# THE EFFECT OF NATURAL DISASTERS ON ECONOMIC INEQUALITY

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M.Sc. Thesis

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*To the difficulties that build character and to the people who are patient enough to guide us through them – Thank you.*

# Abstract

With increasing frequency and severity of natural disasters resulting from climate change, understanding their implications for economic inequality is crucial. This study examines the effects of natural disasters on income and wealth inequality across 149 countries. The results show that disasters slightly reduce income inequality over time, while wealth inequality seems to remain largely unaffected apart from a small decrease observed in the 4$^{th}$ year after the disaster has taken place. Looking into the effects of natural disasters by type reveals that heatwaves lead to a slight increase in income inequality whereas floods have been shown to marginally reduce it. Wealth inequality has been found to decrease modestly after droughts. These findings highlight that the relationship between disasters and economic inequality is heterogenous and depends on the disaster type and severity, underscoring the need for tailored policy responses.



**Key words: Income, Wealth, Inequality, Palma ratio, Climate change, Panel data, Fixed effects model**

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# 1 Introduction

There is accumulating evidence that human-induced climate change is affecting weather and climate extremes on a global scale. The latest report of the Intergovernmental Panel on Climate Change (IPCC, 2023) summarizes the current state of knowledge on climate change and its adverse impacts and risks. According to the report, "[h]uman influence has *likely* increased the chance of compound extreme events […], including increases in frequency of concurrent heatwaves and droughts" (IPCC, 2023, p.5). Furthermore, the report states that climate change is also expected to lead to higher spread of food-, water-, and vector-borne diseases, as well as to increased instances of floods, landslides, fire weather, storms, and cyclones. Henceforth, all the abovementioned will be considered as climate-change-induced natural disasters.

The resulting increased frequency and severity of natural disasters are linked to higher mortality, morbidity, injuries, and damage to nature and infrastructure that are disproportionately affecting people of lower socioeconomic status. In more severe cases, this can even lead to self-perpetuating cycles of poverty (Cappelli et al., 2021; Groeschl and Noy, 2020; Hallegatte et al., 2020; IPCC, 2023; Šedová et al., 2019). Consequently, climate-change-induced natural disasters can have a long-lasting effect on human and economic development, particularly exacerbating poverty and worsening the distribution of wealth and income (Groeschl and Noy, 2020).

However, thus far, the long- and short-term effects of disasters on income and wealth inequality remain insufficiently explored, with most papers addressing the topic focusing only on location- and/or disaster-specific effects (e.g., Abdullah et al., 2016; Pleniger, 2022, Šedová et al., 2019). This thesis aims to narrow the research gap by exploring the long- and short-term effects of various disaster types on wealth and income inequality over 149 countries for the period 1970 to 2020.

The objective is twofold: (i) to examine whether climate-change-induced natural disasters persistently alter the distribution of income and wealth across countries; and (ii) to assess whether the resulting changes differ across disaster types and severity levels. Findings may provide evidence for policies that mitigate the re-distributive effects of disasters.

The objective of this thesis leads to the following specific research questions:

- What are the long- and short-term effects of climate-change-related natural disasters on economic inequality (i.e., wealth and income inequality)?
- What are the effects of severe disasters on economic inequality?
- Do effects vary between natural disaster types?

This thesis is structured as follows. Chapter 2 reviews the literature on the relationship between natural disasters and economic inequality. Chapter 3 develops a conceptual framework, which is then translated into an empirical model in Chapter 4. Chapter 5 presents and discusses the results, followed by conclusions and a critical reflection in Chapter 6.

# 2 Natural disasters and economic inequality

## 2.1 Theoretical frameworks on the determinants of inequality

The theoretical literature discussing the determinants of inequality is generally separated into two contradicting narratives regarding impacts of disasters (or shocks in general). For the majority, shocks are a potent equalizing force, whereas others argue that in times of crisis elites manage to seize the opportunity to expand their fortune thereby widening the economic gap.

Massive structural shocks (i.e., wars, revolutions, state collapse, and pandemics) have been prominently framed by Scheidel (2017) as a "Great Leveler", implying that these tend to decrease pre-existing inequalities. In fact, Scheidel argues that massive and violent disruptions of the established order have historically been the only drivers of significant and sustained compressions of inequality. According to Scheidel, shocks decrease inequality through subsequent "[l]ow savings rates and depressed asset prices, physical destruction and the loss of foreign assets, inflation and progressive taxation, rent and price controls, and nationalization […]" (Scheidel, 2017, p.188).

Similar observations of historical inequality being suppressed (partially) by exogenous shocks are also present in Piketty (2014) and Milanovic (2016). However, there are discrepancies between these three theories and proposed mechanisms.

For Piketty (2014), the wealth distribution is dictated by the interchange of powerful mechanisms of convergence (i.e., equality) and divergence (i.e., inequality). The most potent force of divergence, Piketty sums up in one inequality: $r > g$, where $r$ is the average annual rate of return on capital and $g$ is the annual growth rate of the economy (i.e., the annual increase in income or output). High rates of return to capital ($r$) relative to economic growth ($g$) result in societies in which inheritance provides significantly larger economic opportunities compared to career advancements. In a review of Piketty's book, Milanovic (2014, p. 525) claims that such conditions "[…] make a mockery of equal opportunity and meritocracy and undermine democracy as the rich use their money to buy policies they like".

However, historically this inequality has always been valid except for a large part of the twentieth century (see Figure 1). Piketty argues that there were several reasons why inequality was historically low ($r > g$ was no longer valid and even reversed) in the period of the two world wars. For one, the rapid population growth succeeding WWII has resulted in increasing $g$. Secondly, $r$ has been kept low around the time by progressive taxation as well as high taxation on inheritance, which have been necessary to sustain the war effort; high influence of communist and left-wing socialist parties, which ultimately lead to a more labor-friendly political atmosphere; the physical destruction of capital, which decreased the ratio between capital and annual income as well as the share of capital in national income; and finally the high inflation rates, which have favored debtors over creditors.

Nevertheless, not too long after the end of WWII these processes have lost their initial momentum. Particularly in developed countries, as high levels of income were reached, the growth rate $g$ began to decrease (due to decreased population growth and changing taxation policies) whereas $r$ tends to remain relatively constant. Presently, expanding financial sophistication and international competition are said to maintain $r$ at high levels. However, in post-war times there are also forces pushing towards convergence, the main ones being, according to Piketty, diffusion of knowledge and investment in training skills. Nevertheless, the latter principal forces of convergence are also dependent on educational policies and accessibility. Other forces of convergence mentioned in the book are the law of supply and demand, as well as the mobility of capital and labor although these are said to be of lesser importance. Finally, despite acknowledging that economic mechanisms play a role in determining the levels of wealth and income inequality, Piketty points out that these processes are deeply political and therefore one should be wary of economic determinism.

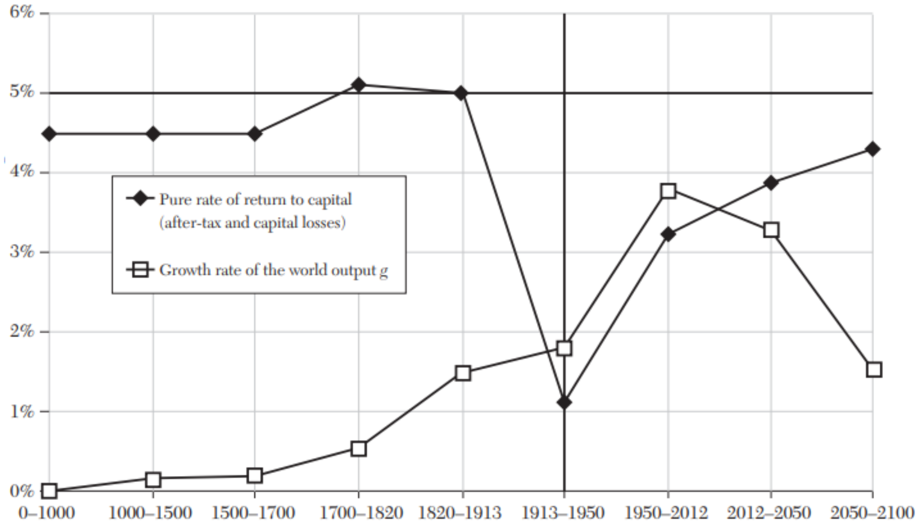


*Figure 1. After-tax rate of return versus growth rate at the world level, from Antiquity until 2100. Source: Piketty (2014, p.356)*

In his book “Global Inequality: A New Approach to the Age of Globalization” Milanovic (2016) proposes that within-country inequality follows a pattern of Kuznets waves. Essentially, the author extends the Kuznets hypothesis (i.e., rising inequality at very low levels of income followed by a decrease at higher levels of income) by suggesting a wave-like pattern of rising and declining inequality. The most recent rise of inequality observed in rich countries the author attributes to a new technological revolution taking place in the early 80s, which has strongly rewarded highly skilled labor, driven up the share of and return to capital, and opened the economies of rich countries to competition. Furthermore, these trends have been reinforced by pro-rich policies such as reducing tax rates on high income and lower taxation of capital income compared to labor income. Conversely, the downward trend has historically been driven by an interplay between what Milanovic calls benign and malign forces, with the former being active only in growing economies. Unlike Scheidel, who considers solely violent conflicts and catastrophes (i.e., malign forces) as drivers, Milanovic recognizes that there are also economic and demographic mechanisms (i.e., benign forces) which drive within-country inequality down. These are namely rising education, greater political participation, an aging population requiring social protection, as well as low-skilled-based technological change. Malign forces, on the other hand, include wars, civil conflicts, and epidemics. The leveling effects of wars, in recent times, are attributed to mass mobilization, destruction of property and progressive taxation. Disease is another malign force which drives down inequality predominantly in developing countries as it can take the lives of many in a short period of time, thereby increasing the demand for and subsequently the real wages of labor.

The opposite narrative is posed by van Bavel and Scheffer (2021) who recently questioned the great leveler notion and argued in favor of the opposing view, namely that historical disasters including natural disasters and social turmoil have resulted in wider wealth gaps. The main point emphasized in their work is that the effects of disasters are shaped during three stages: the immediate impact, which varies depending on the nature of the shock as well as the initial wealth distribution, and the institutional outlay; the mid-term effects formed by the institutional response to the catastrophic event; and the indirect long-term outcomes which depend on the joint effects of the previous two stages. From here, the authors describe the two key conditions which determine the direction of the disasters’ effect on inequality: pre-existing inequality levels and political leverage. The pre-disaster economic inequality is considered relevant as it provides wealthier individuals with the capacity to buffer harmful consequences and even to make use of opportunities resulting from the shock. Contrariwise, individuals who lack the means to recover are pushed into selling-off goods and land, inevitably leading to an exacerbated economic situation. Political skewness is another important condition which can shape long-term outcomes. In the general case, responses to disasters result in alteration of policies which tend to benefit individuals with a higher political leverage. However, as economic wealth and political power become increasingly intertwined due to lobbying and financing campaigns, it is becoming inevitable, as per van Bavel and Scheffer, that wealth becomes highly concentrated.

Despite the theoretical disparities, there appears to be a partial agreement on some of the relevant mechanisms which impact inequality. For instance, conflicts, savings rates, foreign portfolios, political landscape, rate of inflation, and education are present in most of the latter theories (for overview, see Table 1). When it comes to disasters, most of the theories touch upon the role of pandemics and only one explicitly mentions other forms of natural disasters. However, some of the mechanisms which are enabled because of wars such as physical destruction, loss of foreign assets, and inflation can also be initiated by natural disasters (Doytch, 2019; Parker, 2016). Moreover, natural disasters can also increase the instances of armed conflicts (Shimada, 2022), thereby indirectly reinforcing war-related mechanisms and influencing inequality. Conclusively, the role which disasters play in the income and wealth distribution is worth examining. The following subsection provides empirical insights which are available on the topic this far.

*Table 1. Theoretical literature describing drivers on inequality.*

<table>
<tr><th>SOURCE</th><th>DRIVER</th><th>MECHANISMS</th><th>EFFECT ON INEQUALITY</th></tr>
<tr><td>Scheidel, 2017</td><td>Violent conflicts and pandemics</td><td>Low savings rates;<br>Depressed asset prices;<br>Physical destruction;<br>Loss of foreign assets;<br>Inflation;<br>Progressive taxation;<br>Rent and price controls;<br>Nationalization</td><td>Decreasing</td></tr>
<tr><td rowspan="3">Piketty, 2014</td><td>Access to education</td><td>Diffusion of knowledge and skills</td><td>Decreasing</td></tr>
<tr><td>Wars</td><td>Destruction of capital;<br>Collapse of foreign portfolios;<br>Low savings rates;<br>Low asset prices;<br>Inflation;<br>High taxation</td><td>Decreasing</td></tr>
<tr><td>Low growth & high average rate of return on capital (r>g)</td><td>Declining population growth;<br>Expanding financial sophistication;<br>International competition</td><td>Increasing</td></tr>
<tr><td rowspan="4">Milanovic, 2016</td><td colspan="3">Benign forces (only in societies with rising mean income)</td></tr>
<tr><td>Social pressure;<br>Widespread education;<br>Aging population;<br>Technological change favoring low-skilled workers.</td><td>Socialism;<br>Trade unions;<br>High demand for social protection;<br>Increased demand for low-skilled labor</td><td>Decreasing</td></tr>
<tr><td colspan="3">Maling forces (all countries)</td></tr>
<tr><td>Violent conflicts;<br>Pandemics.</td><td>Destruction;<br>State breakdown;<br>Higher taxation</td><td>Decreasing</td></tr>
<tr><td rowspan="2">van Bavel and Scheffer, 2021</td><td rowspan="2">Structural shocks</td><td>Political and economic skewness</td><td>Increasing</td></tr>
<tr><td>Increased political participation of ordinary people</td><td>Decreasing</td></tr>
</table>

## 2.2 Empirical insights into the relationship between disasters and economic inequality

Without effective mitigation and adaptation measures, the losses resulting from increased disaster instances have been found to disproportionately affect the poorest and most vulnerable populations (Capelli et al., 2021; IPCC,2023). Hallegatte et al. (2020) attribute the uneven distribution of impacts to three main factors: exposure, vulnerability, and socioeconomic resilience. According to the authors, less affluent individuals and communities often have a higher exposure to natural hazards, as these are often driven to inhabit the more affordable but also riskier areas (e.g., flood-prone areas). Additionally, higher proportions of the personal total wealth are lost by people with lower assets, making them increasingly vulnerable. Lastly, limited resources hinder one's capacity to cope with and recover from disaster impacts (i.e., socioeconomic resilience).

The increased frequency and severity of natural disasters combined with a higher level of exposure and vulnerability as well as low socioeconomic resilience have been found to lead to a self-perpetuating cycle of impoverishment of people of low socioeconomic status (Carter et al., 2007; Rodriguez-Oreggia et al., 2013; Šedová et al., 2019). For some, these impacts have been found to last only temporarily. For instance, a study by Dercon (2004) exploring the effects of Ethiopia's 1984-1985 famine finds that it had taken asset-poor households an average of ten years to recover their initial livestock capital back to pre-disaster levels. On the other hand, Carter et al. (2007) who analyzed the long-term effects of Hurricane Mitch (1998) in Honduras and a prolonged drought period (1998-2000) in Ethiopia, conclude that there exists a critical threshold of asset ownership, below which recovery becomes impossible. In such cases, households generally have been found to resort to coping mechanisms, such as employment of child labor, sale of productive goods, changes in agricultural practices and diet, and out-migration, which end up further exacerbating their fragile economic situation (Cappelli et al., 2021).

Nevertheless, some studies examining the aggregate effects of disasters on national economies have found that disasters can increase productivity at a national level in the long-run, thereby leading to an overall positive effect on economic growth (Albala-Bertrand, 1993; Skidmore and Toya, 2002). In particular, Skidmore and Toya (2002) attribute their findings primarily to higher uptake of newer, more efficient technologies but also to an increased relative return to human capital. Nevertheless, not all countries possess the necessary economic resources to turn a disastrous event into an economic opportunity (Budina et al., 2023). In developing economies, high public debt, low fiscal buffers, poor healthcare, widespread poverty, and food insecurity can act as important shock amplifiers. Meanwhile, more resource-affluent countries can afford to implement timely and effective responses which could benefit the economy in the long term. For instance, restoration activities could increase the demand for and income of less-skilled laborers. Berlemann and Wenzel (2018) find evidence that growth effects of tropical storms depend on a country's level of development, with slightly positive long-run effects found in high-income countries. The authors ascribe these findings to stable investment shares of GDP alongside a strongly decreasing net fertility. In contrast, low- and middle-income countries have been found to experience acute and moderate negative impacts, respectively. These findings are generally in line with Naoaj (2023), Panwar and Sen (2019), and Nishizawa et al. (2019).

Conclusively, evidence suggests that structural shocks can have an overall neutral to slightly beneficial long-term impact on developed countries, whereas total effects in developing countries are generally negative (Cappelli et al., 2021). Nevertheless, studies addressing the impacts on aggregate economic growth (as commonly measured by a GDP-based metrics), although useful in certain cases, can undermine the distributional effects taking place within countries (Hallegatte and Rozenberg, 2017). This is because economically underprivileged individuals hold only a small fraction of the national income and wealth. Hence, impacts affecting the latter demographic will not be effectively addressed by solely examining the effects on growth at a national level (Šedová et al., 2019). However, whilst there is an abundance of literature addressing the consequences on overall growth, literature on inequality implications of climate-related disasters remains scarce and inconclusive.

Income inequality has been found to decrease succeeding Cyclone Aila in Bangladesh (Abdullah et al., 2016), Hurricane Katrina in New Orleans, US (Shaughnessy et al., 2010), and generally after a natural disaster in Sri Lanka (Keerthiratne and Tol, 2018). Decreasing effects are mostly attributed to the fact that wealthier individuals endure larger total losses (Abdullah et al., 2016; Keerthiratne and Tol, 2018). Conversely, Bui et al. (2014) and Milijkovic and Milijkovic (2014) find inequality-increasing effects from natural disasters in Vietnam and from catastrophic hurricane events on a state-level in the US, respectively.

Moreover, another study from the US (Pleninger, 2022) looking at the effects from different disasters on income distribution at county level from 1996 to 2017 finds that inequality levels generally remain unchanged. This, according to the findings of the paper, is because low-income households and individuals largely benefit from post-disaster aid. However, this is not the case for middle-income households and individuals. Hence, larger and more significant impacts are observed at this level, thereby leaving the overall distribution unchanged. For the high-income earners, the effects on earnings and capital income were found to be significant only after severe disasters. Furthermore, the study also distinguishes between the effects of different disasters. Findings suggest that the only disaster types with significantly large negative effects were tornadoes and storms. Finally, Pleninger also investigates long-term effects, concluding that for all income groups total incomes tend to increase in the long run compared to pre-disaster levels. The author attributes this to an after-disaster boom.

However, when looking at the effects of natural hazard damages on wealth inequality in the US, Howell and Elliott (2018) reach a somewhat less optimistic conclusion. The findings of their study suggest that increasing hazard damages lead to wider wealth gaps especially along the lines of race, education, homeownership. Furthermore, the study finds that the current manner of disaster aid distribution further exacerbates the problem. An explanation provided by the authors as to why this may be is that presently aid provision in the US is focused on wealth restauration while ignoring other dimensions of recovery, thereby leading to a segmented system of recoveries and subsequently to larger wealth disparities.

At a cross-country scale, a study by Ymamura (2015) based on panel data covering 86 countries finds that only floods lead to short term within-country income inequality increase as measured by the Gini coefficient. Whereas earthquakes and storms have had no significant impact on inequality levels. However, these findings differ somewhat from Budina et al. (2023), who also account for heterogeneous effects depending on countries' level of development. The latter study finds increasing inequality (based on market Gini) in developed countries only after severe disasters. For developing countries, effects are observed only if the severe disaster coincides with a growth slowdown or if there are several disasters occurring in the same year. Additionally, there seem to be heterogeneous effects across disaster types. Earthquakes have been found to have a significant impact on inequality in developed countries, whereas developing countries were mostly affected by droughts, floods, and severe epidemics. Finally, Budina et al. (2023) provide a nice overview of the channels which can exacerbate inequality following a natural disaster (see Table 2).

*Table 2. Macro-, micro vulnerabilities and drivers of inequality succeeding natural disasters.*

<table>
<tr><th colspan="12">MACRO VULNERABILITIES</th></tr>
<tr><td colspan="2">Weak public institutions: Medical care, disaster relief, corruption</td><td colspan="2">Undiversified economies: Reliance on vulnerable sectors</td><td colspan="2">Financial vulnerability: Policy space and banking sector absorption capacity</td><td colspan="2">Inadequacy of social security: Informality and poverty</td><td colspan="2">Food insecurity: Vulnerable supply chains</td><td colspan="2">Within-country income inequality: High levels of pre-existing inequality</td></tr>
<tr><th colspan="12">MICRO VULNERABILITIES</th></tr>
<tr><td colspan="2">Position in wealth or income distribution: Low wealth and income levels</td><td colspan="2">Education: Little formal education</td><td colspan="2">Gender: Women</td><td colspan="2">Race: Racial ethnic groups</td><td colspan="2">Age: Young individuals at onset of career</td><td colspan="2">Citizenship status: (Illegal) migrants</td></tr>
<tr><th colspan="12">MACROECONOMIC EFFECTS</th></tr>
<tr><td colspan="4">GDP effects: Negative supply shocks with an immediate negative effect on growth</td><td colspan="4">External fiscal balance: Increased imports, lower exports</td><td colspan="4">Migration</td></tr>
<tr><th colspan="12">POLICY RESPONCES</th></tr>
<tr><td colspan="3">Reconstruction efforts: None or at a lower paste</td><td colspan="3">Provision of aid flows: Minimal or lacking</td><td colspan="3">Ex-ante risk mitigation policies: No action taken to reduce future risk</td><td colspan="3">Fiscal buffers, disaster insurance or contingency financing: Minimal or lacking</td></tr>
</table>

*Note: Adapted from Budina et al. (2023, p. 16).*

# 3 Conceptual Framework

From all the literature mentioned thus far, it appears that the effects of natural disasters on economic inequality are exceedingly heterogeneous and dependent on an intricate interplay of various drivers. Considering these complexities, a conceptual framework is introduced describing the relationship between natural disasters and inequality which will be applied in this thesis (Figure 2).

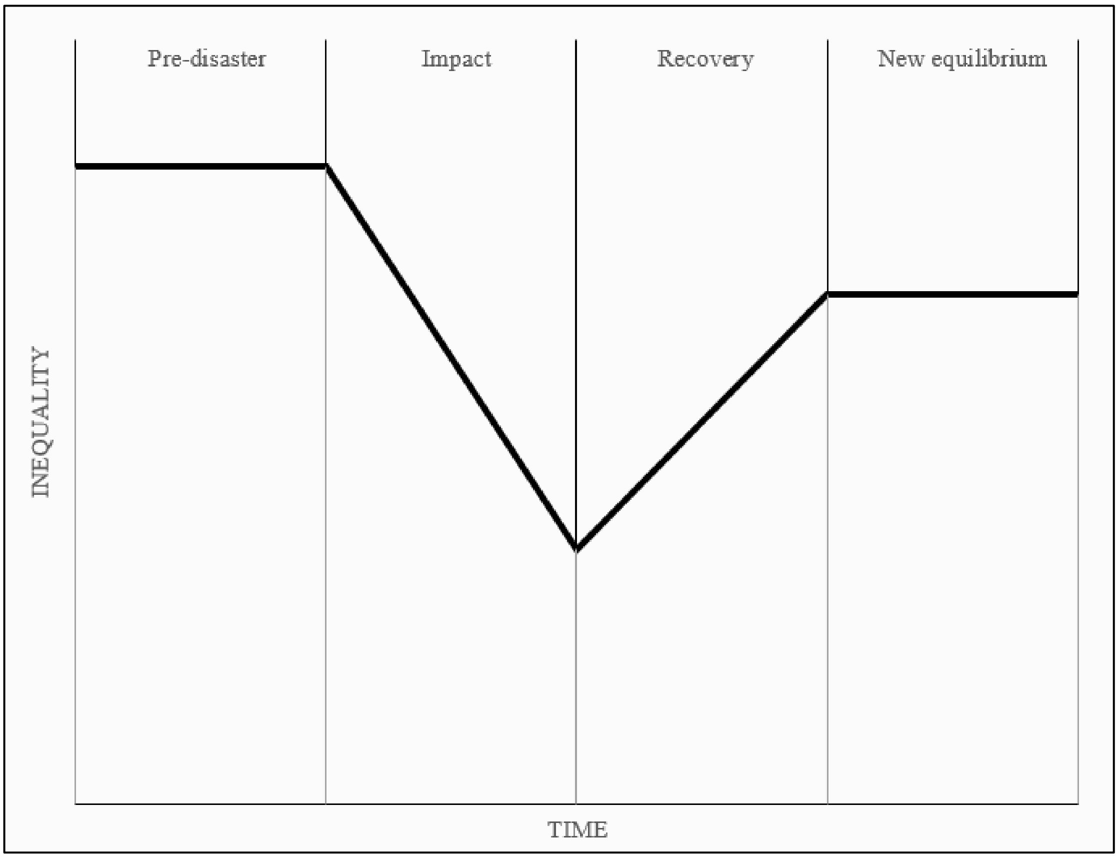


*Figure 2. Inequality in the context of climate-related natural disasters (author's own work).*

As in van Bavel and Scheffer (2021), it is hypothesized that the impacts of disasters on inequality are formulated in stages: pre-disaster, impact, recovery, and new equilibrium. In the pre-disaster stage inequality levels are in a virtual equilibrium which is maintained through the comparatively stable interaction of the social, economic, and institutional systems in a given country. This stage is considered relevant as the size of any potential effect of disasters on inequality will be partially dependent on the latter systems' ability to absorb shocks (i.e., the systems' resilience). Subsequently the resilience will be determined by the presence (or absence) of mitigation and adaptation strategies, level of exposure, vulnerability, etc.

Consequently, once a natural disaster occurs (i.e., in the impact stage), the impact could be partially mitigated by existing structures. Nevertheless, the size of the observed effect will be also determined by the strength of the shock. In the context of disasters, this will suggest that the impact will be dependent on disaster severity. A natural disaster with sufficient damage capacity is expected to be able to destabilize even highly resilient systems leading to an observable effect. Additionally, it is anticipated that resilience is disaster-specific. While a country may be well adapted to buffer the effects related to one disaster type, it is not excluded that the same country could be ill-equipped to handle the effects of another. Conclusively, the magnitude of initial change in inequality succeeding a natural disaster will be dependent on the socioeconomic and institutional resilience as well as the disaster characteristics.

Nevertheless, countries have the capacity to respond to the initial disturbance by initiating a process of recovery. Here, the interaction between institutional and other socioeconomic factors is central, particularly important are the characteristics and qualities of both governments and individuals which might impact socioeconomic resilience. The presence of adequate medical care, food and water security as well as banking disaster relief programs suggest a larger national capacity to support the recovery of vulnerable communities especially in the early phase of this stage. Another institutional aspect which can be determining for both the magnitude of economic damage as well as for the capacity to recover is the level of economic diversity. For example, if a country which is heavily reliant on agriculture experiences a long period of drought, it is very likely that the economic shock resulting from the disaster is of high magnitude. Subsequently, following the logic of the theoretical frameworks reviewed previously, inequality in such places should decline more substantially compared to more diversified economies due to potentially higher rates of inflation, decreased foreign investments, etc. (similar to the mechanisms triggered by wars in Table 1). Furthermore, countries torn by conflicts, both internal and external, might have lower incentives or means to provide aid to individuals who were affected by disasters. However, as argued by Scheidel (2017), Piketty (2014), and Milanovic (2016) inequality in conflict-torn places might already be lower. Hence, larger parts of the population would be equally vulnerable to a catastrophic event. Therefore, the effects of disasters on inequality in such places might be more neutral. When it comes to characteristics of individuals, the level of education has been mentioned in several of the reviewed papers as one of the more important mechanisms to mitigate the economic consequences of catastrophic events. Hence, limited access to education might slow down the rate of recovery for underprivileged individuals.

Finally, once recovery has concluded, the levels of inequality begin to stabilize again leading to a new equilibrium. This stage uncovers the more long-lasting effects on inequality which are a result of policy changes, shifts in demographic patterns, and economic adjustments for instance in the labour market. Essentially inequality levels during this stage are a reflection of the strength of the shock exerted on a country and its capacity to respond and subsequently to recover and rebuild.

Having outlined a plausible general structure of the relationship between disasters and economic inequality, the following chapter discusses the empirical strategy.

# 4 Methodology and Data

## 4.1 Estimation approach

Based on the proposed conceptual framework, three fixed effect (FE) models were estimated in STATA (v16) per dependent variable (i.e., income and wealth inequality) to answer the research questions stated in the introduction chapter. The models are based on the following general equation:

$$y_{itm} = \alpha_{im} + \boldsymbol{x}_{it}'\boldsymbol{\beta}_m + \boldsymbol{z}_{it}'\boldsymbol{\gamma}_m + \boldsymbol{v}_{it}'\boldsymbol{\delta}_m + \boldsymbol{w}_{it}'\boldsymbol{\vartheta}_m + \boldsymbol{u}_{itm} \tag{1}$$

where $y_{itm}$ stands for either income (*m*=1) or wealth (*m*=2) inequality in country *i* at time *t*; $\alpha_{im}$ is the country specific intercept for either model; $\boldsymbol{x}_{it}$ is a vector of disaster characteristics and other structural shocks, and $\boldsymbol{\beta}_m$ is the corresponding effect vector for models one and two; $\boldsymbol{z}_{it}$ is a vector of institutional characteristics, and $\boldsymbol{\gamma}_m$ is the corresponding effect vector; $\boldsymbol{v}_{it}$ is a vector of economic variables, and $\boldsymbol{\delta}_m$ is the corresponding effect vector; $\boldsymbol{w}_{it}$ is a vector of social characteristics, and $\boldsymbol{\vartheta}_m$ is the corresponding effect vector; and $\boldsymbol{u}_{itm}$ are the standard residuals. The dependent and explanatory variables are presented in detail in Table 3.

Based on this general equation, three models were estimated per dependent variable. In the first model the disaster characteristics ($\boldsymbol{x}_{it}$) specified are lagged disaster dummy variables used to capture the short- and long-term effects. In the second model $\boldsymbol{x}_{it}$ is a measure of disaster severity. The final model uses disaster dummies for each disaster type.

Fixed effects estimation is used instead of random effects (RE) as the former allows for correlation between the country-specific effect ($\alpha_{im}$) and the regressors ($\boldsymbol{x}_{it}$, $\boldsymbol{z}_{it}$, $\boldsymbol{v}_{it}$, and $\boldsymbol{w}_{it}$) unlike the latter which in such cases yields inconsistent and biased estimates (Mátyás & Sevestre, 2008; Baltagi, 2021). Some correlation is expected for this data sample as, for instance, developed countries which tend to have lower $\alpha_{im}$ would also have better access to education and healthcare. Additionally, FE models eliminate time-invariant unobserved heterogeneity, which is also likely present as there are multiple unobserved country characteristics which could potentially affect inequality levels (e.g., history, culture, level of development, etc.). To test the appropriateness of using FE over RE a robust version of the Hausman test was performed using a Sargan-Hansen statistic for both models.

Furthermore, given that migration to neighboring countries from disaster-affected areas is a probable individual response and that disasters could affect global trade patterns (Siddiqui & Sahay, 2022; Adinolfi, 2019), the standard assumption of independent and identically distributed (*i.i.d.*) residuals may not be valid due to spatial autocorrelation, hence resulting in incorrect standard errors. To overcome this potential issue, robust standard errors are applied for both models (Mátyás & Sevestre, 2008; Baltagi, 2021).

Finally, the within transformation FE estimation which uses deviations from individual means (denoted by ¯) results in:

$$\begin{aligned}(y_{itm} - \overline{y_{\iota m}}) = \alpha_m + (\boldsymbol{x}_{it} - \overline{\boldsymbol{x}_{\iota}})'\boldsymbol{\beta}_m + (\boldsymbol{z}_{it} - \overline{\boldsymbol{z}_{\iota}})'\boldsymbol{\gamma}_m \\ +(\boldsymbol{v}_{it} - \overline{\boldsymbol{v}_{\iota}})'\boldsymbol{\delta}_m + (\boldsymbol{w}_{it} - \overline{\boldsymbol{w}_{\iota}})'\boldsymbol{\vartheta}_m + (\boldsymbol{u}_{itm} - \overline{\boldsymbol{u}_{\iota m}})\end{aligned} \tag{2}$$

It should be noted that the standard within transformation removes all country-specific intercepts ($\alpha_{im}$). However, in STATA the report has been reformulated to contain an intercept ($\alpha_m$) which is the average value of the fixed effects.

## 4.2 Data

The data used for this analysis is gathered from multiple sources. A summary of the variables along with some basic statistics and the corresponding sources can be found in Table 3.

*Table 3. Summary and basic statistics of the used data.*

| Variable | Description | Mean | Standard deviation | Source |
|---|---|---|---|---|
| **Economic Inequality ($y_{itm}$)** | | | | |
| Income | Palma ratio of net income of top 10% versus the bottom 40% households | 3.39 | 2.91 | WIID* |
| Wealth | Ratio of net wealth of top 10% versus the bottom 90% households | 1.99 | 0.86 | WID** |
| **Disaster and Emergencies ($x_{it}$)** | | | | |
| Disaster | Disaster dummy (yes=1, no=0) | 0.51 | 0.50 | EM-DAT |
| Drought | Drought dummy (yes=1, no=0) | 0.08 | 0.27 | EM-DAT |
| Epidemic | Epidemic dummy (yes=1, no=0) | 0.12 | 0.33 | EM-DAT |
| Fire | Fire dummy (yes=1, no=0) | 0.04 | 0.19 | EM-DAT |
| Flood | Flood dummy (yes=1, no=0) | 0.32 | 0.47 | EM-DAT |
| Heatwave | Heatwave dummy (yes=1, no=0) | 0.02 | 0.15 | EM-DAT |
| Landslide | Landslide dummy (yes=1, no=0) | 0.05 | 0.22 | EM-DAT |
| Storm | Storm dummy (yes=1, no=0) | 0.19 | 0.39 | EM-DAT |
| Severity | State of national emergency due to a disaster (yes=1, no=0) | 0.03 | 0.08 | V-Dem |
| Protest | State of national emergency due to popular uprising (yes=1, no=0) | 0.04 | 0.10 | V-Dem |
| War | State of national emergency due to war (yes=1, no=0) | 0.08 | 0.16 | V-Dem |
| **Institutional Characteristics ($z_{it}$)** | | | | |
| Access | Access to power across social groups (equal=1, unequal=0) | 0.57 | 0.25 | V-Dem |
| Corrupt | Level of political corruption (high=1, low=0) | 0.48 | 0.30 | V-Dem |
| Democracy | Level to which the egalitarian principle of democracy is achieved (high=1, low=0) | 0.57 | 0.23 | V-Dem |
| Education | Access to education (equal=4, unequal=0) | 2.05 | 1.14 | V-Dem |
| Health | Access to health care (equal=4, unequal=0) | 2.11 | 1.15 | V-Dem |
| Mobilization | Instances of mass mobilization (many=4, none=0) | 1.80 | 1.11 | V-Dem |
| Party | Barriers to forming a political party (many=4, none=0) | 1.26 | 1.30 | V-Dem |
| Polarization | Level of political polarization (high=4, low=0) | 2.11 | 1.06 | V-Dem |
| Power | Power distribution based on socio-economic status (equal=4, unequal=0) | 2.07 | 0.82 | V-Dem |
| Protection | Protection of rights and freedoms across social groups (equal=1, unequal=0) | 0.60 | 0.27 | V-Dem |
| Public service | Access to public services by socio-economic position (equal=4, unequal=0) | 1.81 | 1.05 | V-Dem |
| Resource | Equal distribution of resources (equal=1, unequal=0) | 0.55 | 0.29 | V-Dem |
| State | State participation in key economic sectors (high=4, low=0) | 1.62 | 0.82 | V-Dem |
| Union | Engagement in independent trade unions (high=4, low=0) | 1.79 | 0.93 | V-Dem |
| **Economic Characteristics ($v_{it}$)** | | | | |
| GDP per capita | GDP per capita in 1,000 2015 USD | 14.07 | 16.93 | WIID** |

| | | | | |
|---|---|---|---|---|
| Inflation | Annual inflation rate based on CPI | 3.91 | 2.03 | V-Dem |
| Population | Population in 1,000,000 | 36.20 | 131.07 | WIID** |
| **Social Characteristics ($w_{it}$)** | | | | |
| Above 65 | Share of people from total population above the age of 65 | 0.06 | 0.05 | WB*** |
| Female | Share of women in total population | 0.50 | 0.02 | WB*** |

**World Income Inequality Database, **World Inequality Database, ***World Bank*

### 4.2.1 Economic inequality

Economic inequality is a multifaceted term, which encompasses disparities in income, wealth, as well as access to and necessity for resources, influenced by social, political, and historical factors (Piketty & Cantante, 2018; Sen, 1997). In this thesis, the use of the term is limited to signify solely wealth and income inequality due to the difficulty of measuring access to and need for resources as well as the limited data availability on the subject.

#### *4.2.1.1 Income inequality*

Income inequality is perhaps the most widely researched form of inequality (Sen,1997), with various methods and indices used for quantification (Cobham & Sumner, 2013). The selected method for this thesis is the Palma ratio as it is more responsive to changes at the tails of the income distribution compared to other alternatives. Palma compares the national shares of income of the top 10% of households to the bottom 40%. Subsequently, values between 0 and 1 suggest that the top 10% holds a smaller share of the total income compared to the bottom 40%. Conversely, values above 1 indicate the opposite. Data on the Palma ratio for 149 countries and non-autonomous regions over the period 1970 to 2020 was obtained from the World Income Inequality Database (UNU-WIDER, 2023). The values of the Palma ratio for this period range from 0.25 (in North Korea in 1970) to 31.19 (in Sierra Leone in 1990), with a mean around 3.38. The average Palma ratio follows a decreasing trend, with a steeper decline in the last 30 years (Figure 3).

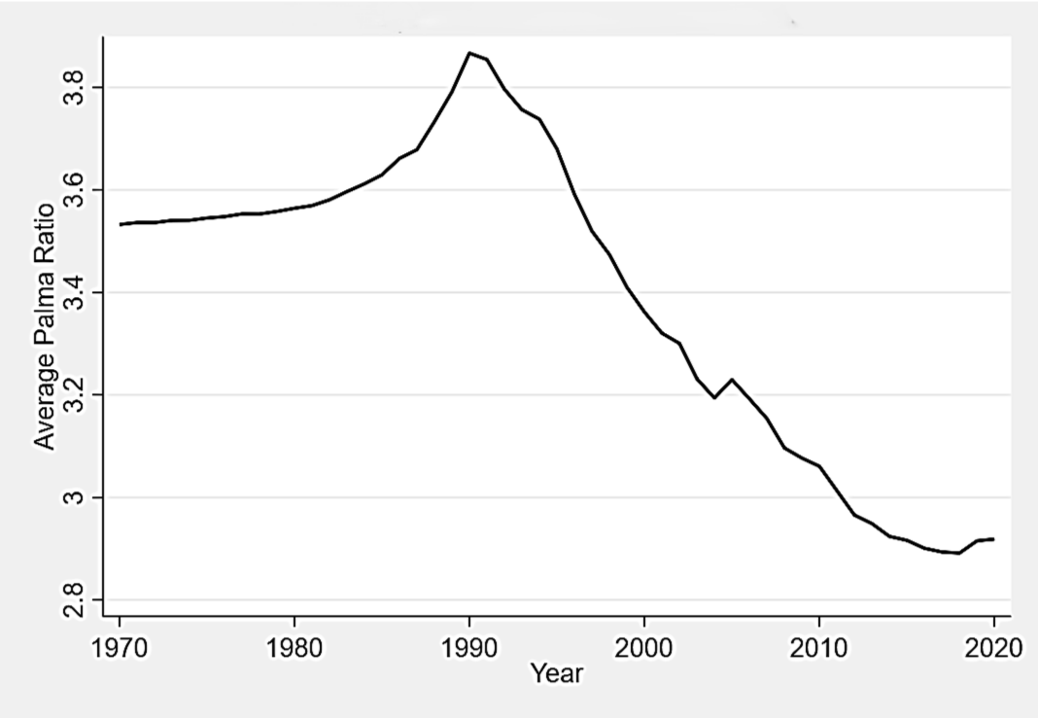


*Figure 3. Average Palma ratio across 149 countries from 1970 to 2020.*
*Source: Own calculations based on (UNU-WIDER, 2023)*

#### 4.2.1.2 Wealth inequality

The dataset used to obtain data on wealth inequality (WID – World Inequality Database, 2024) defines wealth as the sum of all financial (i.e., real estate, land, etc.) and non-financial assets (i.e., bonds, pension funds, etc.) over which households can enforce ownership rights and that provide economic benefits minus the sum of all debts (Blanchet et al., 2024). To enumerate wealth inequality an index is composed, comparing the share of wealth of the top 10% of households to the bottom 90%. This index essentially indicates how many times more wealth is concentrated among the top 10% wealthiest households compared to the remaining households in a given country. The reason for using the bottom 90% instead of composing a Palma index for wealth is that wealth inequality is far larger compared to income inequality. For many countries it is the case that the bottom half of households have a share of the total national wealth which is close to and even sometimes lower than zero. Composing such a ratio, therefore, results in an index which can go to infinity making the data analysis incomprehensible.

For the current dependent variable data is available for 149 countries over the period 1995 to 2020. For this period the wealthiest 10% of households in each country hold on average about 2 times more wealth than the remaining 90% of households. The maximum value of the wealth index for this dataset is 9.89 (in South Africa in 2008) and the minimum is 0.7 (in China in 1995). Following the average time trend of the index suggests that wealth concentration at the top is gradually decreasing on average (see Figure 4).

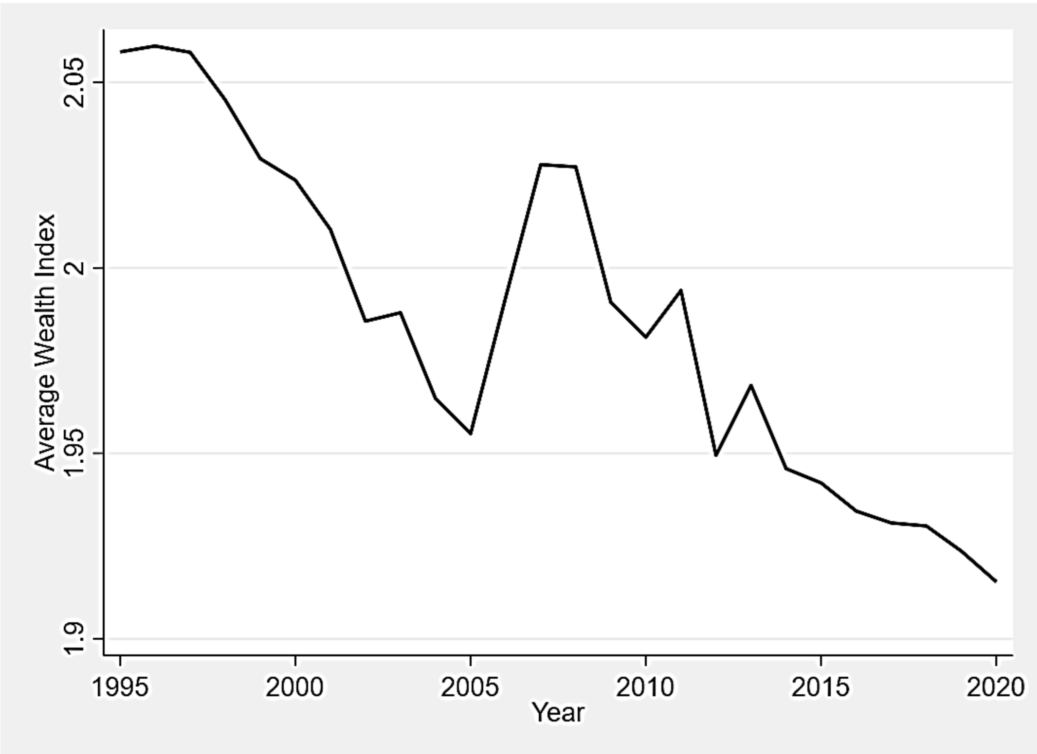


*Figure 4. Average wealth index across 149 countries from 1995 to 2020. Source: Own calculations, based on data from* WID (2024)

### 4.2.2 Disaster characteristics and other structural shocks

#### 4.2.2.1 Disasters

The Emergency Events Database (EM-DAT, n.d.) is one of the most comprehensive databases on natural disasters (Wirtz et al., 2014). A natural event is registered as a disaster if it leads to damage, dislocation, or loss of life. For this research the scope of natural disasters is limited to events which are likely to become more frequent and/or more severe because of climate change. Following the latest report of the IPCC (2023), these include heatwaves, droughts, epidemics, floods, landslides, fire weather, storms, and cyclones. All other disasters were excluded from the dataset. For the period of interest (1970 to 2020), a total number of 12,250 of the abovementioned disasters have been registered globally. By far the most common disasters for the period are storms and floods with approximately 4,000 and 5,000 recorded instances, respectively. Together, these represent roughly 75% of all natural disasters included in the dataset.

To account for the severity of a disaster, a proxy from the V-Dem dataset is used (Coppedge et al., 2024a), which indicates whether a country has declared a state of emergency due to a disaster (see variable *Severity* in Table 3). A state of emergency is defined as a legal act which allows actors and institutions to change their roles in case of an international or a domestic crisis. The variable does not distinguish between different types of disasters unlike the previous dataset, meaning other disasters (e.g. earthquakes) are also considered. Based on this data, the instances of countries declaring a state of emergency because of a natural disaster in a given year are increasing in recent decades with the highest number reported in the year 2020.

##### *4.2.2.2 Wars and protests*

As wars and violent conflicts are heavily emphasized in theoretical literature as some of the most potent forces of diminishing inequality, these are also incorporated in the analysis. Once again, state of emergency variables by V-Dem are used as proxy (variables *War* and *Protest*). These indicate if a state of emergency has been declared in a given year due to either domestic or international armed conflict or mass protest.

### 4.2.3 Other explanatory variables

#### *Institutional characteristics*

Variables related to institutional characteristics are all sourced from the V-Dem database. Some variables are aggregated indices with values ranging from 0 to 1. These include the access to political power across social groups (*Access*), a corruption index (*Corrupt*), achievement of the egalitarian democratic principle (*Democracy*), equal access to high quality education (*Education*) and healthcare (*Health*), protection of rights and freedoms across social groups (*Protection*), and distribution of resources (*Resource*). The remaining variables in this group are the mean values across experts' ratings of institutional characteristics rated on an ordinal scale of 0 to 4. These are instances of mass mobilization (*Mobilization*), existence of restrictive barriers to forming a political party (*Party*), level of political polarization (*Polarization*), distribution of political power across socio-economic positions (*Power*), access to public services by socio-economic position (*Public service*), level of state involvement in key economic sectors (*State*), and engagement of general population in independent trade unions (*Union*). For a more detailed description of the variables and indices see the V-Dem Codebook (Coppedge et al., 2024b).

#### *Socio-economic characteristics*

The analysis also includes social characteristics such as the percentage of women (*Female*) and the percentage of individuals aged 65 and older (*Above65*) from the total population. This data is collected from the World Bank's World Development Indicator (WDI, n.d.) dataset. Furthermore, economic characteristics such as the total population (*Population*), GDP per capita (*GDP per capita*) and annual inflation rate (*Inflation*) have been included as explanatory variables. These are also based on data from the World Bank (n.d.).

# 5 Results and discussion

In this section the results of the FE analysis for income and wealth inequality are presented and discussed. The section starts with some general findings, followed by results and discussion of income and then wealth inequality models.

Across all models, multiple explanatory variables were dropped due to strong correlation between political, and social variables (see correlation table in Appendix I). The variables related to protection of rights and freedoms (*Protection*), access to education and healthcare (*Education* and *Health)*, distribution of power (*Power*), access to public services and power (*Public service* and *Access*), fair distribution of resources (*Resource*), and the percentage of people above the age of 65 (*Above 65*) were found to have a strong positive correlation (> 0.7) with the index for egalitarian principles (*Democracy*). The former have been dropped in favor of the latter. Additionally, strong negative correlation between corruption (*Corrupt*) and egalitarian principles (< -0.7) has resulted in corruption being excluded from the analysis. Finally, the variable for state ownership of key economic sectors (*State*) has been dropped due to strong positive correlation with the variable for barriers to formation of political parties (*Party*).

Regarding model specification, significant F-tests and Sargan-Hansen test statistics suggest that a FE model is preferred to ordinary least squares (OLS) or RE approach for all models, respectively (see Table 4 and Table 5).

Finally, it should be noted that the overall predictive capacity of all the models ($R^2_{overall}$) is quite low, meaning that the variation in income and wealth inequality is only limitedly captured by the explanatory variables. While this is somewhat common across models using social indices as explanatory variables, it still suggests that the results should be interpreted with caution.

## 5.1 Income inequality

### 5.1.1 Results

In Table 4 the results of the FE analysis for income inequality are presented. From the first model it can be seen that an average disaster (*Disaster*) would have a small but significant (at $\alpha$=0.05) negative effect on income inequality of -0.142 units with the effect persisting for at least up to 5 years after the event has taken place. The strongest decreasing effect (-0.158) of an average disaster is estimated to occur a year after the disaster has taken place (*Disaster_l1*) with the magnitude gradually decreasing (but remaining significant) in the following years (*Disaster_l2* to *Disaster_l5*).

The second model showcases that the effects of more severe disasters (*Severity*), particularly ones leading to a declared state of emergency, have a significant negative effect (-1.519) which is an order of magnitude higher compared to that of disasters on average. This would suggest that a severe disaster would reduce the difference in net income between the top 10% and bottom 40% of households by approximately 1.5.

The final model disaggregates the effects by disaster type. The results of this analysis suggest that heatwaves (*Heatwave*) have a small but significant positive effect (0.096) on income inequality as expressed by the Palma ratio. Conversely, floods (*Flood*) are found to significantly reduce income inequality by 0.137 units. For the remaining disasters no significant effects were found.

Across all three models population size (*Population*) and inflation (*Inflation*) are found to have a significant positive effect on income inequality of 0.002 and 0.177 units, respectively. A significant positive effect is also detected for wars (*War*), but only for the third model (approximately 1.2 unit increase). Similarly, GDP per capita (*GDP per capita*) is found to be a significant predictor of income inequality only in the first model (0.009 unit increase). For the remaining variables no significant effects were found.

*Table 4. FE estimation results for income inequality*

| | (1)<br>Income inequality | (2)<br>Income inequality | (3)<br>Income inequality |
|---|---|---|---|
| Disaster | -0.142* | | |
| | (0.065) | | |
| Disaster_l1 | -0.158* | | |
| | (0.069) | | |
| Disaster_l2 | -0.136* | | |
| | (0.059) | | |
| Disaster_l3 | -0.130* | | |
| | (0.055) | | |
| Disaster_l4 | -0.130** | | |
| | (0.049) | | |
| Disaster_l5 | -0.126* | | |
| | (0.054) | | |
| Severity | | -1.519* | |
| | | (0.610) | |
| Drought | | | -0.061 |
| | | | (0.051) |
| Epidemic | | | -0.145 |
| | | | (0.100) |
| Fire | | | 0.059 |
| | | | (0.058) |
| Flood | | | -0.137* |
| | | | (0.069) |
| Heatwave | | | 0.096* |
| | | | (0.043) |
| Landslide | | | 0.073 |
| | | | (0.053) |
| Storm | | | -0.015 |
| | | | (0.051) |
| Protest | -0.638 | -0.604 | -0.594 |
| | (0.371) | (0.355) | (0.361) |
| War | 0.922 | 1.139 | 1.185* |
| | (0.562) | (0.582) | (0.585) |
| Democracy | -1.071 | -0.932 | -0.946 |
| | (1.179) | (0.973) | (0.972) |
| Mobilization | 0.027 | 0.017 | 0.015 |
| | (0.090) | (0.085) | (0.083) |
| Party | -0.076 | -0.015 | -0.033 |
| | (0.109) | (0.110) | (0.107) |
| Polarization | -0.060 | -0.074 | -0.065 |
| | (0.137) | (0.123) | (0.122) |
| Union | 0.001 | -0.042 | -0.032 |
| | (0.237) | (0.204) | (0.206) |
| GDP per capita | 0.009* | 0.006 | 0.005 |
| | (0.004) | (0.004) | (0.003) |
| Inflation | 0.174** | 0.177** | 0.177** |
| | (0.062) | (0.062) | (0.059) |

| | | | |
|---|---|---|---|
| Population | $0.002^{**}$ | $0.002^{**}$ | $0.002^{**}$ |
| | (0.001) | (0.001) | (0.001) |
| Female | 1.181 | -0.466 | -0.846 |
| | (6.138) | (5.481) | (5.411) |
| Intercept | 3.088 | 3.517 | 3.725 |
| | (3.012) | (2.655) | (2.642) |
| *N* | 6854 | 7599 | 7599 |
| *$R^2$ overall* | 0.081 | 0.089 | 0.096 |
| *$R^2$ within* | 0.074 | 0.058 | 0.058 |
| *$R^2$ between* | 0.088 | 0.099 | 0.111 |
| *Sargan-Hansen* | $73.808^{***}$ | $57.829^{***}$ | $67.732^{***}$ |
| *F-test* | $1.73^{*}$ | $2.59^{**}$ | $2.26^{**}$ |

*Note: Robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

### 5.1.2 Discussion

Based on this analysis it seems that on average a disastrous event results in slightly decreased income inequality as expressed by the Palma ratio (Model 1). These results are in line with the findings of Abdullah et al. (2016), Shaughnessy et al. (2010), and Keerthiratne and Tol (2018). Following the proposed conceptual framework (see Figure 2), the observed decrease could be a result of adequate political and individual recovery strategies. These could be in the form of disaster relief programs targeting low-income earners (as suggested by Pleninger, 2022), disaster training programs, which endorse diversified livelihood strategies, or high individual disaster prevention, management, and reconstruction capabilities (Li et al., 2025). Additionally, disasters could trigger a demand for more affordable labor (Budina et al., 2023), thereby reducing the income gap. Conversely, there is also a possibility that the observed decrease is a consequence of disproportionately increased morbidity and mortality of low-income households or due to increased emigration resulting from the initial loss of income (Carter et al., 2007; Cappelli et al., 2021; García et al., 2023). Moreover, all the latter mechanisms might also occur in parallel, ultimately leading to a sustained slight decrease in income inequality.

Furthermore, the results suggest that the more severe a disaster is, the stronger (i.e. the higher the magnitude of) the effect on income inequality (see Model 2). These results are in line with the findings of Pleninger (2022) and Budina et al. (2023) although the effects found in the latter paper are in an opposite direction compared to the findings of this thesis. This finding supports the hypothesis stated in the conceptual framework that a more powerful shock would weaken a country's resilience and would therefore result in a substantially stronger effect. The higher magnitude of the effect of severe disasters compared to this of an average disaster could be explained with the amplified force of the proposed mechanisms driving inequality down. For instance, a more destructive disaster would be likely to further increase the demand for low-cost labour and possibly also the demand for an adequate post-disaster response. The considerable difference between average and severe disasters is also an indication that countries have some level of ability to mitigate the effects rather than having to simply react and adapt.

Finally, previous studies disaggregating the effects by disaster type have come to conflicting conclusions. While in the US only storms were found to have a significant effect (Pleninger, 2022), on a global level Ymamura (2015) finds that only floods have an impact on the income distribution, conversely for developing countries floods but also droughts and epidemics have led to a significant increase in inequality (Budina et al., 2023). Findings of the current thesis are largely misaligned with the latter studies (see Model 3). While the effects of floods have been shown to be significant, the direction of the effect is the opposite of what has been found by Ymamura (2015) and Budina et al. (2023). As suggested for average disasters, the observed decrease in inequality resulting from floods could be due to adequate policies, increased morbidity and mortality amongst low-income households, emigration, or a combination of all the latter.

Additionally, heatwaves were found to slightly increase the levels of income inequality within a country. These results could be explained by the fact that occupancies requiring intense outdoor physical labour, which also tend to be poorly compensated would be most impacted by heatwaves. As these lead to reduced physical performance and morbidity (World Health Organization, 2004), the ability of individuals working under such conditions to earn income could be compromised thereby resulting in increased levels of inequality.

## 5.2 Wealth inequality

### 5.2.1 Results

In Table 5 the results of the FE analysis for wealth inequality are presented. A small but significant negative effect of an average natural disaster on wealth inequality can be observed only in the 4th year after the event has taken place (-0.034; see Model 1, *Disaster_l4*). The effect however appears to be short lived as it is no longer detected in the following year.

Additionally, unlike income, wealth does not appear to be susceptible to severe disasters (*Severity*) as no significant effect was found (Model 2).

Disaggregating the effects by type of disaster (see Model 3) shows that only droughts (*Drought*) bring about a slight significant decrease in wealth inequality (-0.062 units).

From the remaining explanatory variables once again population size (*Population*) and inflation (*Inflation*) have been found to increase the wealth gap across all models by 0.004 and approximately 0.13 units, respectively.

*Table 5. FE estimation results for wealth inequality*

| | (1)<br>Wealth inequality | (2)<br>Wealth inequality | (3)<br>Wealth inequality |
|---|---|---|---|
| Disaster | -0.013<br>(0.020) | | |
| Disaster_l1 | -0.008<br>(0.019) | | |
| Disaster_l2 | -0.017<br>(0.018) | | |
| Disaster_l3 | -0.030<br>(0.019) | | |
| Disaster_l4 | -0.034*<br>(0.017) | | |
| Disaster_l5 | -0.019<br>(0.016) | | |
| Severity | | 0.006<br>(0.182) | |
| Drought | | | -0.062*<br>(0.025) |
| Epidemic | | | -0.021<br>(0.024) |
| Fire | | | -0.020<br>(0.030) |
| Flood | | | -0.021<br>(0.015) |
| Heatwave | | | -0.022<br>(0.017) |

| | | | |
|---|---|---|---|
| Landslide | | | -0.014 |
| | | | (0.023) |
| Storm | | | 0.030 |
| | | | (0.017) |
| Protest | 0.193 | 0.181 | 0.191 |
| | (0.178) | (0.177) | (0.178) |
| War | 0.173 | 0.189 | 0.188 |
| | (0.177) | (0.181) | (0.183) |
| Democracy | 0.253 | 0.212 | 0.246 |
| | (0.527) | (0.525) | (0.527) |
| Mobilization | -0.003 | -0.003 | -0.002 |
| | (0.029) | (0.029) | (0.029) |
| Party | 0.084 | 0.086 | 0.086 |
| | (0.055) | (0.055) | (0.055) |
| Polarization | -0.069 | -0.065 | -0.066 |
| | (0.049) | (0.048) | (0.048) |
| Union | -0.132 | -0.132 | -0.131 |
| | (0.136) | (0.138) | (0.139) |
| GDP per capita | 0.005 | 0.005 | 0.005 |
| | (0.003) | (0.003) | (0.004) |
| Inflation | $0.122^{*}$ | $0.129^{*}$ | $0.130^{*}$ |
| | (0.054) | (0.053) | (0.052) |
| Population | $0.004^{**}$ | $0.004^{*}$ | $0.004^{*}$ |
| | (0.002) | (0.002) | (0.002) |
| Female | 2.191 | 2.272 | 2.202 |
| | (3.465) | (3.460) | (3.472) |
| Intercept | 0.480 | 0.359 | 0.388 |
| | (1.827) | (1.826) | (1.830) |
| *N* | 3703 | 3703 | 3703 |
| *$R^2$ overall* | 0.001 | 0.000 | 0.000 |
| *$R^2$ within* | 0.059 | 0.056 | 0.060 |
| *$R^2$ between* | 0.003 | 0.001 | 0.002 |
| *Sargan-Hansen* | $41.090^{***}$ | $22.260^{*}$ | $36.234^{**}$ |
| *F-test* | $2.24^{**}$ | $2.14^{*}$ | $2.46^{*}$ |

5.2.2 Discussion

The findings of this analysis suggest that on average natural disasters slightly and only briefly reduce wealth inequality 4 years after the disaster has taken place. This delayed effect could be a result of maladaptation to a gradual loss of income caused by natural disasters. In Table 5, it can be seen that wealth inequality is most significantly decreased in the 4$^{th}$ year after a disaster has taken place. This could suggest that the damage form natural disasters on capital assets is generally only partial, so that the assets remain functioning, however maintenance and insurance costs increase as a result of the damage leading to overall decrease in earnings over time. Subsequently, it could be the case that around the 4$^{th}$ year after the event it becomes uneconomical to maintain damaged assets. While this may affect capital owners on both sides of the wealth distribution, wealthier individuals would endure larger total losses, hence leading to the slight temporary decrease in wealth inequality (Abdullah et al., 2016; Keerthiratne and Tol, 2018). Overall, the decreasing effect is aligned with theoretical literature on inequality (Scheidel, 2017; Piketty, 2014; Milanovic, 2016), suggesting that damage and destruction of assets would suppress wealth inequality levels. The delayed and short-term nature of the observed impact suggests that the effect is likely not a result of policy adaptation.

Furthermore, the results suggest that severe disasters do not affect the wealth distribution. These findings are at odds with the ones from Howell and Elliott (2018), who observe that increased hazard damages have resulted in wider wealth gaps in the US. This disparity could be related to the way in which severity is approximated in the present study (i.e., by events which lead to a state of emergency rather than by the economic damage inflicted). Perhaps approximating severity based on economical damage would result in a different outcome.

Finally, the only type of natural disaster which has been found to have a marginal, negative effect on wealth inequality are droughts. Although droughts do not cause a substantial direct damage to assets in the way that storms, floods or landslides, for instance, could, these can affect assets indirectly. Water intensive economic sectors, such as agriculture, energy generation, manufacturing and fluvial transportation also happen to rely heavily on capital assets. In an event of drought these sectors can be inflicted with heavy economic losses. Hence, capital owners may choose to sell some of their resources at a discounted price or export them abroad to mitigate the temporary diminished profits. Ultimately this could lead to a re-distribution of wealth on the national level.

# 6 Conclusion

## 6.1 Summary and implications

More frequent and severe disasters resulting from climate change have been shown to cause adverse negative impacts that fall disproportionately on people with lower socioeconomic status. This thesis focused on exploring the effects of disasters on the distribution of wealth and income, employing a fixed-effects model with panel data from 149 countries between 1970 to 2020.

The analysis showed that disasters, on average, lead to a small but persistent reduction in income inequality, which becomes more pronounced following severe disasters. On the other hand, wealth inequality appears to remain more rigid and less responsive to disaster-related shocks apart from a marginal decrease around the 4$^{th}$ year after a disaster has taken place. Observing the effects per disaster type indicated that income disparities tend to increase slightly as a result of heatwaves and decrease after floods. Whereas the wealth gap appears to be slightly narrowed by droughts.

From a policy perspective, this suggests that countries exposed to heatwaves should consider integrating distributional concerns into their climate adaptation and recovery strategies, particularly addressing income disparities.

## 6.2 Critical reflection, limitations, and future recommendations

This thesis contributes to an understanding of how different types of disasters shape economic inequality, highlighting that their effects are neither uniform nor straightforward. The analysis provides an overview of general patterns which can be difficult to capture in localized case studies. While this is beneficial for providing guidance and directing the focus of future research efforts, it fails to provide a better understanding of the underlying processes. Future research could, therefore, aim to complement this analysis by investigating the specific mechanisms and policy responses which result in lasting changes in economic inequality. This could help clarify whether disasters' effects on income inequality reflect the widespread adoption of equitable policies or unequal harm.

Furthermore, using a fixed effects model, while beneficial for limiting unobserved heterogeneity, holds some relevant limitations. Firstly, fixed effect models cannot estimate the impact of time-invariant factors, which restricts the scope of analysis (see for example Baltagi, 2021). Furthermore, the efficiency of the estimates may be reduced as between-unit information is disregarded. A Bayesian hierarchical model could address these limitations by combining within- and between-unit variation as well as prior knowledge, allowing partial pooling across units (Lambert, 2018). Future research could therefore benefit from applying such framework to obtain a more robust analysis.

Beyond methodological limitations, the study also faces data-related and conceptual limitations. The analysis relies on annual data at the national level, which may obscure the immediate and local effects. Furthermore, the manner of quantification of disaster severity could influence the results. Hence, in the future research could focus on effects based on different definitions of severity. Finally, in countries with larger surface areas, significant regional effects could be averaged out and diminished when data is consolidated at a higher level. By relying on more disaggregated data, future work could provide more precise estimates.

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# Appendix I

*Table A1. Correlation table*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) | (23) | (24) | (25) | (26) | (27) | (28) | (29) | (30) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1.Disaster | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2.Drought | 0.287899 | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 3.Epidemic | 0.362025 | 0.097462 | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 4.Fire | 0.193939 | 0.057296 | 0.035273 | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 5.Flood | 0.669386 | 0.111845 | 0.170642 | 0.122 | 1 | | | | | | | | | | | | | | | | | | | | | | | | | |
| 6.Heatwave | 0.149484 | 0.038488 | 0.031541 | 0.134269 | 0.119956 | 1 | | | | | | | | | | | | | | | | | | | | | | | | |
| 7.Landslide | 0.231315 | 0.050261 | 0.090796 | 0.071794 | 0.212697 | 0.064956 | 1 | | | | | | | | | | | | | | | | | | | | | | | |
| 8.Storm | 0.475015 | 0.0817 | 0.028155 | 0.139863 | 0.223225 | 0.163307 | 0.121676 | 1 | | | | | | | | | | | | | | | | | | | | | | |
| 9.Severity | 0.011313 | 0.006865 | -0.00478 | -0.00608 | 0.010884 | -0.0307 | 0.009002 | 0.009218 | 1 | | | | | | | | | | | | | | | | | | | | | |
| 10.Protest | -0.02731 | -0.00012 | 0.024374 | -0.03304 | -0.03134 | -0.04848 | -0.00762 | -0.05119 | -0.02688 | 1 | | | | | | | | | | | | | | | | | | | | |
| 11.War | -0.08102 | -0.02538 | 0.031764 | -0.05821 | -0.05791 | -0.05715 | 0.004431 | -0.12652 | -0.09895 | 0.034316 | 1 | | | | | | | | | | | | | | | | | | | |
| 12.Access | 0.127236 | -0.02391 | -0.00853 | 0.114848 | 0.068492 | 0.105793 | 0.004243 | 0.166046 | 0.052081 | -0.24065 | -0.24719 | 1 | | | | | | | | | | | | | | | | | | |
| 13.Corrupt | 0.106343 | 0.085875 | 0.212033 | -0.09358 | 0.140503 | -0.07798 | 0.076628 | -0.1003 | -0.00138 | 0.188785 | 0.145156 | -0.56174 | 1 | | | | | | | | | | | | | | | | | |
| 14.Democracy | 0.013374 | -0.07901 | -0.11453 | 0.106513 | -0.03108 | 0.094024 | -0.05317 | 0.126263 | 0.021647 | -0.26547 | -0.29672 | 0.881024 | -0.70345 | 1 | | | | | | | | | | | | | | | | |
| 15.Education | -0.09539 | -0.11563 | -0.19574 | 0.074802 | -0.11414 | 0.057422 | -0.09427 | 0.083595 | 0.006107 | -0.22396 | -0.25509 | 0.587227 | -0.66043 | 0.839136 | 1 | | | | | | | | | | | | | | | |
| 16.Health | -0.08689 | -0.11748 | -0.20788 | 0.079194 | -0.09668 | 0.072662 | -0.09113 | 0.084872 | 0.00716 | -0.23908 | -0.23693 | 0.594809 | -0.69457 | 0.856429 | 0.907095 | 1 | | | | | | | | | | | | | | |
| 17.Mobilization | 0.221544 | 0.052278 | 0.133764 | 0.088493 | 0.218429 | 0.048738 | 0.102544 | 0.092631 | -0.04539 | 0.188716 | 0.125655 | 0.059345 | 0.215345 | -0.05217 | -0.12023 | -0.12058 | 1 | | | | | | | | | | | | | |
| 18.Party | -0.25497 | -0.01291 | -0.08197 | -0.11228 | -0.18057 | -0.09932 | -0.07582 | -0.17593 | -0.12213 | 0.122388 | 0.170858 | -0.59323 | 0.271209 | -0.47629 | -0.19921 | -0.24552 | -0.17098 | 1 | | | | | | | | | | | | |
| 19.Polarization | 0.022494 | 0.04547 | 0.084291 | -0.03218 | 0.043675 | -0.05007 | 0.040301 | -0.08936 | -0.11116 | 0.242659 | 0.305695 | -0.34063 | 0.467859 | -0.44106 | -0.40135 | -0.43184 | 0.284274 | 0.239565 | 1 | | | | | | | | | | | |
| 20.Power | 0.023152 | -0.03359 | -0.05566 | 0.068278 | -0.01383 | 0.060101 | -0.01151 | 0.089265 | -0.00671 | -0.19802 | -0.14233 | 0.836919 | -0.50965 | 0.756341 | 0.517857 | 0.519865 | -0.01304 | -0.34539 | -0.19405 | 1 | | | | | | | | | | |
| 21.Protection | 0.004784 | -0.07255 | -0.08243 | 0.091102 | -0.04502 | 0.081708 | -0.05399 | 0.087438 | 0.005102 | -0.23572 | -0.28377 | 0.772663 | -0.61405 | 0.925113 | 0.683588 | 0.697359 | -0.06367 | -0.47163 | -0.39022 | 0.666188 | 1 | | | | | | | | | |
| 22.Public_servi | -0.04705 | -0.10837 | -0.18459 | 0.105963 | -0.06964 | 0.101211 | -0.07117 | 0.122299 | 0.013336 | -0.18617 | -0.25939 | 0.594479 | -0.66194 | 0.795877 | 0.827432 | 0.851502 | -0.08637 | -0.30484 | -0.42836 | 0.496021 | 0.668296 | 1 | | | | | | | | |
| 23.Resource | -0.07984 | -0.10842 | -0.19973 | 0.082626 | -0.09284 | 0.066906 | -0.08695 | 0.089121 | 0.0086 | -0.23724 | -0.26191 | 0.629596 | -0.70298 | 0.887317 | 0.955276 | 0.980794 | -0.12062 | -0.24589 | -0.43808 | 0.557811 | 0.729007 | 0.852249 | 1 | | | | | | | |
| 24.State | -0.25282 | -0.03024 | -0.08133 | -0.11761 | -0.17552 | -0.10342 | -0.08079 | -0.21388 | -0.12664 | 0.02262 | 0.12836 | -0.32822 | 0.166617 | -0.25699 | -0.07346 | -0.10515 | -0.11168 | 0.688716 | 0.22104 | -0.07074 | -0.28701 | -0.1858 | -0.09249 | 1 | | | | | | |
| 25.Union | 0.077066 | -0.02921 | 0.030576 | 0.075132 | 0.029865 | 0.039264 | -0.03173 | 0.021132 | 0.032607 | 0.005746 | -0.11567 | 0.473865 | -0.3358 | 0.470297 | 0.304319 | 0.334117 | 0.13429 | -0.62558 | -0.1925 | 0.337417 | 0.465834 | 0.375429 | 0.335098 | -0.51827 | 1 | | | | | |
| 26.GDP_c | -0.05769 | -0.10365 | -0.17253 | 0.108624 | -0.0694 | 0.116339 | -0.05867 | 0.117845 | -0.07792 | -0.1544 | -0.19105 | 0.316214 | -0.54577 | 0.520216 | 0.617261 | 0.651843 | -0.13557 | -0.17464 | -0.37171 | 0.252409 | 0.420913 | 0.679009 | 0.627214 | -0.23522 | 0.278843 | 1 | | | | |
| 27.Infation | -0.13456 | 0.040318 | 0.15678 | -0.15071 | -0.12785 | -0.12428 | -0.07863 | -0.25382 | -0.04993 | 0.13826 | 0.256271 | -0.51163 | 0.451991 | -0.62946 | -0.6564 | -0.67273 | -0.08393 | 0.442751 | 0.218195 | -0.37351 | -0.49414 | -0.6943 | -0.67299 | 0.294306 | -0.31778 | -0.53254 | 1 | | | |
| 28.Population | 0.185214 | 0.148901 | 0.07831 | 0.1252 | 0.240014 | 0.248484 | 0.338917 | 0.275762 | -0.05511 | 0.015643 | -0.07352 | 0.027109 | 0.020202 | -0.02862 | -0.08382 | -0.08409 | 0.15956 | -0.0018 | 0.012908 | 0.05219 | -0.02506 | -0.02689 | -0.07006 | 0.012001 | -0.1154 | -0.03721 | -0.11628 | 1 | | |
| 29.Above65 | 0.07162 | -0.0736 | -0.17331 | 0.155453 | 0.032916 | 0.196714 | -0.02776 | 0.21336 | -0.00927 | -0.16508 | -0.22512 | 0.627954 | -0.58513 | 0.707563 | 0.671392 | 0.684147 | 0.034003 | -0.40526 | -0.29243 | 0.499408 | 0.586224 | 0.741863 | 0.676382 | -0.30841 | 0.386799 | 0.617915 | -0.69446 | 0.039917 | 1 | |
| 30.Female | 0.122559 | 0.048693 | 0.04332 | 0.054621 | 0.072065 | 0.022581 | -0.00737 | 0.06658 | 0.050163 | -0.00823 | 0.013619 | 0.323563 | -0.04977 | 0.15822 | -0.02296 | -0.04496 | 0.157258 | -0.3126 | 0.107673 | 0.26333 | 0.163401 | -0.01217 | -0.03323 | -0.13801 | 0.225992 | -0.28637 | -0.07583 | -0.0282 | 0.307496 | 1 |