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Abstract

Diese Arbeit untersucht die Einflüsse volkswirtschaftlicher Charakteristika auf die Regenerationszeit eines Landes nach einer Naturkatastrophe. Der Fokus liegt auf Einkommensungleichheit, Handelsoffenheit und Regierungsführung. Mit dem Solow Model als theoretische Grundlage, analysiert die Arbeit Regenerationsdynamiken in zwei Ansätzen: Lineare Regressionen, mit Regenerationszeit (Tage bis das BIP pro Kopf Niveau vor der Katastrophe wieder erreicht wird) als abhängige Variable, und Panel Regressionen, welche die direkte Veränderung des BIP pro Kopf Wachstums ein, zwei und drei Jahre nach der Katastrophe analysieren. Die Daten stammen aus den EM-DAT, UNU-WIDER und World Bank Datenbanken. Die Ergebnisse der Linearen Regressionen zeigen eine Erhöhung der Regenerationszeit um 6.41 Tage pro Prozentpunkt mehr Einkommensungleichheit (Gini Koeffizient). Des Weiteren reduziert eine mehr demokratische Regierungsführung (Polity Score) die Regenerationszeit um 9.1 bis 10.8 Tage pro Punkt (Polity Score, -10 bis +10). Handelsoffenheit zeigt keinen signifikanten Effekt auf die Regenerationszeit. Die Panel Regressionen zeigen einen positiven Effekt auf BIP pro Kopf Wachstum im zweiten Jahr nach einer Naturkatastrophe, was auf einen 'catching-up' Prozess nach dem Solow-Modell hinweist. Interaktionen der volkswirtschaftlichen Variablen mit den Jahren nach einer Katastrophe bleiben insignifikant. Die Ergebnisse deuten auf die Wichtigkeit von geringerer Einkommensungleichheit und einer stärkeren Ausprägung demokratischer Regierungsformen hin, um die Regenerationszeit nach Naturkatastrophen zu verkürzen.

This thesis examines the influences of economic characteristics on a country's recovery time after natural disasters. It focuses on the role of income inequality, trade openness, and governance. With the Solow growth model as a theoretical framework, the thesis analyzes recovery dynamics with two approaches: Firstly, linear regressions, with recovery time (days to restore pre-disaster GDP per capita) as the dependent variable, and secondly, panel regressions, analyzing the impact on GDP per capita growth one, two and three years after a disaster. The datasets are derived from the EM-DAT, UNU-WIDER, and World Bank databases. The results from the linear regressions indicate that higher inequality (Gini coefficient) increases recovery time by 6.41 days per percentage point, and a more democratic governance (Polity Score) reduces it by 9.1 to 10.8 days. Trade openness shows no significant effect on recovery time. The Panel regressions show a positive effect on GDP growth two years post-disaster, which could indicate a catching-up process. Interactions with the three economic variables remain insignificant. These findings highlight the importance of addressing inequality and strengthening democratic governance to improve recovery post-disaster.

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List of Abbreviations

GDP:	Gross Domestic Product
OLS:	Ordinary Least Squares
EM-DAT:	International Disaster Database
CRED:	Centre for Research on the Epidemiology of Disasters
PPP:	Purchasing Power Parity
UNO:	United Nations Organization
WIID:	World Inequality Database
LSH/RHS:	Left-/Right-Hand Side
MA:	Moving Average
FE:	Fixed Effects
VIF:	Variance Inflation Factor

1. Introduction

In 1992 the Hawaiian Island Kauai was struck by Hurricane “Iniki”, a tropical storm. It destroyed houses, killed people, and had a huge impact on the economy of the island. Coffman and Noy (2011) have found that the population decline is still affecting the country 17 years later, and the island has not recovered from the economic damage by certain measures (Coffman & Noy, 2011, p. 201). In 1995 Kobe, Japan was hit by a massive earthquake. It was the first to reach a magnitude of ‘7’ on the magnitude scale of the Japan Meteorological Agency and led to more than 5,000 deaths. As stated by Horwich (2000), the estimated damage has been more than US$ 170 billion. Besides this massive damage, the city had managed to recover at a rapid pace (Horwich, 2000, pp. 1-2). These two contrasting recovery scenarios motivate an analysis of the economic factors driving these differences in recovery duration across countries.

Kahn (2003) found that poorer countries are exposed to roughly the same number of natural disasters in comparison to richer countries (Kahn, 2003, p. 10). That raises the question: How do certain economic variables, such as income inequality, trade openness and governance influence a country’s recovery time after a natural disaster? As the literature suggests, this question is answered by a range of different factors which affect the duration of recovery-time of a country. Noy (2009) has found a variety of intrinsic factors to a country’s resilience. Cappelli et al. (2021) argue that income inequality amplifies disaster impacts and potentially prolongs recovery time (Cappelli et al., 2021, p. 8). Toya and Skidmore (2007) find that trade openness leads to fewer deaths and less damage after a disaster (Toya & Skidmore, 2007, p. 20).

While the literature suggests answers to which factors lead to more resilience in the aftermath of a natural disaster, the duration of recovery - measured as the time to restore pre-disaster GDP per capita - is not yet explored, a gap this thesis addresses.

To answer this question, with the Solow growth model’s prediction of accelerated recovery after a disaster as addressed in Chapter 2, two regression types will be introduced, implemented to answer the research question: How influential are the different economic characteristics on a country’s recovery after a natural disaster?

The first regressions will be OLS regressions with the duration of recovery - the time in years it takes the country to reach the pre-disaster GDP level as a measure for economic reconstruction - as the dependent variable. The independent variables will be selected based on the influential factors identified in the literature on this topic. As an overview, these factors are Gini coefficient, trade openness as the percentage of GDP coming from import and export, a polity score ranging from total authority to full democracy and the population to control for different sized countries.

The results of the later performed regressions indicate that the Gini coefficient affects recovery time positively by around 6.41 days of increased recovery time for every one-point increase. However, this finding is significant at a 95% level only in one model with fixed effects for the end year of the disaster and fixed effects for the continent the country lies on. Surprisingly, trade volume as a percentage of GDP shows no significant impact on recovery time, suggesting that positive and negative effects may cancel each other out or are overshadowed by other factors. GDP growth is significant; a one percent increase in GDP per capita reduces recovery time by 18.7 to 20.2 days. Additionally, a one-point increase in the Policy Score decreases recovery time by 9.1 to 10.8 days, indicating that more democratic systems recover faster.

Afterwards, a panel regression is implemented which is designed to dive deeper and answer the question if the economic variables have a direct effect on the GDP growth per capita one, two or three years after the disaster hit the country. Therefore, the dependent variable will be GDP per capita growth, and the independent variables are Gini coefficient, trade openness and the polity score. Additionally, three dummy variables are implemented which indicate whether the country got hit one, two or three years ago to see if the interaction between these variables and the time dependent dummies indicate direct after-disaster effects of the variables on GDP per capita growth - and faster recovery time.

However, the effect of a disaster happening one year before is not significant, indicating no direct effect of a disaster on the GDP per capita growth in the following year. In two of the three models the dummy variable for a disaster happening two years ago is significant and positive, suggesting a potentially starting recovery process. For the third year, the impact is insignificant, likely due to unobserved factors. The interactions between the economic measures and the dummy variables show no significance, indicating no or unobserved effects on the GDP per capita growth post-disaster.

The thesis is structured as follows: Chapter 2 establishes the theoretical foundations as a basis for the upcoming chapters. Chapter 3 reviews already existing literature to identify key economic factors. The suggestions of the theoretical foundation and the empirical literature are then used to outlay the thesis' empirical analysis in the next Chapter 4. Here, the data, the sample used, and methodology are explained. The analysis' results are presented in Chapter 5. Starting with the plain results and followed up by an interpretation of the results. Afterwards the results get tested for their explanatory power using robustness checks. At the end of this chapter the results are compared to prior studies. Chapter 6 lays foundations for potential future research and Chapter 7 then closes the thesis by summarizing and evaluating the results.

2. Theoretical Foundations

To build a foundation for the following literature review and analysis, firstly, the Solow Model of Economic Growth and its predictions for the analysis is discussed.

The Solow Model is a neoclassical economic model developed by Robert M. Solow (1956). It emphasizes the economic growth of countries to lie on three aspects: capital stock, labor/human capital, and technological change. It tries to explain the long-term growth of countries' GDP. In the Solow Model the short- and medium-term economic growth is primarily driven by two inputs: The capital stock and labor. Technological change is the key aspect of long-term growth. The model predicts a steady state in which a country grows at a stable growth rate that is determined by technological advancements. Capital and labor both have diminishing returns which lead to technological change to play the major role in long term growth (Solow, 1956, p. 85).

For this thesis, the Solow Model provides a framework for understanding how natural disasters affect economic growth and recovery. In the context of natural disasters, this implies that destruction of infrastructure production facilities represents a negative shock to the capital stock. This then shifts the economy below its steady state. Assuming savings and technological growth rates don’t change, the model predicts an accelerated growth to converge to its steady state. The economy rebuilds its capital stock and moves back towards its long-run equilibrium. This mechanism, supported by studies like Okuyama (2003, pp. 8-20), provides the basis for the assumption that countries have faster GDP growth post-disaster to restore pre-disaster GDP levels, a process measured as recovery time in this analysis.

If the disaster is sufficiently severe, it will most likely also cost human lives and could lead to displacements. These aspects reduce the labor capital and therefore the growth of the country, as labor is the second primary part of the input function in the Solow Model (Okuyama, 2003, pp. 13-14). Technological progress is crucial for long term growth but is not likely to be significantly diminished by disasters, as it reflects general structural advancements rather than immediate changes (Solow, 1956, p. 85). On the other hand, economic models suggest that a natural disaster could be an opportunity to replace ‘old’ technology with new one (Okuyama, 2003, pp. 16-17). However, as the analysis is focused on the rebuilding of the country and not its further improvement, it will solely focus on the GDP per capita. Despite being beyond the scope of this analysis, technological change after a natural disaster may present an opportunity for future research.

The Solow Model implies that the growth of GDP of a country after a natural disaster should be bigger than before to get back to the country's steady-state (catch up effect). This suggests that countries may recover by rebuilding their destroyed capital stock. Therefore, it is likely that variables which accelerate the rebuilding of capital structures positively influence the recovery duration after a disaster.

3. Existing empirical literature

Extensive research has explored how economic characteristics influence the recovery process after natural disasters, justifying the selection of variables in this thesis (see Chapter 4). In the following, this review highlights critical economic factors that the literature identifies as determinants of recovery duration, building on the Solow Model's framework of capital and labor dynamics (see Chapter 2).

3.1. Inequality

Research consistently highlights inequality as a key determinant of recovery time following natural disasters. However, the underlying mechanisms vary across studies.

Cappelli et al. (2021) explored natural disasters in 149 countries between 1992 and 2018 and found that in countries with more income inequality, significantly more people are affected from natural disasters compared to more equal countries (Cappelli et al., 2021, p. 8). Furthermore, they use the term 'disaster-inequality-trap' to emphasize the relationship between more inequality and more severe damage from disasters and vice versa. This dynamic suggests that unequal countries may face prolonged recovery challenges (Cappelli et al., 2021, p. 10).

This is in line with Sovacool et al. (2008), who find that natural disasters intensify already existing social and structural differences. Disasters have a bigger impact if human factors like mismanagement or underdevelopment are severe. Additionally, the country takes longer to recover, as inequalities make it harder to get resources to where they are needed (Sovacool et al., 2018, p. 243). Well-situated people are more likely to be insured against the damage of a disaster, whereas poorer people cannot afford such insurance. Rebuilding resources are therefore favorably distributed among already better off people, leaving rural or marginalized areas behind (Sovacool et al., 2018, pp. 251-253). This strengthens already existing inequality even more. The authors call for policies that address specifically vulnerable communities to insure these groups to "spread and socialize the risks (and cost) of disasters so they do not fall inequitably on the poor and helpless", (Sovacool et al., 2018, p. 253).

In this regard, Horwich (2000) finds that income provides protection, and that wealthier people have a higher propensity to insure themselves and are therefore better off, after a disaster hits a country. He notes that "private saving is perhaps the least recognized source of disaster self-help" (Horwich, 2000, p. 4).

Not only the capital stock, but the labor is influenced by inequality as well. Yabe & Ukkusuri (2020) have looked at the evacuation and return behavior after disaster. They have found that wealthier people have better means of transportation and are therefore more easily evacuated. They find that people with higher incomes tend to reach less damaged locations (Yabe & Ukkusuri, 2020, p. 12). Following these findings, they suggest that policy should better address social inequalities in both "disaster evacuation and reentry" (Yabe & Ukkusuri, 2020, p. 13).

3.2. Trade

Toya and Skidmore (2007) find several factors that enhance the resilience of countries when hit by a natural disaster. They discover that next to a more complete financial system and better education, trade openness contributes to fewer deaths and less damage per capita after a disaster (Toya & Skidmore, 2007, p. 20). They stress that openness to trade is a valuable variable to indicate the "degree of competition and transferal of technological knowledge from abroad that reduces risk.", (Toya & Skidmore, 2007, p. 22). This is in line with the Solow model, which states that technological change is the key driver of long-term economic growth. Therefore, countries which are more technologically advanced tend to grow faster over the long run, which may give greater resilience to the impacts of natural disasters. However, these effects may fluctuate depending on other economic influences, as explored later (see Chapter 5).

Noy (2009) finds that a higher level of exports as percent of GDP is negatively correlated with the macroeconomic costs of a disaster. They theorize that countries with higher exports do not suffer as much from diminished demand for their products. Also, countries more open to trade might be more likely to get disaster aid by other countries to help reconstruction (Noy, 2009, p. 228).

3.3. Polity

In a study of Muzamil et al. (2021), the authors observe the disaster recovery of Swat, Pakistan which was hit by a flood during a phase of political instability and terrorism due to Taliban-induced conflicts. They find that disaster recovery and political conflicts are 'highly interconnected' (Muzamil et al., 2021, p. 12). After the flood, especially people with fewer assets had bigger difficulties securing aid and were often left out on restoration activities due to "politically motivated exclusion" (Muzamil et al., 2021, p. 3). Muzamil et al. (2021) discovered that during post-conflict recovery, dominant political agendas tended to benefit those with existing power and privilege and further marginalizing already vulnerable populations (Muzamil et al., 2021, p. 11).

Following Noy (2009), countries with better institutions are more able to withstand the negative effects of a disaster. He finds a statistically significant diminishing effect of institutional quality on the macroeconomic costs of a disaster. The author states that this effect is either due to a directly more efficient public intervention after a disaster, or to the indirect effect of 'shaping private sector response' (Noy, 2009, p. 227).

Ahlbom and Povitkina (2016) find similar influences. They find that democracies bring the people's topics on the political agenda. Taken together with "quality of government, […] well-functioning bureaucracy and lack of corruption in the public sector, ensure the supply and delivery of public goods.", (Ahlbom & Povitkina, 2016, p. 9). The authors discover that in countries where egalitarian democracies are strongly developed, fewer people are affected by natural disasters. However, democracy and institutional quality are both main factors in a country's vulnerability to natural disasters. They stress that democracies only provide better disaster preparedness when institutional quality is also high. In countries with low institutional quality, more democratic countries seem to suffer more from natural disasters (Ahlbom & Povitkina, 2016, p. 21).

4. Empirical Analysis

Building on the theoretical framework (Chapter 2) and the economic factors identified in the literature review (Chapter 3), this chapter introduces the methodology, data, and analytical framework used to assess how economic characteristics shape recovery duration after natural disasters.

4.1. Data

The primary dataset, which is used in the analysis, is the International Disaster Database (EM-DAT) from the Centre for Research on the Epidemiology of Disasters (CRED). The dataset represents a collection of disasters for 228 recorded countries - including historic entities that do not exist anymore, such as the Soviet Union, the German Democratic Republic (GRP), and Yugoslavia. It was initially created by the World Health Organization and the Belgian Government in 1988. It gets updated frequently and is used regularly for scientific papers (e.g. Toya & Skidmore, 2007). Its 'Inclusion Criteria' are as follows; The dataset contains disasters or emergencies that cause at least ten deaths - including 'dead and missing', affected at least 100 people (affected, injured, or homeless) or if there was a call for international assistance or an emergency declaration. For older events lacking detailed quantitative information only particularly severe disasters were implemented into the dataset ('worst disaster in a country or region', 'event that resulted in considerable damage'). The institute states potential inaccuracies due to missing events, incomplete data or inaccurate sources. Also, different countries' institutions could differ in their thresholds to report an event (CRED, 2023). These constraints may affect the reliability of the dataset, particularly for less-developed nations or earlier time periods.

Furthermore, the World Development Indicators from the World Bank are used for economic variables. The first variable used is the Gini index. It measures how much the distribution of income of a country compares to an equal distribution of income. It is measured from 0 to 100, with a bigger index meaning more inequality (World

Bank Open Data, 2024). This variable is used because of research discussed in Chapter 3 - e.g. Cappelli et al., 2021 - argue that inequality in income strengthens the effects of natural disasters and therefore prolongs the recovery time. To close the gaps in the data, the Gini coefficient data from the World Inequality Database is also included and then both datasets are combined into one variable (UNU-WIDER: World Income Inequality Database (WIID), 2023).

Second, the GDP per capita, PPP (current international $) from the World Bank is employed. This variable measures Gross Domestic Product (GDP) per capita in current international dollars, adjusted by the purchasing power parity (PPP), which accounts for price differences across countries using mid-year population estimates (World Bank Open Data, 2024). It is later used to calculate the recovery time, which is the dependent variable in the linear regressions.

Third, the GDP per capita growth (annual %) is used, representing the annual percentage change in GDP per capita, calculated with mid-year population (World Bank Open Data, 2024). This variable is smoothed out using a 10-year moving average and is then used as a control variable in the linear regressions, to filter out the general level of GDP growth, as this thesis is focused on the sudden changes a natural disaster shock has on the GDP growth post-disaster. In the panel regressions the GDP growth is used without the moving average to examine the direct effects of the economic factors and their interactions post-disaster.

Next, trade as a percentage of GDP is included, defined as the sum of exports and imports of goods and services as a share of a country's GDP (World Bank Open Data, 2024). This measure of trade openness is used as already discussed research, such as Toya and Skidmore (2007) and Noy (2009), indicates that it may weaken disaster damage and support recovery by enabling technological transfers and stabilizing economic demand, which is relevant to evaluating its effect on recovery time within the Solow framework.

Additionally, total population is employed, as the mid-year average of all residents (World Bank Open Data, 2024). It is used in linear regressions to control for the different population sizes of countries. As the recovery time is already based on GDP per capita, this does not include general structural and administrative differences different population sizes may have. Therefore, population is used as a control for structural heterogeneity.

For governance data, the Polity5 dataset from the Center for Systemic Peace is utilized. It gives each country an annual Polity Score, ranging from -10 (hereditary monarchy) to +10 (consolidated democracy). It covers all major independent states from 1800 to 2018 (PolityProject, 2018). This variable is included because research, such as Noy (2009) and Ahlbom and Povitkina (2016), indicates that higher institutional quality and democratic governance may help in being prepared for disasters and improve efficiency in recovery, which both influences the recovery time.

The dependent variable for the linear regressions, recovery time, is manually calculated: The GDP per capita in the year before a disaster is compared with the following years, with recovery as the number of years until the GDP per capita returns to its pre-disaster level (e.g., a recovery time of 3 if the GDP ist at the pre-disaster level three years later, or 0 if the GDP is equal or higher the year after the disaster). This approach focuses only on restoring pre-disaster GDP levels, as the focus of this thesis is on economic stabilization rather than long-term improvement, which resembles the catch-up effect of the Solow Model's steady-state concept.

To address missing data, a 10-year moving average was applied to the variables Gini index, population, trade, Polity Score and GDP per capita growth, smoothing out gaps while preserving general trends. For the panel regressions, GDP per capita growth was not smoothed out to keep annual fluctuations, which provide insights into short-term recovery dynamics.

For the panel regression, three dummy variables were created to indicate whether a disaster occurred one, two or three years prior, enabling the analysis of lagged recovery effects.

The dataset has some important limitations. First, only complete cases are used, which reduces the sample size due to missing data. This holds especially for less-developed countries with weaker statistical institutions. Recent years generally have better coverage as the data quality improves over time. The use of a 10-year moving average is used to make up for missing data but may therefore hide short-term fluctuations. It reflects longer trends rather than sudden changes. Moreover, recovery time is measured in whole years, which potentially underestimates short-term impacts (e.g., a disaster with only a few months recovery time is calculated as 0 years). This simplification is addressed in future research recommendations.

4.2. Used Sample

Following the data preparation as described in Chapter 4.1, the sample used for the regressions is chosen based on data quality and in line with the economic factors as identified in Chapter 3.

The analysis uses data in the period from 1990 to 2021 to make sure to have reliable and consistent data. Before 1990, geopolitical changes, for example the dissolution of the Soviet Union, the breakup of Yugoslavia, and German reunification, complicate the use of country specific data because of changing borders and names (World Bank Open Data, 2024). Additionally, as discussed in Chapter 4.1, data quality for earlier periods is worse, particularly in less-developed countries, as noted in the EM-DAT documentation (CRED, 2003). Therefore, the sample is restricted to the years after 1990 to improve data reliability. Data after 2021 are omitted to ensure complete and comparable data.

For the disaster dataset, only countries with a population of at least 2 million inhabitants at any point between 1990 and 2021 are included. This threshold excludes small island states and microstates, which may have different disaster recovery behavior due to their small demographic and economic scale. The 2 million cutoff is self-imposed, chosen to enhance comparability by omitting extreme demographic outliers that could skew the analysis of recovery time. This choice is motivated by Kahn, who shows that population size significantly affects the likelihood of disaster occurrences and the magnitude of its impact, implying a generally different risk profile for small countries (Kahn, 2003, pp. 9-10). Countries falling below this threshold at any time during the period are excluded, even if they later exceed it, to maintain consistency in the sample.

Additionally, to focus on significant disasters in the disaster dataset, only events affecting a population greater than the dataset's median are considered. This criterion mitigates biases from overreporting minor incidents in countries with advanced statistical systems, as discussed in the EM-DAT methodology (CRED, 2023). Including only larger disasters also prevents the sample from being dominated by frequent small-scale events, which could diffuse insights into effective disaster management, especially in countries with minor incidents almost every year.

This selection yields 1,565 observations in the disaster dataset, with 1,249 complete cases, meaning all non-missing values for all variables after applying the 10-year moving average, as described in Chapter 4.1, and 3,097 country-year combinations in the panel dataset. The data structure and regression specifications are described in detail in the following sections.

4.3. Descriptive Statistics

Building on the sample defined in Chapter 4.2, this section presents the descriptive statistics of the variables used in the regression analysis, providing insights into their distributions.

Both datasets contain the external variables Gini coefficient, trade openness, population and Polity Score. Both datasets also contain the same years and countries. In the following, the characteristics of each dataset are described to contextualize the regression analysis.

4.3.1. Disaster Data

Table 1 Descriptive Statistics of Disaster Recovery Data (1990–2021)

N: 1565	*Year*	*Recovery Time*	*Gini (MA)*	*Trade (MA)*	*GDP p.c. Growth (MA)*	*Population (MA)*	*Polity (MA)*
Mean	2007,25	102,62	42,34	62,24	2,22	90,8	4,15
Std.Dev	8,49	444,96	8,92	32,92	3	239,25	5,04
Min	1991	0	19,1	13,82	-17,7	2,22	-10
Q1	2000	0	34,93	39,44	0,76	9,3	0,8
Median	2008	0	41,88	54,91	2,16	20,18	5,8
Q3	2014	0	49	75,63	3,7	56,68	8
Max	2021	6570	74,6	379,01	15,37	1381,98	10
N.Valid	1565	1565	1462	1418	1563	1565	1454
Pct.Valid	100	100	93,42	90,61	99,87	100	92,91

Notes: The table reports descriptive statistics for the disaster recovery dataset, including the number of observations (N), mean, standard deviation (Std.Dev), minimum (Min), quartiles (Q1, Median, Q3), maximum (Max), number of valid observations (NValid), and percentage of valid observations (PctValid). Units: Recovery (Days), Gini (0–100), Trade (% of GDP), GDP p.c. Growth (%), Population (Millionen), Polity (-10 to +10).

The most important variable in the disaster dataset is the recovery time. It is explained in Chapter 4.1 how this variable is calculated. Over all disasters the mean recovery time is 102.62 days, reflecting that many disasters result in zero years of recovery time due to the annual measurement, as noted in Chapter 4.1. This is also shown by the median being zero and by Q1 and Q3 segments being zero as well. The maximum recovery time is 6,570 days, or (/365) 18 years.

The Gini coefficient ranges from 19.1 to 74.6 with a mean of 42.34 and a standard deviation of 8.92. The trade volume has a mean of 62.24% of GDP and ranges from 13.82% to 379.01%. Growth per capita has a minimum of negative 17.7% and a maximum of 15.37% and a mean of 2.22%. The population ranges from 2.22

million to 1,381.98 million and has a mean of 90.80 million. The Polity Score ranges from -10 to 10 and has a mean of 4.15 and a median of 5.8.

The disaster dataset has 1565 observations in total. The validity of the variables, however, is not at 100% each. While most variables have around 99% validity, the Gini coefficient has a completeness of 93.42%, as discussed in Chapter 4.1, the polity score has 92.91%. The trade volume has the lowest number of complete observations with 1418 out of 1565 or 90.61%. These shortcomings in complete cases provide for a lack of usable data in the regressions, as only observations that have data in every variable can be used.

4.3.2. Panel Data

Table 2 Descriptive Statistics of Panel Data (1990-2021)

N: 3097	*GDP p.c.*	*GDP p.c. Growth*	*Gini (MA)*	*Trade (MA)*	*Polity (MA)*	*Disaster (t-1)*	*Disaster (t-2)*	*Disaster (t-3)*
Mean	12019,8	1,99	40,27	71,03	3,94	0,46	0,44	0,43
Std.Dev	13860,47	6,13	9,02	42,7	5,82	0,5	0,5	0,49
Min	257,56	-64,43	19,53	13,39	-10	0	0	0
Q1	2249,37	0,07	33,06	45,49	-1	0	0	0
Median	6618,32	2,2	39,12	61,65	6	0	0	0
Q3	16609,45	4,48	46,24	85,43	9	1	1	1
Max	131864,09	90,76	74,6	393,23	10	1	1	1
N.Valid	3030	3054	2797	2831	2723	3097	3097	3097
Pct.Valid	97,84	98,61	90,31	91,41	87,92	100	100	100

Notes: The table reports descriptive statistics for the panel dataset used in the disaster impact analysis, including the number of observations (N), mean, standard deviation (Std.Dev), minimum (Min), quartiles (Q1, Median, Q3), maximum (Max), number of valid observations (NValid), and percentage of valid observations (PctValid). Units: GDP p.c. (constant 2017 PPP $), GDP p.c. Growth (%), Gini (0–100), Trade (% of GDP), Polity (-10 to +10). Disaster (t-1), Disaster (t-2), and Disaster (t-3) are dummy variables indicating whether a disaster occurred one year prior (t-1), two years prior (t-2), or three years prior (t-3).

The panel data has a higher number of observations of 3097 as this dataset contains country – year combinations of the affected countries even for years without disasters.

In this dataset the LHS variable will be growth per capita. In this case fluctuations provide direct information, therefore in the panel data there is no Moving Average over the growth variable. Growth per capita has a mean of 1.99% with a minimum of -64.43% and a maximum of 90.76%. With Q1 at 0.07% and Q3 at 4.48%, most of the data lies around these percentages, which is also confirmed by the median of 2.20 and the standard deviation of 6.13% around the mean.

GDP per capita ranges from 257.56 $US to 131,864.09 $US with a mean of 12,019.80 $US. The Gini coefficient in the panel data has a mean of 40.27 and ranges from 19.53 to 74.6. Population in the panel data has a mean of around 50.6 million, a maximum of around 1,671.5 million and a minimum of around 1.5 million. As discussed in Chapter 4.2, the threshold of 2 million inhabitants needs to be surpassed at any given time. Therefore, it is possible that country-year combinations with a population of less than 2 million are part of the panel dataset, as this country surpasses the 2 million population threshold in another year. Trade ranges from 13.39% to 393.23% with a mean of 71.03% and the Polity Score again ranges from -10 to 10 and has a panel dataset mean of 3.94.

For the panel data the three dummies Disaster (t-1), Disaster (t-2) and Disaster (t-3) were created. These represent a dummy variable for the case that any disaster happened in the last year, the year before or the year two years before last year. As they are dummy variables, they only take on the value of 0 or 1. With the means of 0.46, 0.44 and 0.43, it shows that almost half of all country-year combinations have had a disaster in at least one of the last three years.

The weakest link in observations for the panel data is the polity score with 2723 out of 3097 observations or 87.92%. Gini and trade volume lie a little bit above 90% and the other variables have higher numbers of complete observations from 97.84% to 99.1% (With dummies at 100%).

4.4. Specifications

Based on the descriptive statistics presented in Chapter 4.3, this section outlines the regression models used to examine the impact of economic characteristics on recovery time and GDP per capita growth, building on the theoretical and empirical foundations from Chapters 2 and 3.

First, a linear regression is performed with recovery time as the dependent side variable. On the right-hand side (RHS) the variables Gini coefficient (Moving Average [MA]), Trade (MA), GDP per capita Growth (MA), Polity Score (MA) and Population (MA) are considered. This regression aims to estimate the direct effects of these variables on recovery time, consistent with standard econometric approaches (Wooldridge, 2019, pp. 20-65; Angrist & Pischke, 2009, pp. 22-37). Additionally, the year and the continent of the specific country are used as fixed effects to account for unobserved heterogeneity. This regression goal gets split up into four regressions. The first regression considers the variables Gini, trade volume, GDP growth, population and Polity Score without any fixed effects. Afterwards the same regression is performed with year-fixed effects, and separately with continent-fixed effects. These regressions provide deeper insights into whether the variables are directly affecting the recovery time or just representing time or region related effects. The last regression then combines everything into one – all variables with fixed effects on year and continent. The regression specifications are as follows:

$$\textbf{I.}\quad Recovery\ Time_i = \beta 0 + \beta 1 \cdot Gini\ (MA)_i + \beta 2 \cdot Trade\ (MA)_i + \beta 3 \cdot GDP\ p.c.\ Growth\ (MA)_i + \beta 4 \cdot Polity\ (MA)_i + \beta 5 \cdot Population\ (MA)_i + \varepsilon_i$$

$$\textbf{II.}\quad Recovery\ Time_i = \beta 0 + \beta 1 \cdot Gini\ (MA)_i + \beta 2 \cdot Trade\ (MA)_i + \beta 3 \cdot GDP\ p.c.\ Growth\ (MA)_i + \beta 4 \cdot Polity\ (MA)_i + \beta 5 \cdot Population\ (MA)_i + \gamma_t + \varepsilon_i$$

$$\textbf{III.}\quad Recovery\ Time_i = \beta 0 + \beta 1 \cdot Gini\ (MA)_i + \beta 2 \cdot Trade\ (MA)_i + \beta 3 \cdot GDP\ p.c.\ Growth\ (MA)_i + \beta 4 \cdot Polity\ (MA)_i + \beta 5 \cdot Population\ (MA)_i + \delta_c + \varepsilon_i$$

$$\textbf{IV.}\quad Recovery\ Time_i = \beta 0 + \beta 1 \cdot Gini\ (MA)_i + \beta 2 \cdot Trade\ (MA)_i + \beta 3 \cdot GDP\ p.c.\ Growth\ (MA)_i + \beta 4 \cdot Polity\ (MA)_i + \beta 5 \cdot Population\ (MA)_i + \gamma_t + \delta_c + \varepsilon_i$$

where *Recovery* $Time_i$ is the time in days for country *c* to recover from disaster *i* to its pre-disaster GDP per capita level, based on the disaster's end year *t*. *Gini* $(MA)_i$, *Trade* $(MA)_i$, *GDP p.c. Growth* $(MA)_i$, *Polity* $(MA)_i$, and *Population* $(MA)_i$ are the 10-year moving averages of the Gini coefficient, trade openness, GDP per capita growth, Polity score, and population for the country which is affected by the disaster *i*. γ_t and δ_c are year- and country-fixed effects, and ε_i is the error term.

For the panel regression the setup is different. To check whether the economic variables influence the growth of GDP in the aftermath of a disaster, three dummy variables are introduced, which indicate whether a disaster hit the country last year, two years or three years ago. Firstly, the basis regression looks at growth per capita as the dependent variable. The RHS variables are the Gini coefficient, the trade volume and the Polity Score. Population is excluded, as the dependent variable, GDP per capita growth, already accounts for population size. These results are supposed to show what the general effect of these variables on economic growth is. Besides that, the three dummy variables on the RHS show whether the growth per capita of a country is affected by a disaster in the last one to three years. panel regression number 2 does the same but also uses year-fixed effects. This shows whether the results from regression 1 are solid or due to time and/or continent related changes. For panel regression 3, the same setup as for 2 is used – but here interactions between the variables Gini coefficient, trade volume and Polity are introduced. With this combination of RHS variables, the estimated results are effects on a country's GDP per capita growth of these variables in one to three years after a disaster. In other words, how does this variable effect growth in the corresponding country one, two or three years after a disaster hits the country. The regression specifications are as follows:

$$\textbf{I.} \quad \textit{GDP p.c. Growth}_{it} = \beta 0 + \beta 1 \cdot \textit{Disaster (t-1)}_{it} + \beta 2 \cdot \textit{Disaster (t-2)}_{it} + \beta 3 \cdot \textit{Disaster (t-3)}_{it} + \beta 4 \cdot \textit{Gini (MA)}_{it} + \beta 5 \cdot \textit{Trade (MA)}_{it} + \beta 6 \cdot \textit{Polity (MA)}_{it} + \varepsilon_{it}$$

$$\textbf{II.} \quad \textit{GDP p.c. Growth}_{it} = \beta 0 + \beta 1 \cdot \textit{Disaster (t-1)}_{it} + \beta 2 \cdot \textit{Disaster (t-2)}_{it} + \beta 3 \cdot \textit{Disaster (t-3)}_{it} + \beta 4 \cdot \textit{Gini (MA)}_{it} + \beta 5 \cdot \textit{Trade (MA)}_{it} + \beta 6 \cdot \textit{Polity (MA)}_{it} + \gamma_t + \varepsilon_{it}$$

$$\begin{aligned} \textbf{III.} \quad \textit{GDP p.c. Growth}_{it} = {} & \beta 0 + \beta 1 \cdot \textit{Disaster (t-1)}_{it} + \beta 2 \cdot \textit{Disaster (t-2)}_{it} + \beta 3 \cdot \textit{Disaster (t-3)}_{it} \\ & + \beta 4 \cdot \textit{Gini (MA)}_{it} + \beta 5 \cdot \textit{Trade (MA)}_{it} + \beta 6 \cdot \textit{Polity (MA)}_{it} \\ & + \beta 7 \cdot (\textit{Gini (MA)}_{it} \cdot \textit{Disaster (t-1)}_{it}) + \beta 8 \cdot (\textit{Gini (MA)}_{it} \cdot \textit{Disaster (t-2)}_{it}) \\ & + \beta 9 \cdot (\textit{Gini (MA)}_{it} \cdot \textit{Disaster (t-3)}_{it}) + \beta 10 \cdot (\textit{Trade (MA)}_{it} \cdot \textit{Disaster (t-1)}_{it}) \\ & + \beta 11 \cdot (\textit{Trade (MA)}_{it} \cdot \textit{Disaster (t-2)}_{it}) + \beta 12 \cdot (\textit{Trade (MA)}_{it} \cdot \textit{Disaster (t-3)}_{it}) \\ & + \beta 13 \cdot (\textit{Polity (MA)}_{it} \cdot \textit{Disaster (t-1)}_{it}) + \beta 14 \cdot (\textit{Polity (MA)}_{it} \cdot \textit{Disaster (t-2)}_{it}) \\ & + \beta 15 \cdot (\textit{Polity (MA)}_{it} \cdot \textit{Disaster (t-3)}_{it}) + \gamma_t + \varepsilon_{it} \end{aligned}$$

where *GDP p.c. Growth*$_{it}$ is the per capita GDP growth rate in percentage for country i in year t. *Disaster (t-1)*$_{it}$, *Disaster (t-1)*$_{it}$, and *Disaster (t-1)*$_{it}$ are dummy variables indicating whether a disaster occurred one, two, or three years prior. *Gini (MA)*$_{it}$, *Trade (MA)*$_{it}$, and *Polity (MA)*$_{it}$ are the 10-year moving averages of the Gini coefficient, trade openness, and Polity Score for country i in year t. γ_t is the year-fixed effects, and ε_{it} is the error term. It is to note that continent-fixed effects were initially considered but are not included in the final specifications, as they are time-invariant and are therefore eliminated in the fixed effects estimation (Woolridge, 2019, pp. 463-469).

In all regressions, robust standard errors were used to address potential heteroscedasticity and improve the reliability of the estimates. The reasons for using robust standard errors will be explained later in Chapter 5.3 (White, 1980, pp. 817-828).

5. Results

Table 3 Linear Regression Results for Disaster Recovery Time

	Dependent Variable:			
	Recovery Time in Days			
	No FE	Year FE	Continent FE	Year and Continent FE
	(1)	(2)	(3)	(4)
Gini (MA)	2.081	2.855	4.591	6.410*
	(2.232)	(2.164)	(3.790)	(3.711)
Trade (MA)	0.124	0.236	0.083	0.164
	(0.273)	(0.307)	(0.274)	(0.300)
GDP p.c. Growth (MA)	-19.790***	-20.239***	-18.702***	-19.263***
	(6.889)	(6.771)	(6.870)	(6.937)
Polity (MA)	-9.226***	-9.104***	-10.767***	-10.228***
	(2.732)	(2.593)	(2.983)	(2.773)
Population (MA)	-0.027	-0.017	0.006	0.014
	(0.026)	(0.026)	(0.025)	(0.027)
Constant	83.314	-58.188	-6.656	-154.163
	(92.381)	(87.447)	(155.400)	(145.336)
Observations	1,249	1,249	1,249	1,249
R^2	0.033	0.075	0.054	0.100
Adjusted R^2	0.029	0.049	0.047	0.071
Residual Std. Error	389.611 (df = 1243)	385.722 (df = 1213)	386.104 (df = 1239)	381.211 (df = 1209)
F Statistic	8.563*** (df = 5; 1243)	2.825*** (df = 35; 1213)	7.809*** (df = 9; 1239)	3.439*** (df = 39; 1209)

Notes: *p<0.1; **p<0.05; ***p<0.01.
The table reports linear regression results for the disaster dataset, with recovery time in days as the dependent variable. Coefficients are presented with robust standard errors in parentheses. Model (1) includes no fixed effects, Model (2) includes year-fixed effects, Model (3) includes continent-fixed effects, and Model (4) includes both year- and continent-fixed effects.

5.1. Results

This section presents the results of the regression models specified in Chapter 4.4, examining the impact of economic characteristics on recovery time and GDP per capita growth after natural disasters, as motivated by the research question in Chapter 1. The findings are detailed in Table 3 (linear regressions) and Table 4 (panel regressions).

5.1.1. Linear Regressions

The four linear regressions aim at determining the impact of the economic variables on the recovery time after natural disasters in days.

Across the first three regressions, the Gini coefficient is not significant and positive. The significance increases from insignificance in the first three regressions to a confidence level of 95% in the last regression, indicating a weak, but positive effect on recovery time. A higher Gini coefficient represents more inequality, so a significant and positive impact indicates that more inequality leads to a longer recovery time after a disaster. Introducing regional and year-fixed effects, the magnitude and significance level of the Gini coefficient on the recovery time increases, indicating that the effect without time- and continent-fixed effects may be understated. The magnitude ranges from 2.081 days to 6.410 days increase in recovery time for every one-point change in Gini coefficient.

Trade in percentage of GDP, on the other hand, has no significant effect in any regression, and its effect is close to 0. This indicates that the role of trade on disaster recovery might be negligible, or that its effect might be overshadowed by other variables such as GDP per capita growth and Polity Score, which exhibit significant effects as discussed below.

GDP per capita growth exhibits the largest effect on recovery time. It is significant at the confidence level of 99.9% for all regressions. It also has a rather large magnitude on the recovery time, ranging from -18.702 to -20.239 days. The effect decreases slightly when introducing continent-fixed effects but still resembles a strong influence of GDP per capita growth on the recovery time. The results indicate that for every 1% more growth per capita, the duration of recovery decreases by around 19 to 20 days.

The second strongest effect inhibits the Polity Score. It is significant across all four regressions at the 99.9% confidence level. The magnitude ranges from -9.104 to -10.767 days of recovery time difference for every Polity Score Point (from -10 to 10). When introducing continent-fixed effects, the magnitude increases, while it decreases slightly with the introduction of year-fixed effects.

The population of the affected country in millions does not seem to have an impact on the recovery time. There is no significance shown across the four regressions, and the magnitude fluctuates around 0.

The fixed effects help control for unobserved heterogeneity and time- or region-specific shocks that could influence recovery time. With the introduction of the fixed effects the magnitude of the Gini coefficient and Polity Score increases, while the magnitude of GDP per capita growth slightly decreases.

Overall, the four regressions are statistically significant, with all four F statistics being significant at the 99.9% confidence level. The adjusted R-squared ranges from 0.029 to 0.071, which indicates a generally low level of explanation for variance of the recovery time. It seems that a lot of unobserved variables influence the recovery time besides the ones considered in this model.

Table 4 Panel Regression Results for Per Capita GDP Growth

	Dependent Variable:		
	Growth per capita in %		
	No FE	Year FE	Year FE and Interaction
	(1)	(2)	(3)
Disaster (t-1)	-0.102 (0.216)	-0.171 (0.227)	0.859 (1.466)
Disaster (t-2)	0.556*** (0.199)	0.418** (0.193)	1.666 (1.114)
Disaster (t-3)	0.331 (0.232)	0.014 (0.235)	1.085 (1.379)
Gini (MA)	0.116 (0.088)	0.050 (0.077)	0.089 (0.089)
Trade (MA)	0.006 (0.015)	-0.015 (0.019)	-0.023 (0.021)
Polity (MA)	0.234* (0.130)	0.072 (0.113)	0.111 (0.145)
Disaster (t-1): Gini (MA)			-0.034 (0.031)
Disaster (t-2): Gini (MA)			-0.031 (0.023)
Disaster (t-3): Gini (MA)			-0.033 (0.030)
Disaster (t-1): Trade (MA)			0.005 (0.007)
Disaster (t-2): Trade (MA)			0.003 (0.006)
Disaster (t-3): Trade (MA)			0.007 (0.007)
Disaster (t-1): Polity (MA)			0.010 (0.042)
Disaster (t-2): Polity (MA)			-0.029 (0.040)
Disaster (t-3): Polity (MA)			-0.042 (0.058)
Observations	2,322	2,322	2,322
R^2	0.016	0.111	0.114
Adjusted R^2	-0.028	0.060	0.060
F Statistic	5.885*** (df = 6; 2223)	8.274*** (df = 33; 2196)	6.717*** (df = 42; 2187)

Notes: *p<0.1; **p<0.05; ***p<0.01.

The table presents the panel regression results for the panel dataset, with per capita GDP growth in percentage as the dependent variable. Coefficients are calculated with robust standard errors (Arellano method, HC1) in parentheses. Model (1) includes no fixed effects, Model (2) includes year-fixed effects, and Model (3) includes year-fixed effects along with interaction terms between disaster dummies and economic variables (Gini, Trade, Polity).

5.1.2. Panel Regressions

Building on the linear regressions, the panel regressions further explore the dynamic effects of economic variables on GDP per capita growth in the aftermath of a disaster, as specified in Chapter 4.4.

The three disaster-year dummies indicate whether a disaster hit the country one, two or three years ago. In all three regressions, Disaster (t-1) does not have a significant effect on GDP per capita growth, indicating that GDP per capita growth might not be influenced by a disaster in the last year. The dummy Disaster (t-2) is significant in the first regression without fixed effects at the 99.9% confidence level. The magnitude is presented as 0.556 (% increase in GDP growth per capita). When introducing year-fixed effects, the effect gets diminished and is now only present with 0.418 (%) at a confidence level of 99%. In the third regression, the significance of all dummies vanishes completely, suggesting that when considering year-fixed effects and interactions of the years after a disaster with other variables, the isolated time since a disaster happened does not independently predict GDP per capita growth. Disaster (t-3) is insignificant, indicating no direct correlation of GDP growth per capita and a disaster three years ago.

The Gini coefficient and trade volume in percent of GDP do not have a significant effect on growth per capita in percent in these regressions. The magnitudes are also close to zero, suggesting no impact on growth per capita.

The Polity Score, on the other hand, is only significant in the first regression without interactions or fixed effects. Polity positively influenced GDP per capita growth by 0.234 (%) at the 95% confidence level.

Finally, all three dummies are interacting with the variables to see whether the effect of one variable on GDP per capita growth is influenced by the presence of a disaster in the last three years. However, in this regression no variable or interaction has any significant impact on the GDP per capita growth level and all interaction term magnitudes fluctuate around zero.

The adjusted R-squared of the regressions is low, even negative in the first regression, indicating low to no explanatory power. There are likely other factors influencing GDP growth post-disaster, such as disaster severity, institutional quality, or infrastructure, as highlighted in Chapters 2 and 3. The adjusted R-squared value increases with the introduction of fixed effects and stays the same when including interaction terms (-0.028, 0.060, 0.060). Despite limited explanatory power, the F-statistics indicate the general statistical significance of the models at the 99.9% confidence level each.

5.2. Interpretation

5.2.1. Linear Regressions

Building on the results presented in Chapter 5.1 and Table 3, this section interprets the effects of economic variables on recovery time after natural disasters, addressing the research question outlined in Chapter 1.

The linear regressions interpretation aims at explaining possible influences of the economic variables on the recovery time of countries after natural disasters in days. In the following a possible interpretation of the influences per variable is given.

The Gini coefficient is insignificant throughout the first three regressions. Only in the last regression does it gain some significance at the 95% confidence level at a magnitude of 6.410 days. As a higher Gini coefficient resembles more inequality, this leads to the conclusion that more unequal countries are slower in recovery than more equal countries. A one-point increase in Gini coefficient leads to 6.410 days longer recovery time. As the Gini coefficient reaches from 0 to 100, this resembles an increase of 1 unit on the Gini scale (equivalent to 1 percentage point of inequality) leading to 6.410 days longer recovery time. There could be multiple reasons for this relationship to hold. One could be that more unequal countries have less optimal resource allocations and are therefore less likely to transport the resources needed to the damaged areas. As discussed in the literature review (Chapter 3), possessions of insurance and the ability to flee and mobilize resources greatly differ among people of different wealth levels. Therefore, in unequal countries the probability that the disaster hits a poor neighborhood without the means to flee or mobilize rebuilding resources may be a problem. One might hypothesize that more unequal countries are not as prone to working together in a community to rebuild their country, as suggested in the literature review in Chapter 3. However, it is to note that this effect only holds at a relatively low significance level of 95%.

Trade was expected to have an impact on the recovery time due to better connections with other countries and therefore the ability to trade even when the country's demand is diminished. It was also expected that trade openness might be an indicator of other countries helping the country. However, trade openness in percentage of GDP does not have a significant impact on recovery time in these regression results. Trade openness and its effect on recovery could be influenced by many factors such as economic growth, political stability, or structural differences, as captured by variables like GDP per capita growth and Polity Score in the model. It could also mean that the influence of trade is fully encapsulated in the positive impact of GDP per capita growth or via the Polity Score.

The finding that GDP per capita growth is significant and comparatively strong in its magnitude aligns with expectations. The value measured by *Recovery Time* is the time the GDP - when dropped - climbs back up to its previous value. Therefore, stronger growth is expected to indicate shorter recovery time. However, we can observe the magnitude. One percent increase in GDP per capita growth leads to around 18.702 to 20.239 days less recovery time at a strong confidence level of 99.9%.

In case of the Polity Score, the results indicate that a more democratic country is better off after a disaster than a more autocratic country by around 9.104 to 10.767 days recovery time for every point increase in the Polity Score. This could have multiple reasons. Firstly, in a functioning democracy the institutions and bureaucracies could function more efficiently and therefore provide faster aid after a disaster. Democratic countries might be associated with lower corruption levels, as discussed in the literature review (Chapter 3), and therefore foreign aid should reach the designated goal. In general, one could argue that democratic countries and their people are more often working in union. Democratic people look after each other more often. On the other hand, one must consider that autocratic countries might have an advantage in other scenarios: It might be possible that autocratic countries are in general faster in delivering aid to the affected places due to less bureaucratic burdens, and other effects overshadow this advantage. This direct comparison is beyond the scope of this thesis but represents an interesting opportunity for further research.

The effect of the population variable is not significant throughout all linear regressions and its magnitude fluctuates around 0. Therefore, population plays no role in recovery time in these models. However, this is hard to interpret, as there were some limitations in the data. First, countries with less than 2 million inhabitants were left out, therefore many small countries are not in the data sample. This sample restriction is further detailed in Chapter 4.2. Second, only disasters are included that have more people affected than the median of all disasters. It might be less likely that disasters in smaller countries will hit this threshold, as there are less people that could be affected in general. In conclusion, the population size of a country might not influence disaster recovery. However, it could have also been the sample limitations that lead to no statistically significant effect of population on recovery in these regressions.

5.2.2. Panel Regressions

Building on the results presented in Chapter 5.1 and Table 4, this section interprets the effects of economic variables on GDP per capita growth in the aftermath of natural disasters, following the analysis of linear regressions in V.B.1 and addressing the research question outlined in Chapter 1. The panel regressions examine the relationship between economic variables and GDP per capita growth post-disaster, with the following interpretation of each variable's influence.

Disaster (t-1) is insignificant throughout all regressions. This implies that there might be no direct effect of a disaster happening a year ago and the GDP per capita growth in the following year. It could be that direct aid programs and rebuilding efforts might compensate for potential losses in capital stock, as suggested by the Solow model's focus on recovery through capital accumulation (Chapter 2). The positive growth rate in the last regression possibly indicates that direct aid and rebuilding might even outperform diminished growth due to capital destruction. However, this relationship is not significant. It is important to consider that disasters are not presented on their exact date in the regressions data. That leads to a disaster getting counted for 'last year' when it is on the 1st of January as well as last of

December. To really control for these timeframes, one might want to include the month or even exact date of the disaster.

For Disaster (t-2) there is significance for the no fixed effects and the year-fixed effects regression. The effect is positive on GDP per capita growth (0.556*** in model 1, 0.418** in model 2). That could mean that direct help programs or aid funds start working. It could also resemble the start of the ‘catching up’ process in which investments and technological changes might contribute to higher growth rates, consistent with the Solow model’s predictions (Chapter 2). In the third model with interaction terms the significance vanishes, which could mean that the positive effects of rebuilding might be overshadowed by other factors such as disaster severity or infrastructure, as noted in Chapter 4.1

For Disaster (t-3) there is only an insignificant positive effect on GDP growth. The positive magnitude could be due to the fact that the catching up effects of rebuilding still last on. However, as the effect is not significant, it is likely that the effects will get overshadowed by other factors.

The Gini coefficient and trade volume in percentage of GDP do not have any significant effect on these regressions. It is to note that these variables without interaction terms are not interpretable as a correlation with the GDP per capita growth post-disaster, as these variables impacts are measured over all years, independent of possible disasters. However, it is interesting that these variables do not significantly influence GDP per capita growth in these models, though this was not the primary focus of the regression setup (Chapter 4.4).

The Polity Score is only significant in model 1 (0.234*) indicating that more democratic countries in general have higher GDP per capita growth rates. This effect vanishes when introducing year-fixed effects and/or interaction terms. Therefore, these positive effects might not hold when controlling for Year FE or get overshadowed by other factors such as economic structures or unobserved heterogeneity, as controlled for in the model (Chapter 4.4). Also, this result is - as stated above - not applicable in the event of a disaster.

The interaction terms were supposed to show the impact of Gini, trade openness and Polity Score on GDP per capita growth 1, 2 and 3 years after a disaster hit the country. This impact could not be observed with this regression setup. All interactions between the variables and the dummies are insignificant and fluctuate around zero. Therefore, there either is no effect of these economic variables on the GDP per capita growth post-disaster, or this setup is not sufficient to capture this effect.

In summary, the linear regressions (V.B.1) highlight that higher GDP per capita growth and more democratic governance, as measured by the Polity Score, significantly reduce recovery time after natural disasters, while the Gini coefficient shows a limited effect and trade and population have no significant impact. The panel regressions (V.B.2) suggest that disasters two years prior can positively influence GDP per capita growth, potentially due to rebuilding efforts, though this effect is not robust across models, and other variables like Gini, trade, and their interactions do not show any significant impact. The low explanatory power of the panel regressions indicate that additional factors may be at play. The robustness of these findings will be tested in the next section Chapter 5.3.

5.3. Robustness Checks

This section assesses the robustness of the regression results presented in Chapter 5.1 and interpreted in Chapter 5.2, ensuring the reliability of the findings related to the research question outlined in Chapter 1.

For the linear regression the following robustness checks are performed: Breusch-Pagan Test, Variance Inflation Factor, Durbin-Watson Test, Shapiro-Wilk Test and CUSUM Test.

First, the models are tested for heteroscedasticity using the Breusch-Pagan Test:

Table 5 Results of the Breusch-Pagan Test for Heteroscedasticity in Linear Regression Models

Regression	*BP*	*Degrees of freedom*	*p-value*
(1)	32.259	5	5.279e-06
(2)	74.796	35	0.0001038
(3)	58.263	9	2.893e-09
(4)	109.080	39	1.491e-08

Notes: The table reports the Breusch-Pagan test statistics (BP), degrees of freedom, and p-values for Linear Regression models (1) to (4). P-values below 0.05 indicate rejection of the null hypothesis of homoscedasticity.

The p-values for all models are below the threshold of 0.05, indicating that the null hypothesis of homoscedasticity is rejected. That suggests that the models do not have a consistent variance in their error terms. This might lead to unreliable standard errors and potentially biasing the significance of the coefficients. This issue is addressed by the robust standard errors already implemented in the regressions, as outlined in Chapter 4.4, following the approach of White to ensure consistent standard errors under heteroscedasticity (White, 1980, pp. 817-828). Note that these test-results were tested on the model with their 'normal' standard errors. This potential error is therefore already considered. (Breusch & Pagan, 1979, pp. 1287-1294)

To test for multicollinearity, the Variance Inflation Factors of the models are calculated:

Table 6 Variance Inflation Factor (VIF) Analysis for Linear Regression Model (1)

Gini (MA)	*Trade (MA)*	*GDP p.c. Growth (MA)*	*Polity (MA)*	*Population (MA)*
1.056781	1.139248	1.216292	1.120438	1.330688

Notes: The table presents VIF values for explanatory variables in Linear Regression model (1). VIF values below 10 suggest no significant multicollinearity.

Table 7 Variance Inflation Factor (VIF) Analysis for Linear Regression Model (2)

Variable	*GVIF*	*Df*	*GVIF^(1/2*Df))*
Gini (MA)	1.094413	1	1.046142
Trade (MA)	1.217640	1	1.103467
GDP p.c. Growth (MA)	1.389424	1	1.178738
Polity (MA)	1.163825	1	1.078807
Population (MA)	1.348393	1	1.161203
Year FE	1.308969	30	1.004497

Notes: The table reports generalized VIF (GVIF), degrees of freedom (Df), and adjusted GVIF^(1/(2*Df)) for Linear Regression model (2). Values below 10 indicate no problematic multicollinearity.

Table 8 Variance Inflation Factor (VIF) Analysis for Linear Regression Model (3)

Variable	*GVIF*	*Df*	*GVIF^(1/2*Df))*
Gini (MA)	2.243504	1	1.497833
Trade (MA)	1.289928	1	1.135750
GDP p.c. Growth (MA)	1.227081	1	1.107737
Polity (MA)	1.414070	1	1.189147
Population (MA)	1.531606	1	1.237581
Year FE	3.623474	4	1.174602

Notes: The table reports generalized VIF (GVIF), degrees of freedom (Df), and adjusted GVIF^(1/(2*Df)) for Linear Regression model (3). Values below 10 indicate no problematic multicollinearity.

Table 9 Variance Inflation Factor (VIF) Analysis for Linear Regression Model (4)

Variable	*GVIF*	*Df*	*GVIF^(1/2*Df))*
Gini (MA)	2.441137	1	1.562414
Trade (MA)	1.442928	1	1.201219
GDP p.c. Growth (MA)	1.422533	1	1.192700
Polity (MA)	1.477812	1	1.215653
Populatin (MA)	1.544013	1	1.242583
Year FE	1.564817	30	1.007491
Continent FE	4.331710	4	1.201109

Notes: The table reports generalized VIF (GVIF), degrees of freedom (Df), and adjusted GVIF^(1/(2*Df)) for Linear Regression model (3). Values below 10 indicate no problematic multicollinearity.

These test-results do not show any problematic multicollinearity between the variables, as no VIF surpasses the commonly accepted threshold of 10. Multicollinearity in a model indicates that the variables influence highly correlate with each other, resulting in unstable coefficients and unreliable standard errors. In this case, there is no problem with multicollinearity (Fox & Monette, 1992, pp. 178-193).

Next, the models are tested for autocorrelation of the residuals using the Durbin-Watson Test. The results are as follows:

Table 10 Results of Durbin-Watson Test for Autocorrelation in Linear Regression Models

Regression	*DW*	*p-value*
(1)	1.9186	0.07389
(2)	1.9769	0.15700
(3)	1.9127	0.05978
(4)	1.9778	0.16030

Notes: The table presents Durbin-Watson (DW) statistics and p-values for Linear Regression models (1) to (4). DW values between 1.5 and 2.5 suggest no significant autocorrelation.

For the Durbin-Watson Test the DW value should be close to 2. Values of 1.5 to 2.5 indicate no problematic autocorrelation (Woolridge, 2019, pp. 403-404). These test-results therefore do not show any sign of significant autocorrelation in the residuals, although the p-value for model (3) (0.05978) is close to the 0.05 threshold, suggesting a need for caution in interpreting this result. Besides that, the assumption of independence of the error terms, which is important for a linear regression, is therefore fulfilled (Durbin & Watson, 1950, pp. 229-236).

Another problem might be that the residuals of a model are not normally distributed. To test for that potential problem the Shapiro-Wilk Test is performed:

Table 11 Results of Shapiro-Wilk Test for Normality of Residuals in Linear Regression Models

Regression	*W*	*p-value*
(1)	0.38297	< 2.2-e16
(2)	0.46098	< 2.2-e16
(3)	0.42866	< 2.2-e16
(4)	0.50339	< 2.2-e16

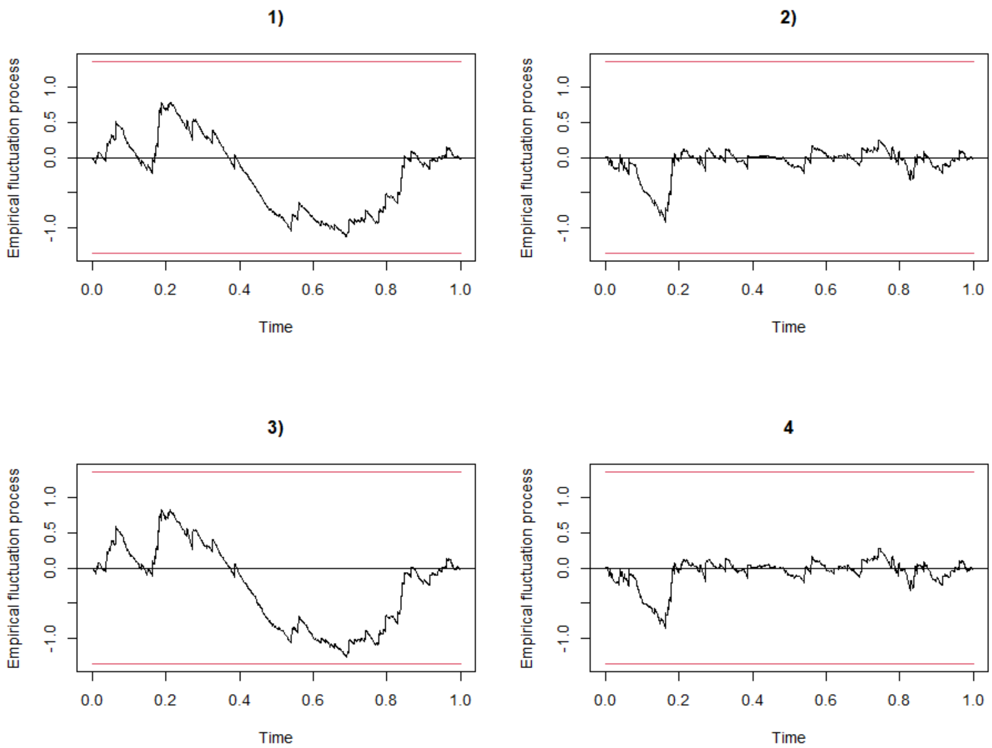
Notes: The table reports Shapiro-Wilk (W) statistics and p-values for Linear Regression models (1) to (4). P-values below 0.05 indicate rejection of the null hypothesis of normally distributed residuals.

The p-values for all models are well below the threshold of 0.05, indicating that the null hypothesis of normally distributed residuals is rejected. This suggests that the residuals of the models are not normally distributed. This would violate the normality assumption of a linear regression model and could lead to invalid significance.

However, robust standard errors have already been implemented in the models. Robust standard errors help address issues with heterogeneity and normality assumption violations. While robust standard errors help mitigate the impact on reliability, it might be reasonable to improve the model in future research by including transformations or by using Bootstrap methods to estimate standard errors and confidence intervals without relying on the normality assumption. These methods are beyond the scope of this thesis, and it is assumed that the implementation of robust standard errors already minimizes the potential effect of not normally distributed residuals (Shapiro & Wilk, 1965, pp. 591-610).

To finally check the structural stability of the coefficients over time the CUSUM test is performed for every model. The test results are presented in the plots below:

Figure 1 CUSUM Test for Structural Stability in Linear Regression Models



Notes: The figure displays CUSUM test plots for Linear Regression models (1) to (4). Plots remaining within the red bounds indicate structural stability of coefficients over time.

This tests for structural instability. If any plot crossed the red lines above and below, it would indicate that the coefficients are not stable over the whole timeframe. Structural instability suggests that the relationship between dependent and independent variables change over time, which could be a problem for the validity of the model. However, in these models no threshold is crossed and therefore shows no hints on structural instability. (Brown et al., 1975, pp. 149-162)

For the panel regression a few other tests are performed, namely Breusch-Pagan Test, the Breusch-Godfrey/Woolridge Test and the Variance Inflation Factor.

As above, the Breusch-Pagan Test checks for heteroscedasticity, i.e. inconsistent variance of the model's error terms. The results for the panel regression models are:

Table 12 Results of the Breusch-Pagan Test for Heteroscedasticity in Panel Regression Models

Regression	*BP*	*DF*	*p-value*
(1)	55.693	6	3.359e-10
(2)	132.060	33	8.473e-14
(3)	145.590	42	2.39e-13

Notes: The table reports Breusch-Pagan test statistics (BP), degrees of freedom (DF), and p-values for Panel Regression models (1) to (3). P-values below 0.05 indicate rejection of the null hypothesis of homoscedasticity.

The p-values are well below the threshold of 0.05, which indicates that the panel regressions have inconsistent variance in their error terms. This violates the assumption of homoscedasticity. This problem is addressed by using robust standard errors. These robust standard errors are already implemented in the above performed analysis, ensuring reliable inference under heteroscedasticity. (White, 1980, pp. 817-826; Breusch & Pagan, 1979, pp. 1287-1294)

Next, the models are tested for serial correlation using the Breusch-Godfrey/Woolridge Test. Serial correlation meaning the residuals are correlated inside a panel - for example over time - which leads to inefficient and biased standard errors if not addressed. The results are as follows:

Table 13 Results of the Breusch-Godfrey/Woolridge Test for Serial Correlation in Panel Regression Models

Regression	*ChiSq*	*DF*	*p-value*
(1)	340.11	1	< 2.2e-16
(2)	325.50	1	< 2.2e-16
(3)	321.62	1	< 2.2e-16

Notes: The table presents Chi-squared (ChiSq) statistics, degrees of freedom (DF), and p-values for Panel Regression models (1) to (3). P-values below 0.05 indicate the presence of serial correlation.

The very low p-value in all test results indicates that the alternative hypothesis of serial correlation in idiosyncratic errors is confirmed. This problem is most likely solved by robust standard errors as used above. Robust standard errors are designed to make up for the impact of serial correlation. Therefore, the issue of serial correlation is addressed by the robust standard errors already implemented in the regressions, as outlined in Chapter 4.4, consistent with standard practices in panel data analysis (Breusch, 1978; Godfrey, 1978). (Woolridge, 2019, pp. 406-407)

As already implemented for the panel regressions, the panel regressions are tested for multicollinearity using the Variance Inflation Factor (VIF). The results are as follows:

Table 14 Variance Inflation Factor (VIF) Analysis for Panel Regression Model (1)

Disaster (t-1)	*Disaster (t-2)*	*Disaster (t-3)*	*Gini (MA)*	*Trade (MA)*	*Polity (MA)*
1.315854	1.284538	1.317818	1.081213	1.091497	1.034164

Notes: The table reports VIF values for explanatory variables in Panel Regression model (1). VIF values below 10 suggest no significant multicollinearity.

Table 15 Variance Inflation Factor (VIF) Analysis for Panel Regression Model (2)

	GVIF	*DF*	*GVIF^(1/(2*DF))*
Disaster (t-1)	1.387324	1	1.177847
Disaster (t-2)	1.378927	1	1.174277
Disaster (t-3)	1.438173	1	1.199239
Gini (MA)	2.313024	1	1.520863
Trade (MA)	1.309400	1	1.144290
Polity (MA)	1.682542	1	1.297128
Year FE	1.254089	27	1.004202
Continent FE	4.702110	4	1.213491

Notes: The table reports generalized VIF (GVIF), degrees of freedom (DF), and adjusted GVIF^(1/(2*DF)) for Panel Regression model (2). Values below 10 indicate no problematic multicollinearity.

Table 16 Variance Inflation Factor (VIF) Analysis for Panel Regression Model (3)

	GVIF	*DF*	*GVIF^(1/(2*DF))*
Disaster (t-1)	6.203150e+01	7	1.342900
Disaster (t-2)	5.804062e+01	7	1.336537
Disaster (t-3)	7.495624e+01	7	1.361178
Gini (MA)	5.903448e+02	7	1.577379
Trade (MA)	2.155973e+04	7	2.039604
Polity (MA)	4.986387e+04	7	2.165490
Year FE	2.124670e+10	0	Inf
Continent FE	2.124670e+10	0	Inf

Notes: The table reports generalized VIF (GVIF), degrees of freedom (DF), and adjusted GVIF^(1/(2*DF)) for Panel Regression model (3). Values below 10 indicate no problematic multicollinearity.

In model (3) the raw GVIF values exceed the threshold of 10, suggesting potential multicollinearity issues. After adjusting for degrees of freedom, these values fall below 10, indicating that multicollinearity is not a concern for these variables. The infinite GVIF values for Year FE and Continent FE in model (3) result from a degree of freedom of 0, likely due to perfect collinearity along the dummy variables, which is expected for fixed effects and does not affect the reliability of the other coefficients. Given that all other values are below the threshold these two values for year and continent can be ignored. (Fox & Monette, 1992, pp. 178-183; Woolridge, 2019, p. 92)

In summary, the robustness checks confirm that the regression results from Chapter 5.1 and 5.2 are reliable despite violations of homoscedasticity and normality assumptions, as these are mitigated by robust standard errors. While some concerns arise with serial correlation in the panel regressions and potential multicollinearity in model (3), these are addressed through robust standard errors and adjusted VIF metrics, respectively. No significant issues with autocorrelation or structural instability are detected for the linear regressions, supporting the validity of the findings, such as the significant effects of Polity Score on recovery time (Chapter 5.2) These results provide a foundation for comparing the findings with existing literature in the next section (Chapter 5.4), where the effects of inequality, trade, and governance will be further contextualized.

6. Comparison to Literature

In the following the literature is compared with the regression results from Chapters 5.1 and 5.2, building on the robustness checks in Chapter 5.3 that confirm the reliability of the findings.

For the linear regressions, the Gini coefficient becomes significant only in the last regression at the 95% confidence interval, indicating that countries with higher inequality tend to take longer to recover than more economically equal countries. This is in line with the findings of Cappelli et al. (2021) who stressed that more unequal countries suffer more damage from disasters. This could even lead to a disaster-inequality-trap (Cappelli et al., 2021, pp. 8-10), where disasters increase existing inequalities, creating a feedback loop that further hinders recovery by limiting access to resources for vulnerable populations. However, with this thesis' results it cannot be concluded if this trap plays any role in the longer recovery times of more unequal countries. Sovacool et al. (2018) and Yabe & Ukkusuri (2020) also discuss the greater damage to countries with more inequality. They also propose that politics should mitigate this effect by making sure inequality is not getting out of hand, as that makes fair and efficient distribution of capital and labor in the aftermath of a disaster more challenging. Although the observed effect of inequality on recovery time in these regressions is modest, a weak positive relationship supports these findings. In future research longer-term post-disaster effects beyond the scope of three years could be explored to assess whether inequality impacts recovery time in the long run.

For trade openness the literature suggested that more trade openness might lead to a country being more resilient to disasters. In the regression results we do not see interpretable effects of trade volume on the recovery time or on the GDP per capita growth. It might be that multiple effects contradict each other. On the one hand the effects stated by the literature, such as reduced demand loss and foreign aid (Noy, 2009, p. 228) or technological change (Toya & Skidmore, 2007, p. 22), help in recovery. On the other hand, this might be contradicted by the possibility that countries with a higher percentage of GDP based on trade are in general more reliant on trade capabilities. With capital and/or labor stock destroyed after a disaster, it could be problematic for the country if it is too dependent on trade with other countries. Such over-reliance on trade may limit a country's ability to rebuild internally, as resources may be used to maintain trade relationships. These effects could cancel each other out, resulting in no significant effect of trade volume on recovery or GDP per capita growth.

The theory regarding the Polity Score suggests that a higher Polity Score - resembling a more democratic Policy should favor faster recovery. This is in line with the findings of the linear regression. The results suggest that for every one-point increase in the Polity Score the recovery time decreases by about 9 to 11 days. Under the assumption that democracies have better institutions these results follow the findings of Noy (2009) who discovered a significant effect of institutional quality on macroeconomic costs of a disaster (Noy, 2009, p. 227). Ahlbom and Povitkina (2016) state that in democracies the quality of government, lack of corruption and functioning bureaucracies lead to better supply and delivery of public goods (Ahlbom & Povitkina, 2016, p. 9). Also, a larger part of the population is entitled to receive public goods which solves the problems stated by Muzamil et al. (2021) that poorer people are left out more often (Muzamil et al., 2021, p. 3). These tendencies seem to be confirmed by the results of this paper. However - as for the other variables - more in-depth exploration is needed to concise the direct effect of policy on recovery.

In summary, the findings of this thesis align with the literature regarding the role of inequality (Cappelli et al., 2021; Sovacool et al., 2018; Yabe & Ukkusuri, 2020) and governance (Noy, 2009; Ahlbom & Povitkina, 2016) in disaster recovery, with higher inequality increasing recovery time and better governance (Polity Score) reducing it by 9-11 days per point. However, the lack of a significant effect of trade volume contrasts with the literature on trade openness (Noy, 2009; Toya & Skidmore, 2007), likely due to conceptual differences and competing effects of trade dependency. These results provide a foundation for future research and discussion in the following chapters.

7. Future Research

While these results provide insights into the relationship of some economic variables on recovery after natural disaster, as discussed in Chapters 5.1, 5.2, and 5.4, several limitations of this study provide areas for future research to better address the research question.

First, the disasters in this thesis are calculated yearly. This annual aggregation means that events occurring on January 1st are combined with those on December 31st, potentially masking short-term variations in disaster impacts. Also, the GDP recovery is calculated yearly, the data these calculations are based on are provided yearly. If future researchers have more granular GDP data on hand - or use any other measure of recovery time, it could give more precise and detailed insights into recovery dynamics.

The variables used for calculations are derived from literature. However, there is a large amount of research papers on the interaction of economic variables and disaster resilience or outcomes. Therefore, many other variables could be used to recalculate recovery times or even other measurements. For example, the international aid provided by other countries is not observed in this thesis. As the suggestion was that trade openness might correlate with international aid post-disaster there is no variable purely for international aid used in this thesis. Also, the role of climate change and its implications for the disasters happening around the world and the country's preparedness is not considered in this thesis.

The dummy variables for the three years after the disaster could be expanded to more years to explore the long-term recovery effect of the variables, aligning with the suggestion in Chapter 5.4 to investigate longer-term post-disaster effects, particularly for variables like inequality that may have delayed impacts.

By improving the database and implementing other variables into calculations, future research could provide a more comprehensive understanding of the interaction of economic variables and post-disaster recovery.

8. Summary

This thesis tries to find the effect of certain variables on the recovery duration of countries after they were hit by a natural disaster, addressing the research question posed in Chapter 1: how do economic variables influence a country's recovery time after natural disasters? As outlined in Chapters 5.1 and 5.2, the variables were found by exploring literature on the topic of recovery after natural disasters. Afterwards these variables were used in a linear regression model to find the direct effect of each variable on the recovery time of countries after the disaster. The recovery time was calculated as the time in years the GDP of the corresponding country took to regain its pre-disaster level. Following, a panel regression was introduced to find out whether the effects of the variables can be linked to certain years after the disaster. Therefore, dummies were introduced to find a relationship between GDP growth and an interaction between each variable and the dummy for a disaster happening one, two, or three years ago.

The linear regression showed a significant effect of the Gini coefficient on recovery time. One percent increase in the Gini coefficient leads to 6.41 days increase in recovery time. This aligns with findings in the literature (Cappelli et al., 2021), suggesting that higher inequality may hinder efficient resource allocation post-disaster, as unequal countries often have limited insurance coverage and tend to neglect poorer regions in recovery efforts (Sovacool et al., 2018). However, this relationship only holds linear regression (4) with fixed effects on endyear of the disaster and continent at a significance level of 95%, indicating that the effect of inequality may be context-specific or influenced by unobserved factors.

Although expected by the literature, trade volume in percentage of GDP does not have a significant effect on recovery time in these regressions. It could mean that either trade does not influence post-disaster recovery, or that positive effects - such as aid from other trading partners - and negative effects - such as reliance on foreign goods - cancel each other out. It could also mean that these effects are absorbed by some unobserved influences.

As anticipated, GDP growth is significant, as the recovery time is calculated in GDP reaching its pre-disaster level. Therefore, the effect of GDP per capita growth on recovery time must be significant. However, we can see the magnitude: Every one percent growth in GDP per capita leads to a 18.7 to 20.2 day decrease in recovery time.

A one score-point increase in Policy Score - measuring autocratic versus democratic governance from -10 to 10 - results in a decrease of 9.1 to 10.8 days of recovery time. Meaning that more democratic polity systems seem to be better off recovering after a disaster. Democratic systems may respond quicker in providing first aid, tend to be less corrupt, and are more likely to work collaboratively compared to autocratic systems. As for any other variable, it is possible that multiple effects overshadow one another. For example, autocratic systems might be faster in delivering first aid due to less bureaucratic burdens, but this effect then gets overshadowed by other negative effects such as uneven distribution or corruption.

Panel regressions were then introduced which tried to find relationships between the GDP per capita growth rate and dummies indicating if a disaster hit the country one, two or three years ago. The effect of the dummy for Disaster (t-1), a disaster happening one year ago, is not significant for all three regressions. That could indicate that there might be no direct effect of a disaster on GDP per capita growth next year. It could also mean that direct aid programs and rebuilding efforts neutralize the negative effects of the disaster and leave non-significant differences.

Disaster (t-2) is significant and positive for the first and second regression model without the introduction of interactions of the dummy variables with the other variables. This could mean that direct aid programs start working or that the catching-up process begins. For the third year after the disaster happened the effect on GDP per capita growth is insignificant. It is likely that the effects are biased/overshadowed by unobserved effects. The interactions between the economic variables and the dummy variables do not have any significance, indicating no or unobserved effects on the GDP per capita growth post-disaster.

For these time-dependent disaster dummies it is important to note that the disasters are not timed perfectly with the yearly time frames. A disaster happening on the first of January and a disaster on the 31st of December of the same year are included in the same dummy variable.

In conclusion, this thesis contributes to the growing body of literature on disaster recovery by empirically analyzing how specific economic variables influence the time countries take to recover after a disaster hits the country. While the results confirm some existing theories, such as the impact of economic growth and governance on recovery time, other findings - like the not significant effects of trade volume on recovery time - contradict the theory. The panel regressions try to further analyze the dynamic nature of recovery, showing that the effects of disasters evolve over time.

Future research could build on these findings by addressing data limitations, such as more precise timing of disaster events, and by exploring additional factors that may affect recovery, such as international aid dynamics. All in all, the results stress the important impact of inequality and governance on the recovery and resilience of countries hit by natural disasters, highlighting the need for policies that reduce inequality and strengthen democratic institutions to enhance recovery outcomes.

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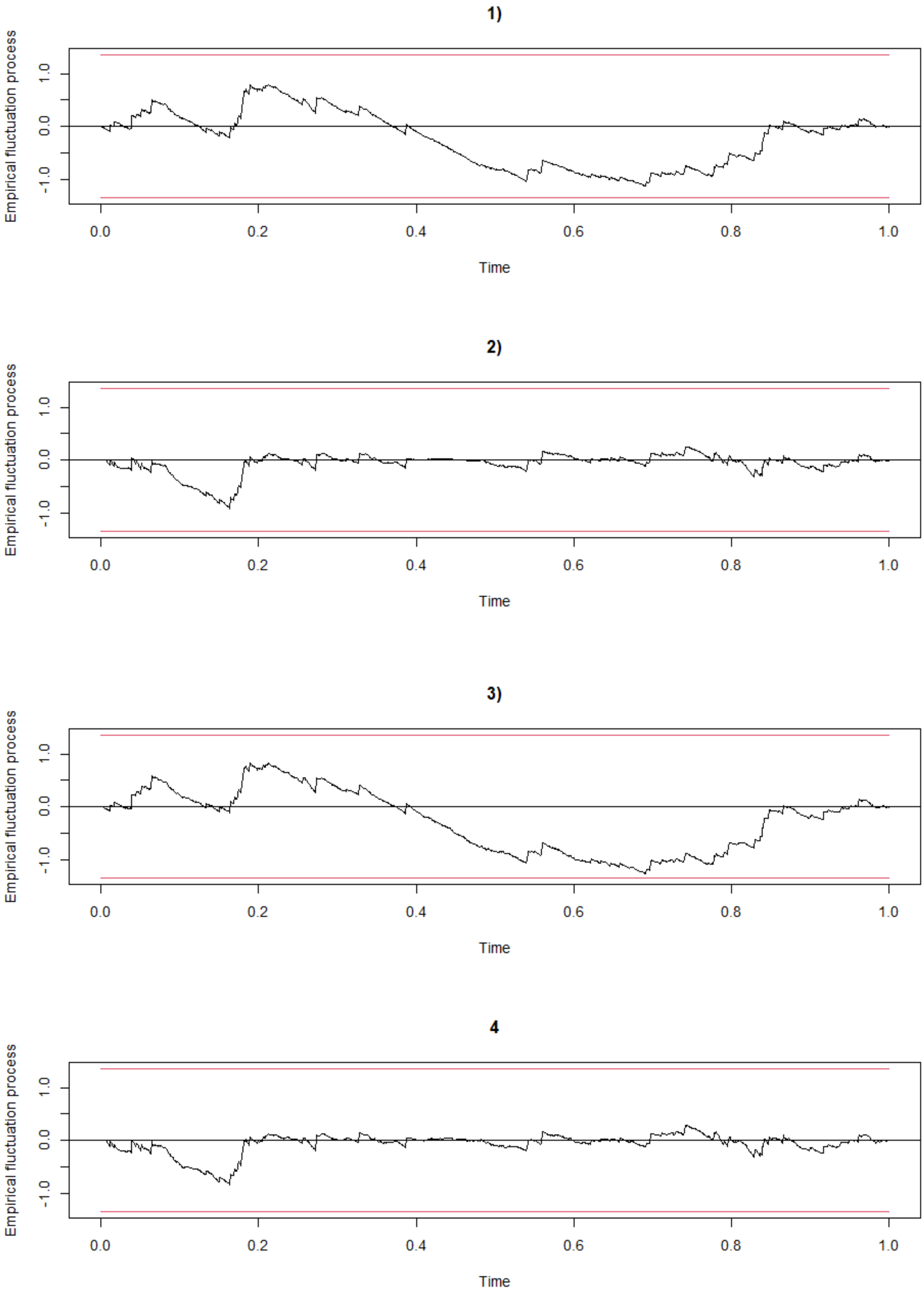
Attachments

Figure 1: CUSUM Test for Structural Stability in Linear Regression Models



Notes: The figure displays CUSUM test plots for Linear Regression models (1) to (4). Plots remaining within the red bounds indicate structural stability of coefficients over time.