  0
##   Cyprus (1975-)                0  9  2
##   Czech Republic                0  2  9
##   Czechoslovakia                0 11  0
##   Denmark                       0  0 11
##   Djibouti                      0 10  1
##   Dominica                      0 11  0
##   Dominican Republic            0  6  5
##   Ecuador                       3  4  4
##   Egypt                         0 11  0
##   El Salvador                   0 11  0
##   Equatorial Guinea             0 11  0
##   Eritrea                       0 11  0
##   Estonia                       0  8  3
##   Eswatini (former Swaziland)   0 11  0
##   Ethiopia (1993-)              0 11  0
##   Fiji                          0 11  0
##   Finland                       0  0 11
##   France (1963-)                3  0  8
##   Gabon                         0 11  0
##   Gambia                        0 11  0
##   Georgia                       0  9  2
##   Germany                       3  0  8
##   Germany, East                 0 11  0
##   Ghana                         0  7  4
##   Greece                        2  0  9
##   Grenada                       0 11  0
##   Guatemala                     0 11  0
##   Guinea                        0 11  0
##   Guinea-Bissau                 0 11  0
##   Guyana                        0 11  0
##   Haiti                         0 11  0
##   Honduras                      0  9  2
##   Hungary                       1  1  9
##   Iceland                       0  5  6
##   India                         5  1  5
##   Indonesia                    11  0  0
##   Iran                          0  6  5
##   Iraq                          0 11  0
##   Ireland                       3  0  8
##   Israel                       10  1  0
##   Italy                         9  0  2
##   Jamaica                       0 11  0
##   Japan                         3  0  8
```

```
##    Jordan                        0 11  0
##    Kazakhstan                    0  1 10
##    Kenya                         2  7  2
##    Kiribati                      0 11  0
##    Korea, North                  0 11  0
##    Korea, South                  3  0  8
##    Kuwait                        0 11  0
##    Kyrgyzstan                    0 11  0
##    Laos                          0 11  0
##    Latvia                        0 11  0
##    Lebanon                       0 11  0
##    Lesotho                       0 11  0
##    Liberia                       0 11  0
##    Libya                         0 11  0
##    Liechtenstein                 0 11  0
##    Lithuania                     0  9  2
##    Luxembourg                    1  1  9
##    Madagascar                    0 10  1
##    Malawi                        0 11  0
##    Malaysia (1966-)              0 11  0
##    Maldives                      0 11  0
##    Mali                          7  4  0
##    Malta                         0  6  5
##    Marshall Islands              0 11  0
##    Mauritania                    0 11  0
##    Mauritius                     0 11  0
##    Mexico                        2  2  7
##    Micronesia                    0 11  0
##    Moldova                       1 10  0
##    Monaco                        0 11  0
##    Mongolia                      0  4  7
##    Montenegro                    0  7  4
##    Morocco                       0  1 10
##    Mozambique                    0 11  0
##    Myanmar                       2  8  1
##    Namibia                       0 11  0
##    Nauru                         0 11  0
##    Nepal                         3  8  0
##    Netherlands                   2  0  9
##    New Zealand                   0  2  9
##    Nicaragua                     0  7  4
##    Niger                         0 11  0
##    Nigeria                       0 11  0
##    North Macedonia               0 11  0
##    Norway                        1  0 10
##    Oman                          0 11  0
##    Pakistan (1971-)              2  8  1
##    Palau                         0 10  1
##    Panama                        1  1  9
##    Papua New Guinea              0 11  0
##    Paraguay                      0 10  1
##    Peru                          1  1  9
##    Philippines                  11  0  0
##    Poland                        2  0  9
```

```
##   Portugal                      6  0  5
##   Qatar                         0 11  0
##   Romania                       1  1  9
##   Russia                        0  2  9
##   Rwanda                        0 11  0
##   Samoa                         0 11  0
##   San Marino                    0 11  0
##   Sao Tome and Principe         0 11  0
##   Saudi Arabia                  0 11  0
##   Senegal                       7  0  4
##   Serbia                        0  4  7
##   Serbia and Montenegro         0 11  0
##   Seychelles                    0 11  0
##   Sierra Leone                  0 11  0
##   Singapore                     0 10  1
##   Slovakia                      3  0  8
##   Slovenia                      0  2  9
##   Solomon Islands               0 11  0
##   Somalia                       0 11  0
##   South Africa                  2  3  6
##   South Sudan                   0 11  0
##   Spain                         9  0  2
##   Sri Lanka                     0 11  0
##   St Kitts and Nevis            0 11  0
##   St Lucia                      0 10  1
##   St Vincent and the Grenadines 0 11  0
##   Sudan (-2011)                 0  2  0
##   Sudan (2012-)                 0  9  0
##   Suriname                      0 11  0
##   Sweden                        1  0 10
##   Switzerland                   0  3  8
##   Syria                         0 11  0
##   Taiwan                        0 11  0
##   Tajikistan                    0 11  0
##   Tanzania                      1  8  2
##   Thailand                      6  5  0
##   Tibet                         0 11  0
##   Timor-Leste                   0 11  0
##   Togo                          1  9  1
##   Tonga                         0 10  1
##   Trinidad and Tobago           0 11  0
##   Tunisia                       0 11  0
##   Turkey                        0  3  8
##   Turkmenistan                  0 11  0
##   Tuvalu                        0 11  0
##   Uganda                        0 11  0
##   Ukraine                       1  0 10
##   United Arab Emirates          0 11  0
##   United Kingdom                4  0  7
##   United States                 0  0 11
##   Uruguay                       0  2  9
##   USSR                          0 11  0
##   Uzbekistan                    0 11  0
##   Vanuatu                       0 11  0
```

```
##   Venezuela                     0 11  0
##   Vietnam                       9  2  0
##   Vietnam, North                0 11  0
##   Vietnam, South                0 11  0
##   Yemen                         0 11  0
##   Yemen, South                  0 11  0
##   Yugoslavia                    0 11  0
##   Zambia                        2  8  1
##   Zimbabwe                      0 11  0
```

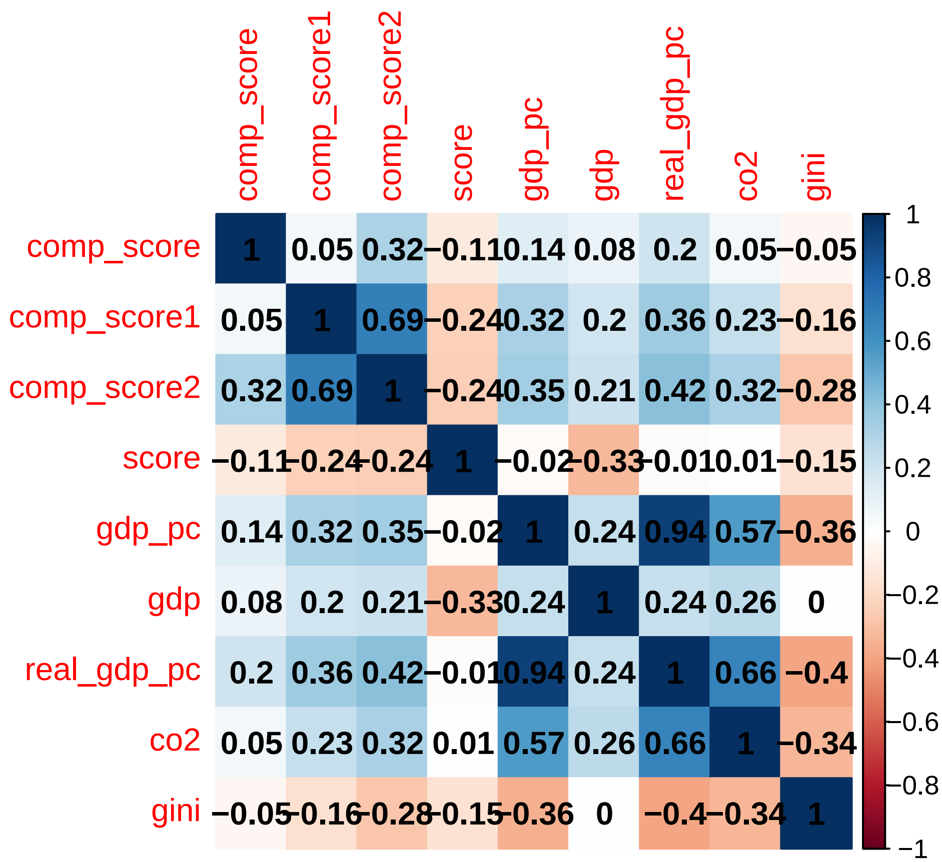
```
compliance$comp_score <- ifelse(compliance$compliance == 0, 6, ifelse(compliance$compliance == 1, 0, ife
compliance$comp_score1 <- ifelse(compliance$compliance1 == 0, 10, ifelse(compliance$compliance1 == 1, 7
compliance$comp_score2 <- ifelse(compliance$compliance2 == 0, 5, ifelse(compliance$compliance2 == 2, 10
```

Merging the datasets

```
ec1 <- filter(econew, gdp_pc >= 4100)
ec1 <- filter(ec1, year == 2011)
countries <- ec1$cname_qog
compliance2 <- filter(compliance, cname_qog %in% countries)
colnames(gwi)[which(names(gwi) == "country")] <- "cname_qog"
gwi$country_year <- paste(gwi$cname_qog, gwi$year)
dshi <- merge(compliance2, gwi, by = c("cname_qog","year"), all = FALSE)
dshi2 <- merge(dshi, econew, by = c("cname_qog","year"), all = FALSE)
```

```
final_data <- dshi2[-c(3,4,5,6,7,12,13)]
```

```
numerical <- final_data[-c(1,2)]
corregraph <- cor(na.omit(numerical))
corrplot(corregraph, method="color", addCoef.col = "black")
```




```
corregraph
```

```
##                comp_score comp_score1 comp_score2        score      gdp_pc
## comp_score   1.00000000  0.05470695   0.3150322 -0.111231902  0.13828167
## comp_score1  0.05470695  1.00000000   0.6893068 -0.238338631  0.32401257
## comp_score2  0.31503225  0.68930683   1.0000000 -0.240945202  0.34909608
## score       -0.11123190 -0.23833863  -0.2409452  1.000000000 -0.02142153
## gdp_pc       0.13828167  0.32401257   0.3490961 -0.021421534  1.00000000
## gdp          0.08316602  0.19733781   0.2130007 -0.328095039  0.23592400
## real_gdp_pc  0.20145826  0.35769372   0.4177102 -0.010912053  0.93811233
## co2          0.05381094  0.23322264   0.3246230  0.008480283  0.56505025
## gini        -0.04718315 -0.16454669  -0.2756603 -0.150282660 -0.35912403
##                      gdp real_gdp_pc          co2         gini
## comp_score   0.083166022  0.20145826  0.053810940 -0.047183148
## comp_score1  0.197337813  0.35769372  0.233222641 -0.164546687
## comp_score2  0.213000675  0.41771024  0.324622980 -0.275660251
## score       -0.328095039 -0.01091205  0.008480283 -0.150282660
## gdp_pc       0.235924004  0.93811233  0.565050247 -0.359124026
## gdp          1.000000000  0.23843733  0.263451855  0.003553616
## real_gdp_pc  0.238437330  1.00000000  0.664403252 -0.397866750
## co2          0.263451855  0.66440325  1.000000000 -0.335949959
## gini         0.003553616 -0.39786675 -0.335949959  1.000000000
```

Fixed Effect Model

Normal

```r
model_fe1 <- plm(comp_score ~ score + gini + co2 + real_gdp_pc,
                data = final_data,
                index = c("cname_qog", "year"),
                model = "within")

summary(model_fe1)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = comp_score ~ score + gini + co2 + real_gdp_pc,
##     data = final_data, model = "within", index = c("cname_qog",
##         "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 798
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -7.620367 -1.273236  0.076048  1.281233  9.493254
##
## Coefficients:
##                Estimate  Std. Error t-value Pr(>|t|)
## score        5.9033e-03  4.1830e-03  1.4113  0.15861
## gini        -1.3718e-01  7.5140e-02 -1.8256  0.06833 .
## co2         -5.6817e-02  1.7882e-01 -0.3177  0.75078
## real_gdp_pc -6.8844e-05  2.9155e-05 -2.3613  0.01848 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    4527.1
## Residual Sum of Squares: 4443.3
## R-Squared:      0.018511
## Adj. R-Squared: -0.1159
## F-statistic: 3.30517 on 4 and 701 DF, p-value: 0.010722
```

```r
model_fe2 <- plm(comp_score1 ~ score + gini + co2 + real_gdp_pc,
                data = final_data,
                index = c("cname_qog", "year"),
                model = "within")

summary(model_fe2)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = comp_score1 ~ score + gini + co2 + real_gdp_pc,
##     data = final_data, model = "within", index = c("cname_qog",
##         "year"))
```

```
##
## Unbalanced Panel: n = 93, T = 1-9, N = 798
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -8.155028 -0.916909 -0.014275  0.783999  8.973741
##
## Coefficients:
##                Estimate  Std. Error t-value Pr(>|t|)
## score       -3.0769e-04  3.8541e-03 -0.0798  0.93639
## gini        -3.8585e-02  6.9233e-02 -0.5573  0.57749
## co2         -2.2978e-02  1.6476e-01 -0.1395  0.88912
## real_gdp_pc  5.8648e-05  2.6863e-05  2.1832  0.02935 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    3803.6
## Residual Sum of Squares: 3772.1
## R-Squared:      0.0082707
## Adj. R-Squared: -0.12754
## F-statistic: 1.46152 on 4 and 701 DF, p-value: 0.2122
```

```r
model_fe3 <- plm(comp_score2 ~ score + gini + co2 + real_gdp_pc,
                data = final_data,
                index = c("cname_qog", "year"),
                model = "within")

summary(model_fe3)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = comp_score2 ~ score + gini + co2 + real_gdp_pc,
##     data = final_data, model = "within", index = c("cname_qog",
##         "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 798
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -9.061870 -0.405462  0.036703  0.960958  9.288538
##
## Coefficients:
##                Estimate  Std. Error t-value Pr(>|t|)
## score       -8.0864e-04  4.5355e-03 -0.1783  0.85855
## gini        -1.4410e-01  8.1473e-02 -1.7686  0.07739 .
## co2         -4.2590e-01  1.9389e-01 -2.1966  0.02837 *
## real_gdp_pc -3.5888e-05  3.1613e-05 -1.1352  0.25666
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    5313.5
## Residual Sum of Squares: 5223.9
## R-Squared:      0.016862
```

```
## Adj. R-Squared: -0.11778
## F-statistic: 3.00567 on 4 and 701 DF, p-value: 0.017821
```

Lagged

```r
data_frame <- final_data

# getting the last row col index
last_row <- -nrow(data_frame)
excl_last_row <- as.character(data_frame$score[last_row])

# create a vector of values of NA and col2
data_frame$lag_value <- c( NA, excl_last_row)

# replace first occurrence by NA
data_frame$lag_value[which(!duplicated(data_frame$col1))] <- NA
```

```r
model_fe1_lag <- plm(comp_score ~ as.numeric(lag_value) + gini + co2 + real_gdp_pc,
                data = data_frame,
                index = c("cname_qog", "year"),
                model = "within")

summary(model_fe1_lag)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = comp_score ~ as.numeric(lag_value) + gini + co2 +
##     real_gdp_pc, data = data_frame, model = "within", index = c("cname_qog",
##     "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 797
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -7.416949 -1.265763  0.096519  1.197349  9.621875
##
## Coefficients:
##                          Estimate  Std. Error t-value Pr(>|t|)
## as.numeric(lag_value) -7.9518e-03  3.8251e-03 -2.0788  0.03800 *
## gini                  -1.4336e-01  7.4944e-02 -1.9129  0.05617 .
## co2                   -1.1869e-01  1.8007e-01 -0.6591  0.51004
## real_gdp_pc           -6.1198e-05  2.9358e-05 -2.0846  0.03747 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    4519.1
## Residual Sum of Squares: 4421.2
## R-Squared:      0.021679
## Adj. R-Squared: -0.11249
## F-statistic: 3.87785 on 4 and 700 DF, p-value: 0.004003
```

```r
model_fe2_lag <- plm(comp_score1 ~ as.numeric(lag_value) + gini + co2 + real_gdp_pc,
                data = data_frame,
                index = c("cname_qog", "year"),
                model = "within")

summary(model_fe2_lag)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = comp_score1 ~ as.numeric(lag_value) + gini + co2 +
##     real_gdp_pc, data = data_frame, model = "within", index = c("cname_qog",
##     "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 797
##
## Residuals:
##     Min.  1st Qu.   Median  3rd Qu.     Max.
## -8.12102 -0.91079 -0.01733  0.76287  8.93505
##
## Coefficients:
##                          Estimate  Std. Error t-value Pr(>|t|)
## as.numeric(lag_value) -8.7060e-04  3.5185e-03 -0.2474  0.80464
## gini                  -3.4265e-02  6.8936e-02 -0.4971  0.61931
## co2                   -1.6445e-02  1.6564e-01 -0.0993  0.92094
## real_gdp_pc            5.7011e-05  2.7004e-05  2.1112  0.03511 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    3770.2
## Residual Sum of Squares: 3740.8
## R-Squared:      0.0078124
## Adj. R-Squared: -0.12826
## F-statistic: 1.37794 on 4 and 700 DF, p-value: 0.2399
```

```r
model_fe3_lag <- plm(comp_score2 ~ as.numeric(lag_value) + gini + co2 + real_gdp_pc,
                data = data_frame,
                index = c("cname_qog", "year"),
                model = "within")

summary(model_fe3_lag)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = comp_score2 ~ as.numeric(lag_value) + gini + co2 +
##     real_gdp_pc, data = data_frame, model = "within", index = c("cname_qog",
##     "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 797
##
## Residuals:
```

```
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -9.055369 -0.403803  0.030633  0.954050  9.309701
##
## Coefficients:
##                           Estimate  Std. Error t-value Pr(>|t|)
## as.numeric(lag_value)  1.7049e-04  4.1580e-03  0.0410  0.96730
## gini                  -1.4348e-01  8.1466e-02 -1.7613  0.07863 .
## co2                   -4.2406e-01  1.9574e-01 -2.1664  0.03062 *
## real_gdp_pc           -3.5799e-05  3.1912e-05 -1.1218  0.26233
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    5313.5
## Residual Sum of Squares: 5224.1
## R-Squared:      0.01682
## Adj. R-Squared: -0.11802
## F-statistic: 2.99395 on 4 and 700 DF, p-value: 0.018177
```

Random Effect Model

Normal

```r
model_re1 <- plm(comp_score ~ score + gini + co2 + real_gdp_pc,
                data = final_data,
                index = c("cname_qog", "year"),
                model = "random")

summary(model_re1)
```

```
## Oneway (individual) effect Random Effect Model
##    (Swamy-Arora's transformation)
##
## Call:
## plm(formula = comp_score ~ score + gini + co2 + real_gdp_pc,
##     data = final_data, model = "random", index = c("cname_qog",
##         "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 798
##
## Effects:
##                 var std.dev share
## idiosyncratic 6.339   2.518 0.596
## individual    4.294   2.072 0.404
## theta:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.2279  0.6246  0.6246  0.6197  0.6246  0.6246
##
## Residuals:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -6.3225 -2.2137  0.3156  0.0085  1.6882  7.6867
##
## Coefficients:
```

```
##                Estimate  Std. Error z-value  Pr(>|z|)
## (Intercept)  5.0760e+00  1.2828e+00  3.9570 7.591e-05 ***
## score        1.4663e-03  3.9583e-03  0.3704    0.7111
## gini        -2.9952e-02  2.7809e-02 -1.0771    0.2815
## co2         -6.4250e-03  6.6591e-02 -0.0965    0.9231
## real_gdp_pc  4.7484e-06  2.3685e-05  0.2005    0.8411
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    5227.6
## Residual Sum of Squares: 5228.5
## R-Squared:      0.00089513
## Adj. R-Squared: -0.0041445
## Chisq: 1.64326 on 4 DF, p-value: 0.801
```

```r
model_re2 <- plm(comp_score1 ~ score + gini + co2 + real_gdp_pc,
                data = final_data,
                index = c("cname_qog", "year"),
                model = "random")

summary(model_re2)
```

```
## Oneway (individual) effect Random Effect Model
##    (Swamy-Arora's transformation)
##
## Call:
## plm(formula = comp_score1 ~ score + gini + co2 + real_gdp_pc,
##     data = final_data, model = "random", index = c("cname_qog",
##         "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 798
##
## Effects:
##                 var std.dev share
## idiosyncratic 5.381   2.320 0.576
## individual    3.954   1.989 0.424
## theta:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.2408  0.6376  0.6376  0.6328  0.6376  0.6376
##
## Residuals:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -7.1935 -1.6449  0.2664  0.0137  1.3515  7.9909
##
## Coefficients:
##                Estimate  Std. Error z-value  Pr(>|z|)
## (Intercept)  5.1361e+00  1.2104e+00  4.2435 2.201e-05 ***
## score       -7.2275e-03  3.6547e-03 -1.9776   0.04798 *
## gini        -2.7940e-02  2.6315e-02 -1.0617   0.28835
## co2          8.7168e-03  6.2873e-02  0.1386   0.88973
## real_gdp_pc  9.0522e-05  2.2020e-05  4.1109 3.942e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Total Sum of Squares:    4579.1
## Residual Sum of Squares: 4416
## R-Squared:      0.036027
## Adj. R-Squared: 0.031164
## Chisq: 34.4512 on 4 DF, p-value: 6.0215e-07
```

```r
model_re3 <- plm(comp_score2 ~ score + gini + co2 + real_gdp_pc,
                data = final_data,
                index = c("cname_qog", "year"),
                model = "random")

summary(model_re3)
```

```
## Oneway (individual) effect Random Effect Model
##    (Swamy-Arora's transformation)
##
## Call:
## plm(formula = comp_score2 ~ score + gini + co2 + real_gdp_pc,
##     data = final_data, model = "random", index = c("cname_qog",
##         "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 798
##
## Effects:
##                 var std.dev share
## idiosyncratic 7.452   2.730 0.506
## individual    7.288   2.700 0.494
## theta:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.2890  0.6806  0.6806  0.6761  0.6806  0.6806
##
## Residuals:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -9.6669 -1.5631 -0.4175  0.0205  1.8624  8.6536
##
## Coefficients:
##                Estimate  Std. Error z-value  Pr(>|z|)
## (Intercept)  8.9568e+00  1.6015e+00  5.5927 2.235e-08 ***
## score       -8.5533e-03  4.4698e-03 -1.9136 0.0556752 .
## gini        -1.2116e-01  3.5157e-02 -3.4463 0.0005684 ***
## co2          1.1930e-01  8.3389e-02  1.4306 0.1525337
## real_gdp_pc  2.1886e-05  2.7555e-05  0.7943 0.4270341
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    6598.7
## Residual Sum of Squares: 6415.8
## R-Squared:      0.028157
## Adj. R-Squared: 0.023255
## Chisq: 27.1136 on 4 DF, p-value: 1.8855e-05
```

Lagged

```
model_re1_lag <- plm(comp_score ~ as.numeric(lag_value) + gini + co2 + real_gdp_pc,
                data = data_frame,
                index = c("cname_qog", "year"),
                model = "random")

summary(model_re1_lag)
```

```
## Oneway (individual) effect Random Effect Model
##    (Swamy-Arora's transformation)
##
## Call:
## plm(formula = comp_score ~ as.numeric(lag_value) + gini + co2 +
##     real_gdp_pc, data = data_frame, model = "random", index = c("cname_qog",
##     "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 797
##
## Effects:
##                 var std.dev share
## idiosyncratic 6.316   2.513 0.601
## individual    4.198   2.049 0.399
## theta:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.2249  0.6216  0.6216  0.6164  0.6216  0.6216
##
## Residuals:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -6.6736 -2.2619  0.4034  0.0081  1.7518  7.9955
##
## Coefficients:
##                          Estimate  Std. Error z-value  Pr(>|z|)
## (Intercept)            6.3377e+00  1.2465e+00  5.0845 3.686e-07 ***
## as.numeric(lag_value) -1.1560e-02  3.6564e-03 -3.1616  0.001569 **
## gini                  -3.6578e-02  2.7391e-02 -1.3354  0.181746
## co2                   -2.2826e-02  6.5983e-02 -0.3459  0.729385
## real_gdp_pc            1.1502e-05  2.3531e-05  0.4888  0.625001
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    5229.4
## Residual Sum of Squares: 5166.3
## R-Squared:      0.012314
## Adj. R-Squared: 0.0073261
## Chisq: 11.5965 on 4 DF, p-value: 0.020618
```

```
model_re2_lag <- plm(comp_score1 ~ as.numeric(lag_value) + gini + co2 + real_gdp_pc,
                data = data_frame,
                index = c("cname_qog", "year"),
                model = "random")

summary(model_re2_lag)
```

```
## Oneway (individual) effect Random Effect Model
##    (Swamy-Arora's transformation)
##
## Call:
## plm(formula = comp_score1 ~ as.numeric(lag_value) + gini + co2 +
##     real_gdp_pc, data = data_frame, model = "random", index = c("cname_qog",
##     "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 797
##
## Effects:
##                 var std.dev share
## idiosyncratic 5.344   2.312 0.559
## individual    4.208   2.051 0.441
## theta:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.2520  0.6484  0.6484  0.6434  0.6484  0.6484
##
## Residuals:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -7.2206 -1.6121  0.2437  0.0148  1.3344  8.0781
##
## Coefficients:
##                         Estimate  Std. Error z-value  Pr(>|z|)
## (Intercept)            4.8842e+00  1.2105e+00  4.0348 5.465e-05 ***
## as.numeric(lag_value) -5.8085e-03  3.3818e-03 -1.7176   0.08588 .
## gini                  -2.4890e-02  2.6742e-02 -0.9307   0.35199
## co2                    6.8283e-03  6.4127e-02  0.1065   0.91520
## real_gdp_pc            9.3357e-05  2.2142e-05  4.2162 2.485e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    4503.7
## Residual Sum of Squares: 4357.9
## R-Squared:      0.032861
## Adj. R-Squared: 0.027976
## Chisq: 31.8639 on 4 DF, p-value: 2.0397e-06
```

```r
model_re3_lag <- plm(comp_score2 ~ as.numeric(lag_value) + gini + co2 + real_gdp_pc,
                data = data_frame,
                index = c("cname_qog", "year"),
                model = "random")

summary(model_re3_lag)
```

```
## Oneway (individual) effect Random Effect Model
##    (Swamy-Arora's transformation)
##
## Call:
## plm(formula = comp_score2 ~ as.numeric(lag_value) + gini + co2 +
##     real_gdp_pc, data = data_frame, model = "random", index = c("cname_qog",
```

```
##     "year"))
##
## Unbalanced Panel: n = 93, T = 1-9, N = 797
##
## Effects:
##                 var std.dev share
## idiosyncratic 7.463   2.732 0.494
## individual    7.631   2.762 0.506
## theta:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.2968  0.6869  0.6869  0.6823  0.6869  0.6869
##
## Residuals:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -9.9297 -1.5499 -0.4230  0.0218  1.8602  8.9645
##
## Coefficients:
##                         Estimate  Std. Error z-value  Pr(>|z|)
## (Intercept)            8.6173e+00  1.5987e+00  5.3904 7.032e-08 ***
## as.numeric(lag_value) -5.3628e-03  4.1340e-03 -1.2972 0.1945458
## gini                  -1.1847e-01  3.5581e-02 -3.3296 0.0008698 ***
## co2                    1.1029e-01  8.4775e-02  1.3009 0.1932810
## real_gdp_pc            2.5813e-05  2.7738e-05  0.9306 0.3520551
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    6546
## Residual Sum of Squares: 6389.7
## R-Squared:      0.024421
## Adj. R-Squared: 0.019493
## Chisq: 24.0361 on 4 DF, p-value: 7.8555e-05
```