SCHOOL OF
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The Effect of Natural Disasters on Economic Growth:

Does Frequency of Disasters Matter?

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Abstract

This paper aims to investigate the effect of natural disasters, with regard to frequency of events, on GDP per capita growth. A panel data regression covering 121 countries between 1960 and 2015 in non-overlapping five-year periods is used. The regression contemplates the size of the agricultural sector in each country and the severity of the disasters. The results show a positive effect on economic growth when two disasters, one moderate and one severe, follow each other within ten years. If a country with a large agricultural sector only experiences one moderate disaster in ten years, the immediate effect is positive, but the effect is negative in the following five years. However, countries that do not have large agricultural sectors do not experience immediate positive effects but negative effects in the following five years. Severe disasters do not show any significance on their own but have positive effects when combined with a moderate disaster. It is concluded that more frequent disasters may lessen the adverse effects on economic growth. Further research is needed to conclude what the different effects stem from, but considering the frequency of events is concluded to be a good path forward.

Keywords: Economic growth, natural disasters, climate change

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1 Introduction

1.1 Background

In recent decades, the number of reported natural disasters has increased substantially (see Figure 1), with scientists predicting that the quantity and magnitude of natural hazards and extreme weather will continue to rise because of climate change (see, for example Hayhoe, 2022, p. 51). Extreme temperatures, storms, droughts, rising sea levels (see, for example Edwards, 2022, p. 122; United Nations, n.d., n.p.), and diseases (see, for example United Nations, n.d., n.p.) are mentioned as increasing hazards causing an upsurge in disasters.

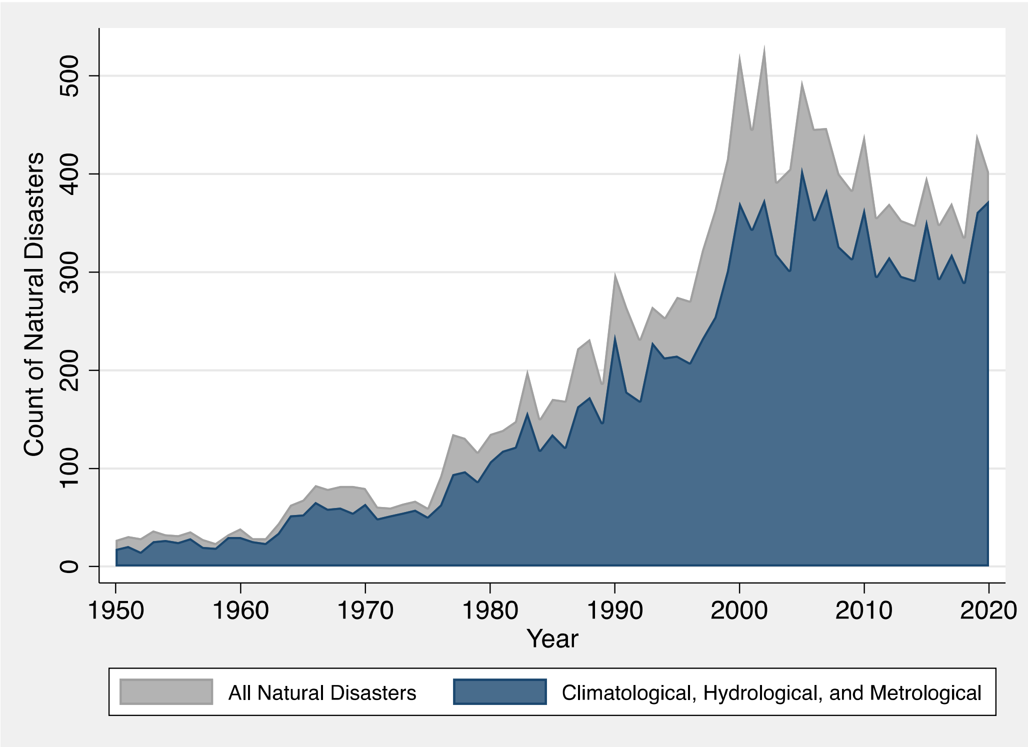

Figure 1 Count of natural disasters between 1950 and 2020. *Source*: Author's calculations based on EM-DAT (2022b).[1]

Economists have attempted to analyse isolated natural disasters' effect on economic growth. Although the results of the studies are conflicting and research investigating the frequency of disasters is scarce. To the author's knowledge, only one study discusses the frequency of events. However, as climate change increases the regularity of disasters, investigating the frequency aspect

[1] Disasters are counted per country, implying that if the same natural disaster affects two countries it is counted twice.

becomes more relevant. Adverse effects of increased frequency could hypothetically result in obstacles to economic development and hinder investments in sustainable technology needed to tackle climate change. Subsequently, information on determinants of economic growth and potential obstacles rooted in climate change should be well-defined to improve the circumstances for policymakers' development strategies to succeed.

1.2 Purpose and Problem Statement

This paper aims to broaden the perspective of which the field is researched and investigate if frequency influences the outcome. The main reason for focusing on the frequency of disasters is that climate change is causing the frequency of events to increase (see, for example Hayhoe, 2022, p. 51). Earlier research aiming to clarify the effect of natural disasters on economic growth tends to focus on single disasters and treat them as isolated events. To the author's knowledge, the frequency of events is only considered in one study. However, it is relevant to investigate if outcomes depend on other disasters within a limited timeframe as the number of events increases. In other words: how does the frequency of natural disasters affect economic growth?

This paper investigates the effects of natural disasters concerning frequency through a panel regression covering the years between 1960 and 2015 for 121 countries.

The second chapter defines natural disasters, specify what subgroups of disasters are relevant to this paper, and assesses economic growth theory and the theoretical effects of natural disasters on growth. The third chapter reviews previous empirical research regarding the relationship between economic growth and natural disasters to investigate what effects one can expect. The fourth chapter describes the methodology and defines the variables included in the model and data sources. The fifth chapter presents the regression diagnostics and the results, which are discussed and analysed in the sixth chapter. The seventh chapter discusses suggestions for further research. Lastly, the eighth chapter summarises and concludes the findings.

2 Natural Disasters and Economic Growth

The following section defines natural disasters and gives an overview of disaster subgroups and types, followed by a discussion of what subgroups this paper covers. After that, economic growth theory and models are presented, followed by a theoretical discussion of what results can be expected regarding the economic impact of frequent natural disasters.

2.1 Definition and Grouping of Natural Disasters

It is essential to understand the difference between a natural hazard and a natural disaster to analyse the impact of disasters on the economy. Natural hazards are, by UNDRR (n.d.-b, n.p.), defined as "[a] process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation". A natural disaster follows when the society hit by a hazard cannot cope with the event, and the hazard causes disruptions to the functioning of the society (UNDRR, n.d.-a, n.p.). The difference is the consequences of the hazard, entailing that harmful consequences that distort the society results in the event also being defined as a disaster. However, an identical hazard can hit a different region and not cause the same disruptions and is hence not defined as a disaster. Hazards are, to some extent, inevitable (Prasad & Francescutti, 2017, p. 215) but disasters are not. However, climate change is increasing the probability of a hazard taking place. Nevertheless, mitigation and adaptation, such as building resilient infrastructure and general disaster preparedness, can help avoid disasters. Countries and regions can thus be at risk for disasters from social, economic, and geographical circumstances.

The Centre for Research on the Epidemiology of Disasters (CRED) collects data about natural disasters in the Emergency Events Database (EM-DAT), which is used in this paper (see section 4.2.3). EM-DAT (2009a, n.p.) defines a natural disaster as a:

> Situation or event, which overwhelms local capacity, necessitating a request to national or international level for external assistance (definition considered in EM-DAT); An unforeseen and often sudden event that causes great damage, destruction and human suffering. Though often caused by nature, disasters can have human origins.

The EM-DAT divides disasters into six disaster subgroups comprising various disaster types (see Figure 2). Scientists expect a surge in hotter temperatures, storms, draughts, health threats, and rising sea levels (see, for example United Nations, n.d., n.p.). According to EM-DAT's (2009b, n.p.) classification, the events expected to upsurge are found in meteorological, hydrological, climatological, and biological disaster subgroups. The disaster subgroups analysed in this paper are meteorological, hydrological, and climatological disasters. However, the database has no documented observations of fog, wave action or glacial lake outbursts for the period.

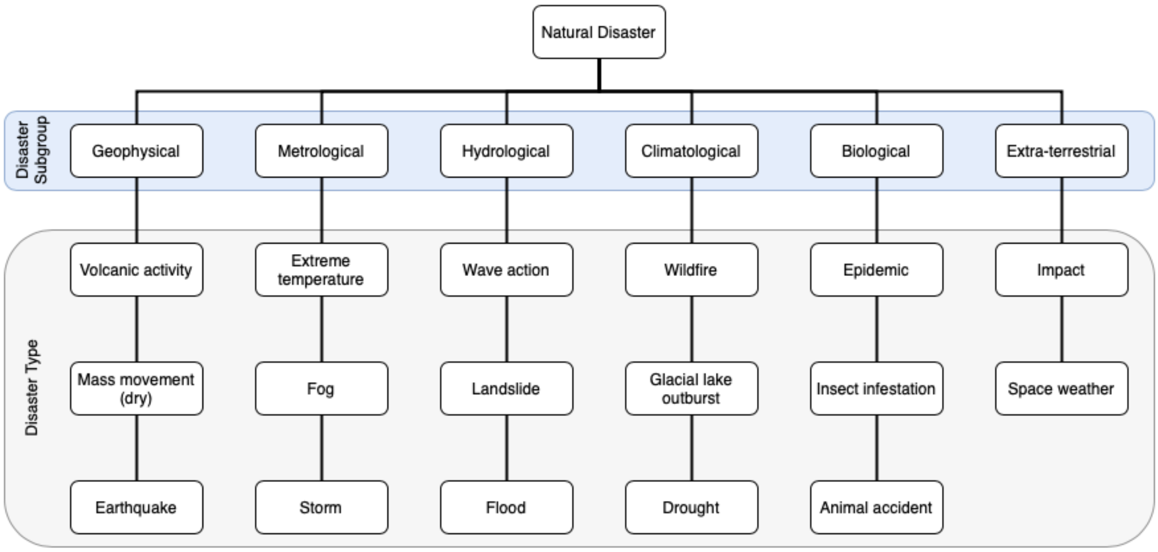

Figure 2 Subgroups and types of natural disasters defined by EM-DAT (2009b, n.p.).

This study does not study biological disasters. Biological disasters differ from meteorological, climatological, and hydrological disasters in some respects. The most significant difference when analysing the recovery after a natural disaster is that the duration of a biological disaster is difficult to define. On EM-DAT's (2009b, n.p.) website malaria is given as an example, and of course, malaria is an ongoing disaster. Consequently, calculating the economic impact and recovery after the disaster is problematic.

2.2 Economic Growth Theory

Robert Solow introduced modern economic growth theory in the 1950s (see, for example Jones & Vollrath, 2013, p. 2). Solow showed the importance of physical capital accumulation and technological development (see, for example Jones & Vollrath, 2013, p. 2). Economists have been examining determinants of sustained growth since and have argued that the role of human capital, ideas and institutions are essential in economic growth, but additional variables can affect the outcome.

Different models highlight distinctive aspects of the economy to be fundamental for growth as well as different processes of accumulating essential assets. For instance, the consensus in multiple models is that technology[2] is a vital resource for growth, but some perceive it as endogenous and some as exogenous (see, for example Jones & Vollrath, 2013, p. 219). Some models, such as the Romer model (see, for example Jones & Vollrath, 2013, p. 100), derive an equilibrium where technology grows at a constant rate, while the Schumpeterian point of view argues for creative destruction and, thus, innovation to occur in steps. Creative destruction entails that new innovation replaces existing inventions (see, for example Aghion, Antonin & Bunel, 2021, pp. 1-5), and is dependent on investment in innovation and argues for technology being cumulative and building on old inventions.

Models tend to have an equilibrium for GDP per capita and its growth rate, where the economy grows at a constant rate. Temporary shocks can move the economy away from equilibrium, but if the equilibrium is unchanged, the growth rate will adjust until the level and growth are back on these paths. Equilibrium can similarly change due to changes in investment or depreciation rates (see, for example Jones & Vollrath, 2013, p. 43), improved institutions and infrastructure, or a changed growth rate in human capital or technology (see, for example Jones & Vollrath, 2013, pp. 219-220) due to, for example, better quality in education. The level of GDP per capita can change its equilibrium alone, or the growth rate can also change.

Thus, the question is how natural disasters affect the determinants of growth and whether these effects are identical for isolated events and higher frequency events.

2.3 Theoretical Effects of Natural Disasters on Economic Growth

Modelling the effect of natural disasters on economic growth can be done in multiple ways, as disasters can affect societies through different channels. The theoretical effects are discussed below, focusing on how disasters are expected to impact the determinants of growth. The determinants of growth that are mainly discussed in literature regarding natural disasters include physical and human capital accumulation, technology, and infrastructure.

[2] Technology is here used as a wide term covering innovations, ideas, and similar.

Models such as the Solow and Romer models do not predict well-defined effects on economic growth of natural disasters. Damage to human and physical capital is expected directly after the disaster. In turn, this might impact productivity, but it is not apparent how nor what it implies for equilibrium in the models.

Some hypotheses argue that the equilibrium will be unchanged as damage done to physical capital does not affect technology (see, for example Barone & Mocetti, 2014, p. 53). According to this reasoning, the economy might experience only a temporary decline in GDP per capita and recover later through an improved growth pace. Others argue for a Schumpeterian effect, implying creative destruction and thus a positive effect on innovation (see, for example Ahlerup, 2013, p. 4; Skidmore & Toya, 2007, p. 665) leading to a higher equilibrium. A similar discussion by Melecky and Raddatz (2011 cited in Ahlerup, 2013, p. 4) mentions that disasters may make people relatively poorer and, in turn, create incentives to work. Ahlerup (2013, p. 4) also highlights that neighbouring regions can experience boosted economic activity when helping an affected area recover after a disaster. Thus, the eventual change in a country's GDP growth is not only dependent on the area directly affected.

Another hypothesis forecasts that regions that frequently experience natural disasters will suffer from damages to physical capital and infrastructure, hindering capital accumulation or disincentivising investment (Skidmore & Toya, 2007, p. 676).[3] Resilient infrastructure, both physical and social, is commonly viewed as a beneficial feature in economic growth and development (see, for example Jones & Vollrath, 2013, p. 167). Moreover, it seems to play an added role in the case of a natural disaster (see, for example Bayoumi, Quayyum & Das, 2021, pp. 12-13; Barone & Mocetti, 2014, p. 65). Thus, the pressure that frequent natural disasters put on the infrastructure in a country can have negative consequences for GDP growth.

As stated above, the models do not predict well-defined effects, and introducing the aspect of frequency causes further complications in modelling the effects. Isolated events can cause incentives to work, and creative destruction, which would imply an increase in growth, and these effects might be similar if disasters become more common than before. An area often experiencing natural disasters might learn how to cope with them and recover quicker, but the

[3] The authors do also discuss potential positive effects on capital accumulation because of natural disasters, similar to the Schumpeterian point of view.

disasters can also cause individuals to move from the area and work as a disincentive to invest. Infrastructure may play an essential part in how the economy handles the disaster. However, disasters can also weaken the infrastructure. An empirical investigation is necessary to examine which contradictory outcomes are more apparent or if other effects follow.

3 Previous Empirical Research

Empirical research focusing on frequency of disasters is seemingly scarce, and to the author's knowledge, only one study discusses the effect of frequency. The literature analyses the effects of singular disasters to a more considerable extent but is still limited. Research has increased in recent years, but the results are highly conflicting. Some studies show positive effects on GDP growth (see, for example Ahlerup, 2013; Skidmore & Toya, 2007), and others negative effects (see, for example Acevedo, 2014; Atsalakis, Bouri & Pasiouras, 2020; Bayoumi et al., 2021). Additionally, a few papers find no significant effect on the economic growth of a natural disaster (see, for example Cavallo, Galiani, Noy & Pantano, 2010).

The following section presents and evaluates the literature discussing the effects of natural disasters on economic growth. Firstly, it discusses the paper contemplating frequency. Secondly, it presents and discusses two classifications of severeness. The third portion will categorise studies after results starting with a discussion of a paper finding positive effects of natural disasters. After this follows three studies that mainly find negative effects and, thereafter, a review of a study showing insignificant results. Two case studies are discussed afterwards to explore regional differences further before summarising the most noteworthy takeaways.

Firstly, Skidmore and Toya (2007, pp. 672-674) use a cross-country ordinary least squares (OLS) regression and calculate the effect of natural disasters, with regard to frequency, on the average growth rate between 1960 and 1990 for 89 countries.[4] The total number of climatological and geological natural disasters occurring in one country is the only indicator of disaster risk utilised, and severeness is hence overlooked. The authors find that, on the one hand, countries that experienced a relatively higher frequency of climatic disasters improve long-term economic growth by stimulating human capital accumulation and technological innovation (Skidmore & Toya, 2007, p. 682). On the other hand, countries experiencing a more significant number of geological disasters experienced a decreased growth rate in GDP per capita (Skidmore & Toya, 2007, p. 682). Although in a case study of Indonesia, Asyahid and Pekerti (2022, p. 502) find that the effects on human capital depend on the initial HDI level, where regions with low HDI levels experience a negative effect on growth and vice versa. Furthermore, Skidmore and Toya

[4] The regression thus utilises 89 observations.

(2007, p. 682) find no effects on the accumulation of physical capital. However, the authors point out that the insurance market possibly plays a significant role in this outcome.

Skidmore and Toya (2007) do not study the time intervals between disasters or the severity of disasters and only consider climatological and geological subgroups. Furthermore, the count of disasters between 1960 and 1990 increased substantially (see Figure 1), and the variable is thus most certainly skewed to the right. The GDP per capita growth rate is more likely to follow a normal distribution; therefore, comparing the mean of GDP per capita growth with the total number of disasters can be misleading. Additionally, the results do not consider changes in severity over time. In other words, the results do not show if the countries had higher or lower growth rates prior to the increased number of events. Additionally, the authors' conclusions conflict with some later empirical research.

Secondly, how the severity of a disaster is classified is slightly inconsistent, varying in the number of severity groups and thresholds for these groups. The most used indicator of severeness is seemingly human suffering, such as deaths and people affected. Some studies use comparative measures such as percentile ranking of fatalities as a share of the population, others use static thresholds, and a few do not consider severity. This inconsistency causes complications in comparing the findings, as some papers conclude that severity is a significant variable.

The percentile classification of disaster severity might be somewhat problematic. The percentile will be inconsistent if natural disasters are assumed to intensify in frequency and magnitude over time. The worst one per cent of natural disasters in the 1950s might differ substantially from the equivalents in the current decade. While the classification may be accurate for one study, implications moving forward might arise. Furthermore, different types of disasters can vary in mortal danger. Subsequently, the authors' choice of disaster types will likely lead to different thresholds.

Thirdly, Ahlerup (2013, pp. 4-5) argues that conflicting results partly stems from studies using different empirical methods and variation in indicators of events. By using the number of events as the only indicator, and thereby not severity, Ahlerup (2013, pp. 15-16) concludes positive effects on economic growth through a linear regression model. Differencing between the subgroup geophysical disasters compared to other natural disasters, the author determines that effects are more significant for geophysical disasters. However, countries hit by whichever natural disasters often experience increased incomes in the short-, medium-, and long run. According to Ahlerup (2013, pp. 14-15), the positive effect of natural disasters only occurs in a democratic developing country if the country receives aid, and neither aid nor natural disasters generate positive effects on their own.

Loayza, Olaberría, Rigolini and Christiaensen (2009, pp. 27-29) argue that using averages while studying the economic impact of natural disasters contributes to inconclusive results. By using different sectors' growth rates as dependent variables in the generalised method of moments (GMM) regressions, the authors find that different sectors are impacted differently, depending on disaster type[5] and severity. Thus, the aggregated effect on economic growth could be inconclusive, even though specific sectors can see positive or negative growth because of a disaster. Furthermore, the study considers severe and moderate disasters, and a disaster is severe if it is in the top ten per cent of disasters studied subject to fatalities as a percentage of the population (Loayza et al., 2009, p. 24).

When utilising GDP per capita growth as the dependent variable, Loayza et al. (2009, pp. 33-34) find a positive statistical significance in the event of floods for all countries and a negative effect of droughts for developing countries. Furthermore, droughts and storms negatively impact the agricultural sector for all countries, but storms and earthquakes positively affect the industrial sector in developing countries. Similarly, moderate floods can result in higher growth rates for the agricultural sector in developing countries (Loayza et al., 2009, p. 20). Although the largest one per cent of disasters never have a positive effect, but the results are sometimes inconclusive (Loayza et al., 2009, p. 28). Additionally, the authors conclude that the negative consequences are more significant for both low-income countries and relatively poor people.

Bayoumi et al. (2021, p. 10) adapt a "growth-at-risk" model using quantile regression investigating the effects of large natural disasters on different quantiles[6] of growth in developing countries. The study differentiates between disaster types in two ways and only considers severe disasters. The first classification uses the one of Fomby, Ikeda and Loayza (2011, p. 415) and is hence different from Loayza et al.'s (2009). The classification is, in short, based on how large a proportion of the

[5] The study considers draughts, floods, earthquakes, and storms.

[6] Quantiles differ from percentiles as quantiles divide the distribution into groups with equal probabilities, and percentiles can have any thresholds and thus unequal probability.

population is either dead or affected (see section 4.2.1 below). The second classification used is a percentile ranking of damages in USD and considers the 90th percentile severe. Bayoumi et al. (2021, pp. 21-24) use GDP per capita growth and investment growth as dependent variables.

Bayoumi et al. (2021) consequently avoid averages in terms of the type of natural disaster, and additionally, by using quantile regression, it is considering extreme tail events. The study does, however, not consider sector growth. Nevertheless, the coefficients are statistically significant in many cases. The authors conclude negative impacts on economic growth in case of any large disaster but minimal effects of droughts. Floodings and storms always have a negative impact, whereas earthquakes positively impact the median, but otherwise negatively. Furthermore, Bayoumi et al. (2021, pp. 12-14) settle that disaster preparedness and fiscal stability significantly lessen the adverse effects.

Another similar approach is the quantile-on-quantile regression used by Atsalakis et al. (2020, p. 85), arguing to take both different quantiles of GDP growth and different quantiles of natural disasters into consideration. As a result, Atsalakis et al. (2020, p. 91) find that different quantiles of growth paths react differently to different quantiles of natural disasters. However, the study finds that the general effect is negative (Atsalakis et al., 2020, p. 106).

A commonly referenced study to argue for insignificant results is the one of Cavallo et al. (2010). Cavallo et al. (2010, p. 15) use percentile ranking to classify natural disaster severeness, similar to Loayza et al. (2009). However, different thresholds are used (75th, 90th, and 99th percentiles instead of only the 90th). Furthermore, the study does not consider different disaster types. The regressions are made through cross-country comparative case studies and use GDP per capita level as the dependent variable. The results only show significance if a political revolution follows a very large disaster (99th percentile). However, Cavallo et al. (2010) find no other effects and do not draw any conclusion about an eventual connection. Ahlerup (2013, p. 10) similarly argues that even though human suffering due to disasters is prominent, it is not clear that it affects enough people and physical capital to impact economic growth unless social or political mechanisms change. Although, in light of the findings of Loayza et al. (2009) and Bayoumi et al. (2021), neither Cavallo et al.'s (2010), Skidmore's and Toya's (2007), nor Ahlerup's (2013) studies differentiate between disaster types which possibly impacts the results.

Economists sometimes argue that the assumption that the entire country has been affected is too strong (Lima & Barbosa, 2018, p. 906) and thus proceed with case studies for specific events and regions. Lima and Barbosa (2018, p. 907) adopt a difference-in-difference model for flash floodings in Brazil and find that GDP per capita decreased by 7.6 per cent the following year in the affected areas. After two years, the GDP per capita level is back to pre-disaster levels (Lima & Barbosa, 2018, p. 920). However, the authors conclude that the agricultural sector is hit substantially harder and therefore takes longer to recover.

Barone and Mocetti (2014, p. 53) investigate earthquakes' impact on regions in Italy by comparing economic patterns over time in regions experiencing an earthquake and regions where no earthquake has appeared. The authors find no significant direct effects, but the later effects heavily depend on institutional quality. Well-managed institutions benefit both resistance and recovery associated with the earthquake (Barone & Mocetti, 2014, p. 65). On the contrary, studying multiple countries, Skidmore and Toya (2007, p. 671) find that earthquakes and other geological disasters negatively correlate with economic growth.

To summarise, the results are highly contradictory. The effects seem to depend on a multitude of factors; however, the discussion of frequency of events is rare. With the literature in mind, frequency can hypothetically impact the results in several ways. For instance, recent natural disasters might prepare specific countries and give them experience, which can cause them to recover more efficiently. The positive relationship found by Skidmore and Toya (2007, p. 664) similarly indicates that the effects might be positive. Although the severity of events seems to have a significant impact when analysing isolated events, and thus including this aspect when investigating frequency could show different results from Skidmore and Toya (2007). Additionally, using panel data instead of cross-country data when analysing the effects and, thus, a larger number of observations could result in a different outcome.

Furthermore, if the disaster hits the agricultural sector substantially harder, as Lima and Barbosa (2018) and Loayza et al. (2009) argue, there is a risk of food shortages which might hurt economic activity depending on the ability to import food. Additionally, the agricultural sector has been shown to require more extended recovery periods, except for the case of moderate floodings. An increase in the occurrence of disasters might thus cause the agricultural sector to decrease its productivity for a prolonged time as it might not have time to recover between events, and this aspect could be beneficial to include when analysing the effects. Moreover, natural disasters might have either a positive or negative impact on human capital. However, if disasters hit lower-income countries, the effects risk being negative.

4 Methodology

There is no clear consensus on what method is more beneficial in the previous research. However, linear models are used to some extent, specifically in the paper mentioning frequency by Skidmore and Toya (2007, p. 672). The model in this paper used to investigate how the frequency of natural disasters affects economic growth is an ordinary least squares regression (equation (1)) for panel data with fixed effects and robust standard errors.

Loayza et al. (2009, pp. 27-29) show that different sectors are impacted differently. Therefore, either analysing sectors separately or investigating countries with similar dominant sectors presumably lessens the risk of conflicting results cancelling the effects. This paper aims to investigate countries' economic growth in case of a natural disaster. Hence, the focus lies on the overall economic growth and not individual sectors or level of GDP per capita.

As mentioned in chapter 3 above, two studies (Lima & Barbosa, 2018, p. 918; Loayza et al., 2009, p. 28) show that the agricultural sector is more sensitive to natural disasters. Furthermore, agriculture is essential for economic development and progress (see, for example Todaro & Smith, 2020, pp. 447-448) and is, at the same time, often a relatively large sector in low-income countries. Considering the sensitivity and importance of the agricultural sector, the most reasonable sector to separate seems to be agriculture. The regression, therefore, takes the size of this sector into account.

$$g_{y_{i,t}} = \beta_0 + \sum \beta_j x_{j,i,t} + \sum \gamma_j ND_{j,i,t} + \sum \eta_j D_{A,i} * x_{j,i,t} + \sum \theta_j D_{A,i} * ND_{j,i,t} + \varepsilon_{i,t} \tag{1}$$

Where $g_{y_{i,t}}$ is GDP per capita growth, $x_{i,t}$ are control variables, $ND_{i,t}$ is a collective name for dummy variables representing natural disasters, and D_A is a dummy variable taking the value one when the agricultural sector is large. Subscripts *i* and *t* denote country and period, respectively.

The regression covers the years between 1960 and 2015, divided into non-overlapping five-year intervals. Consequently, the number of observations is eleven per country, although observations are occasionally missing resulting in the panel being unbalanced for some countries.

In the following sections, the dependent variable, g_y, is identified, followed by the variables of natural disasters, ND, including a severity classification. Thereafter the control variables, x, are selected, and lastly, the definition of a large agricultural sector is stated to identify the interactive variable D_A.

4.1 Dependent Variable

The dependent variable in the regressions is the growth rate in GDP per capita (constant 2015 USD) ($g_{y_{i,t}}$) in non-overlapping five-year periods from 1960 to 2015. The growth rate is calculated with data from the World Development Indicators (WDI) from The World Bank (2022) in the following way:

$$g_{y_{i,t}} = \left(\frac{GDP\ per\ Capita_{i,T+5}}{GDP\ per\ capita_{i,T}}\right)^{1/5} - 1 \tag{2}$$

Where t is the five-year period, T is the starting year of the period, and i is the country.

4.2 Natural Disasters

The variables for natural disasters are estimated to capture the effect that the frequency of events has. The variables take the disaster occurring in the current and previous period into account; thus, every variable covers two five-year periods. The lag of each variable will be included to investigate if there is a delay in effects. Each variable will answer the question "did a natural disaster occur in the previous period?" and "did a disaster occur in the current period?" resulting in different combinations of "yes" and "no". However, if a disaster occurred in the previous period but not in the current period, it only captures a lag of the previous period and will hence be included in the lagged variables. See Figure 3 for a flowchart of the outline of the variables, where the two variables (blue boxes) illustrate different frequencies. Two periods without disasters entail that all dummy variables representing natural disasters take zero value.

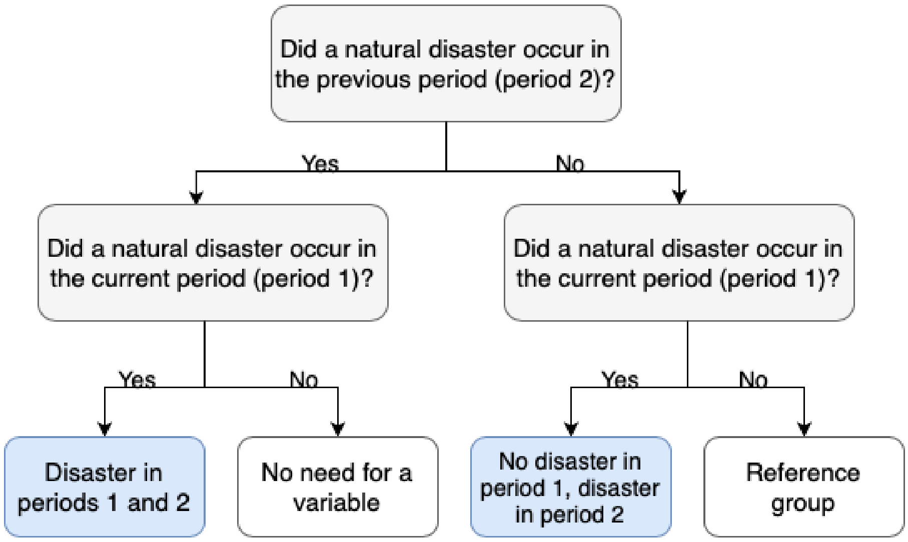

Figure 3 Flow chart of the outline of variables for natural disasters.

The severity (see 4.2.1 below for classification) is the only grouping in terms of disaster characteristics.[7] Consequently, the variables will not only capture if a disaster happened but also if the disaster was moderate or severe. The variables will thus show different combinations of disasters, with respect to frequency and severity, taking place in a limited timeframe. If frequency of events affects the economic impact, the variables are expected to have distinctive effects.

Following Loayza et al. (2009), the regression includes moderate and severe disasters, and more minor disasters are hence overlooked. Disaster types should ideally be separated, but this implies many combinations of different types, which result in a vast number of dummy variables. An extensive number of variables, in turn, leads to the software (Stata) identifying variables as multicollinear as many values are zero. Thus, the regression does not differentiate regarding disaster types, but only severeness. The same problem appears when specifying what year in the period the disaster occurred. Hence no distinction between disasters occurring within the same five-year period exists. Nevertheless, there is a reason for evaluating the general effects of natural disasters with respect to frequency, as research within this area is scarce.

The following sections define the severity classification utilised, present how different dummy variables define disasters depending on the frequency of events and describe the data source of natural disasters.

[7] Disaster subgroups and types are not separated.

4.2.1 Severity of Natural Disasters

When literature considers the severity of a disaster, it tends to have a statistically significant impact (see, for example Loayza et al., 2009, pp. 24-25) on economic growth, and it is thus relevant to contemplate the severity when analysing the significance of frequency of events. As mentioned above, this paper considers moderate and severe disasters. Before specifying the variables for natural disasters, the disasters are defined as either moderate or severe.

Because the definition of natural disasters being reliant on how a society handles a natural hazard (see section 2.1 Definition and Grouping of Natural Disasters), it is expected that measuring the severity can be challenging. Caldera and Wirasinghe (2021, pp. 1534-1535) criticise severity measurements for being ambiguous and propose a universal classification of natural disasters. The authors emphasise that socioeconomic factors, the power and intensity of the hazard, and the country's preparedness contribute to the event's severity (Caldera & Wirasinghe, 2021, p. 1542). The classification suggested utilises damages in monetary measures and human factors, besides qualitative measures (Caldera & Wirasinghe, 2021, p. 1560), but these variables are often missing in historical data. Hence the classification is difficult to apply.

An appropriate measurement must be defined without an applicable universal classification of disaster severity. Previous work regarding economic growth and natural disasters have applied different techniques but are often based on either i) percentile ranking of people passed or ii) Fomby et al.'s (2011) classification, including casualties and people affected as a share of the total population.

Fomby et al. (2011, p. 415) divide the disasters into three groups depending on how large a share of the population either passes or is affected. The total number of fatalities is utilised, together with 30 per cent of total affected. Both variables are documented in EM-DAT (see section 4.2.3 for further description of the data). If the sum of these indicators is larger than 0.01 per cent of the population, the disaster is moderate, see equation (3) (Fomby et al., 2011, p. 415). The disaster is instead severe if the sum exceeds one per cent of the population, see equation (4) (Fomby et al., 2011, p. 415).

$$mod\ intensity_{i,t,j}^{k} \begin{cases} = 1, & if \dfrac{Fatalities_{i,t,j}^{k} + 0.3 \cdot Total\ Affected_{i,t,j}^{k}}{population_{i,t}} > 0.0001 \\ = 0, & otherwise \end{cases} \quad \textbf{(3)}$$

$$sev\ intensity_{i,t,j}^{k} = 1, \quad if \frac{Fatalities_{i,t,j}^{k} + 0.3 \cdot Total\ Affected_{i,t,j}^{k}}{population_{i,t}} > 0.01 \qquad (4)$$
$$= 0, \qquad otherwise$$

The study specifies what type of disaster with variable k, the number of natural disasters with variable j, and then sums the intensity measure with regard to time and country.

This method does not compare different disasters and is thus consistent over time compared to percentile ranking (see discussion above) and is used in this paper.

4.2.2 Natural Disaster Variables

The variables of interest in the regression are the dummy variables representing natural disasters and the frequency with which they occur. The section below thus argues for how frequency is represented. Firstly, clarification of simplifications is stated, and lastly, the variables are constructed.

Several countries in the database experience multiple disasters in one year, and these disasters are added together and viewed as one disaster. Other variables, such as GDP, are measured annually, and thereby separating disasters happening the same year would cause issues regarding the panel regression. Additionally, only the severe disaster is accounted for if a moderate and severe disaster occurs in the same five-year period. Similarly, as the regression utilises dummy variables, the model does not consider the total count of disasters for each period. Easing the latter limitation could be done by adding more dummy variables representing a range of disasters. However, this leads to many dummy variables and thus limits the number of observations. Furthermore, due to the scarcity of research regarding the relationship between disaster frequency and economic growth, the ranges risk being ambiguous.

After the summation of disasters occurring in one year, each disaster has been defined as moderate or severe. As a result, approximately 551 of 1,596 natural disasters in the dataset are severe, and 697 are moderate (34.5 and 43.7 per cent, respectively).

Furthermore, each disaster either appears after a period with no disaster, a moderate disaster, or a severe disaster. The different combinations of disasters that can occur in two periods[8] are illustrated in the flow chart in Figure 4, which is an extension of Figure 3. The blue boxes represent the dummy variables.

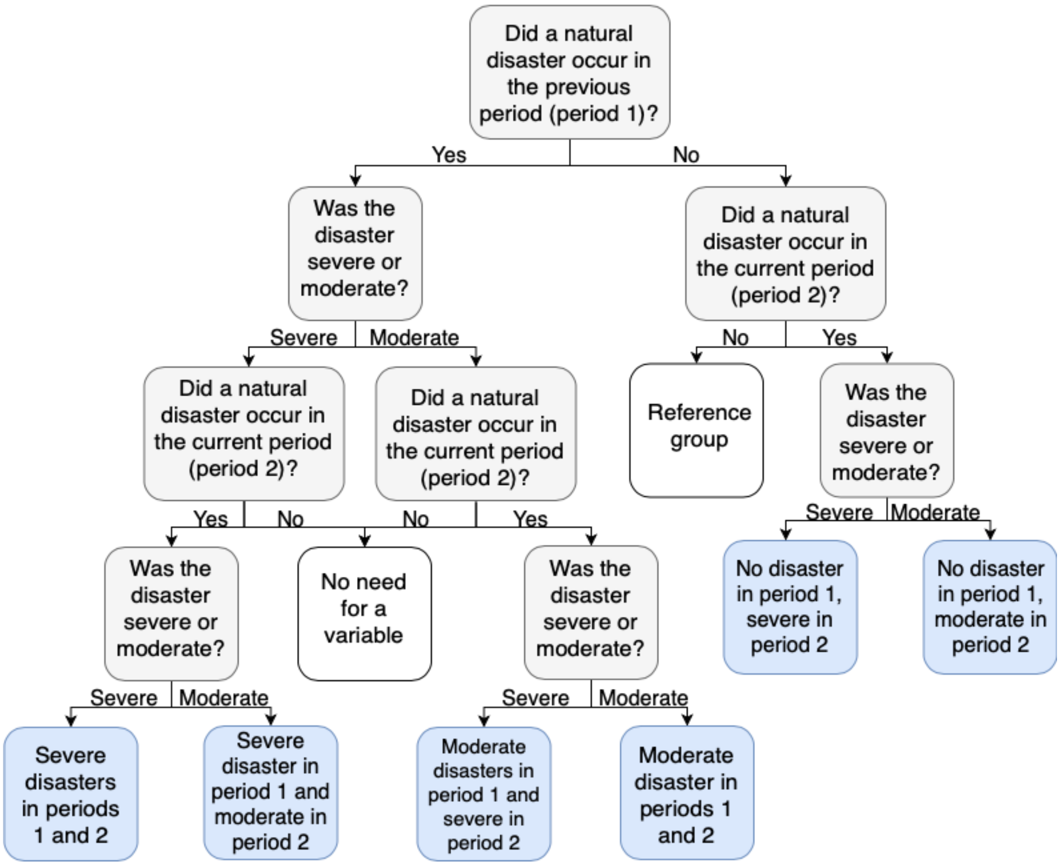

Figure 4 Flow chart of variables representing natural disasters.

According to the definitions above, the following six dummy variables are thus defined,

i) Severe disasters in both the previous and current periods (Severe disasters in periods 1 and 2),

ii) Severe disaster in the previous period, followed by a moderate disaster in the current period (Severe disaster in period 1 and moderate disaster in period 2),

iii) Moderate disaster in the previous period, followed by a severe disaster in the current period (Moderate disaster in period 1 and severe in period 2),

iv) Moderate disasters in both the previous and current periods (Moderate disasters in periods 1 and 2),

[8] As mentioned above, when no disaster hits the country in the current period the event is captured in the lagged variables and there is therefore no need for another variable representing this sequence of events.

v) No disaster in the previous period and a severe disaster in the current period (No disaster in period 1, severe in period 2),

vi) No disaster in the previous period and a moderate disaster in the current period (No disaster in period 1, moderate in period 2).

The regression includes the corresponding lagged variable of all dummies to determine if there is a delay in the effects, resulting in twelve dummy variables explaining natural disasters.

If the variables representing different frequencies are significantly different, it follows that frequency of disasters could play a role in investigating natural disasters' effect on economic growth. The two variables to the far right in Figure 4 (No disaster in period 1, severe in period 2, and No disaster in period 1, moderate in period 2) represent a lower frequency of events than the remaining variables. If the two former variables have negative coefficients while the remaining variables have positive coefficients, it shows that a higher frequency of events positively affects growth and vice versa.

Furthermore, some variables indicate similar things in the current (past) period, only with different events leading up to (following) it. For example, the variable representing a severe disaster in the previous period, followed by a moderate disaster in the current period, effectively represents a lagged severe disaster when a moderate disaster follows it. The single moderate disaster represents a similar situation, only that the severe disaster did not occur.

4.2.3 Data Source

The data describing the events of natural disasters is retrieved from the Emergency Events Database (EM-DAT) (2022b) created by the Centre for Research on the Epidemiology of Disasters (CRED). EM-DAT covers worldwide disasters from 1900 to current time, and researchers use it widely (see, for example Acevedo, 2014; Bayoumi et al., 2021; Cavallo et al., 2010; Fomby et al., 2011; Loayza et al., 2009). Every event in the database fulfils at least one of the following criteria (EM-DAT, 2022a, n.p.):

i) ten or more people are declared dead,

ii) 100 or more people reported affected/injured/homeless, or

iii) the country declares a state of emergency or appeals for international assistance.

CRED collects data from various organisations (EM-DAT, 2022a), such as the United Nations (UN), national governments, non-governmental organisations, and insurance companies[9], implying that methods of collecting data can differ. Furthermore, CRED only registers disasters if at least two sources report the statistics (EM-DAT, 2022a).

Different types of data are collected by CRED, differing between events. Geographical information is available for all events, to varying detail. The number of casualties, injured, affected (needing urgent help after the disaster), and homeless because of the event measures the human impact. The dataset then sums the number of injured, affected, and homeless to a variable called *Total Affected*, which should not be confused with *Number Affected,* which is included in the former variable. Additionally, measurements of economic impact and sectorial impacts are available for some events.[10]

4.3 Control Variables

The control variables included in the regression are anticipated to capture economic activity likely to affect the growth rate and, when excluded, could alter the coefficient of natural disasters.

According to neoclassical growth theory, the growth rates in human and physical capital are expected to significantly impact the accumulation of GDP per capita (see, for example Jones & Vollrath, 2013, p. 49) and are hence included in the regression. Moreover, Acevedo (2014, pp. 12, 22) finds that the debt of the country should be included, as the debt sometimes builds up in the recovery phase, and hence excluding the variable exaggerates the negative impact of a disaster.

Thus, the model includes the following independent control variables:

i) The growth rate of gross fixed capital formation (constant 2015 USD) (g_k), calculated for five-year periods, similar to equation (2), from the WDI (The World Bank, 2022). The World Bank (n.d., n.p.) includes investments in the public and private sectors in this measurement. This variable is expected to have a positive effect on the dependent variable.

[9] See https://public.emdat.be/about for full list of sources.

[10] See https://public.emdat.be/about for list of all variables.

ii) The growth rate of human capital (g_{hc}), which is expected to positively affect the GDP per capita growth, calculated for five-year periods, similar to equation (2), from Penn World Table's (PWT, version 10) (Feenstra, Inklaar & Timmer, 2021) index variable *hc*. The index takes the average years of schooling and quality of education (Feenstra, Inklaar & Timmer, n.d., p. 1) into consideration.

iii) The logarithm of debt as a percentage of GDP averaged over five-year periods from the International Monetary Fund (2022a). IMF defines the variable as the gross debt of both the public and private non-financial sectors (International Monetary Fund, 2022b). The logarithm makes the variable normally distributed. The debt is expected to have a negative effect when the debt initially is large. However, for relatively small debts, the effect might be positive.

When controlling if the model is specified correctly with the Ramsey RESET test, the results indicate non-linearity. Hence the square of g_k and the debt are included. Using the squares of the variables implies that investing in physical capital and changes in debt are not assumed to have constant returns to scale. Through centralising the variables by subtracting the mean (see equation (5)) before squaring, the interpretability of the coefficients increases (Shieh, 2011, p. 472) as it generates practical reference values.

$$Centralised\ Variable = Variable_{i,t} - \overline{Variable} \quad \textbf{(5)}$$

When the actual value is equal to the mean of the dataset, the centralised variable takes zero, and thus the intercept will have fundamental meaning (Shieh, 2011, p. 472).

4.4 Size of Agricultural Sector

The regression includes each variable defined above for all countries in the dataset. Nevertheless, literature (see chapter 3) shows that the agricultural sector is more sensitive to natural disasters. Thereby, separating countries with large agricultural sectors may improve the fit of the model, in addition to showing different effects depending on if the agricultural sector is large. Furthermore, Skidmore and Toya (2007) did not consider dominant sectors when evaluating the relationship between frequency of disasters and GDP per capita growth. Hence giving attention to a sensitive sector can further help understand the patterns.

A dummy variable taking the value of one when the agricultural sector is considered large is thus defined. The variable utilises the average value-added as a percentage of GDP over the entire period. However, the measure and corresponding threshold for determining whether a sector is large or dominant, is not clear and can presumably be calculated in several ways. The WDI data set (The World Bank, 2022) lists employment in, international trade, and value-added as a percentage of GDP for different sectors. Observing trade patterns can be misleading since agriculture is substantially protected in relatively wealthy countries causing disturbances in international trade patterns (Boysen, Jensen & Matthews, 2015, p. 377). Ideally, the measurement would use employment and value-added to determine sector size to include both economic impact on a national level and the impact of the population's ability to work. Unfortunately, employment share in agriculture, forestry, and fishing is missing over 500 more values than the variable for value-added through the same sectors and is therefore not used.

The average value added as a percentage of GDP is used to avoid inconsistency in countries with large agricultural sectors. Furthermore, utilising the sector's importance over time is expected to disregard shocks in sectors that can temporarily influence sector share. The 75th and 90th percentiles of this average, 23 and 33 per cent, respectively, are then utilised as two different thresholds for a large agricultural sector (see Appendix A for a list of countries and the corresponding size of the agricultural sector). Two different regressions are made using the different thresholds, and afterwards, the adjusted R-squared values are compared to decide what thresholds result in a better fit. The variable is included as an interactive variable and multiplied with all variables defined in this chapter (D_A in equation (1)). Every variable is thus included twice for countries with large agricultural sectors and once for the remaining countries. If variables multiplied with the interactive term are significant, a statistical difference between the country groups exists.

5 Results

The following chapter examines the regression and its result. Firstly, the regression diagnostics are discussed, and lastly, the results are presented.

5.1 Regression Diagnostics

Before presenting the results, one needs to investigate whether the inference is correct, unbiased, efficient, and consistent. Thus, variables are tested for the presence of unit-roots and multicollinearity. The error terms are then examined to control for random effects, heteroscedasticity, distribution, and potential correlation to each other. After that, a test for misspecification is performed, followed by a robustness check. The eight different diagnostic tests are presented below.

5.1.1 Unit-Roots and Cointegration

Variables in economics are occasionally non-stationary, which can cause problems with inference (Westerlund, 2006, p. 205). Testing for non-stationarity through unit-roots with the Fisher Type Unit-Root Test based on the Augmented Dickey-Fuller Test in Stata indicates stationarity in the panel on a one per cent significance level for all variables. Thus, the data can also be concluded not to be cointegrated (Westerlund, 2006, p. 209).

5.1.2 Multicollinearity

If variables depend on each other and cause multicollinearity, estimating the coefficients may become problematic (Westerlund, 2006, pp. 159-160). Westerlund explains that, as a rule of thumb, two variables should not have a correlation higher than 0.8 in absolute terms. The variables in the dataset pass this test and are therefore considered not multicollinear.

5.1.3 Test for Random Effects

A Hausman test for random effects is utilised to test whether the individual-specific effects are correlated with the independent variables. If the error terms are correlated with the independent variables, one has to use a fixed effect model to avoid bias and inconsistency (Baltagi, 2021, p. 377). The test shows that the null hypothesis (random effects) can be rejected, and fixed effects are thus utilised.

5.1.4 Heteroscedasticity

The error terms in the regressions must have constant variance, i.e., be homoscedastic. Violating this assumption results in the t-statistics reported being biased and hence the regression not being efficient (Baltagi, 2021, pp. 116-119). Testing for heteroscedasticity through the White procedure shows that the error terms are indeed heteroscedastic. To avoid biased t-statistics robust standard errors are being used.

5.1.5 Distribution of Error Terms

Testing if the residuals in the regression follow a normal distribution through a skewness and kurtosis test for normality in Stata shows that the residuals are not normally distributed. However, since the number of observations is high (833), the residuals are assumed to follow the normal distribution.

5.1.6 Autocorrelation

The error terms must not be correlated across time, causing autocorrelation. Autocorrelation causes similar problems as heteroscedasticity (Baltagi, 2021, pp. 131-133). However, the error terms are not autocorrelated in the regressions when tested with the Breusch-Godfrey Test.

5.1.7 Test for Misspecification

To test if the model is correctly specified, a Ramsey RESET Test for misspecification is performed. The fitted values in the second, third, and fourth power as independent variables do not explain GDP per capita growth when the square of capital per capita and the logarithm of debt are included and thus pass the test (Baltagi, 2021, p. 230) when robust standard errors are being used.

5.1.8 Robustness Check

A country's ability to attract foreign investment and technology transfers has been shown to impact economic growth (see, for example Jones & Vollrath, 2013, pp. 148-149, 164). A measurement for openness has hence been included in the regression to investigate whether these effects alter the results. However, the variable does not show significance with a p-value of 0.866 and does not improve the measure of fit and is thereby excluded.

Furthermore, removing groups of variables representing natural disasters based on degrees of significance from the regression does not result in different quality coefficients. The model is thus considered robust.

5.2 Regression Results

The regression results are presented in Table 1. Variables for natural disasters show different combinations of natural disasters occurring in the previous and current periods concerning severity. If the frequency of disasters impacts the outcome, the coefficients of the different variables are expected to vary.

The regression result defines the agricultural sector as large in countries where it, on average, takes up more than 23 per cent of the value added of GDP (75^{th} percentile). A regression defining the agricultural sector as large when it is larger than 33 per cent (90^{th} percentile) was made but had a lower adjusted R-squared and similar coefficients and is therefore not analysed further.

A dummy variable for the agricultural sector size is included as an interactive variable. The interactive variable is presented below its corresponding non-interactive variable. Thus, odd row numbers consider the entire dataset, and even row numbers consider countries with a large agricultural sector.

Table 1 Regression results

Row		Coefficient	p-value	
1	Real Capital, Growth (g_k)	0.23	0.000	***
2	D_A · Real Capital, Growth ($D_A \cdot g_k$)	-0.165	0.000	***
3	Real Capital, Growth Squared (g_k^2)	-0.342	0.009	***
4	D_A · Real Capital, Growth Squared ($D_A \cdot g_k^2$)	0.295	0.055	*
5	Human Capital, Growth (g_{hc})	0.021	0.887	
6	D_A · Human Capital, Growth ($D_A \cdot g_{hc}$)	0.289	0.201	
7	log of Debt	-0.01	0.000	***
8	D_A · log of Debt	-0.001	0.840	
9	log of Debt Squared	-0.001	0.000	***
10	D_A · log of Debt Squared	-0.003	0.392	
11	Severe Disaster Periods 1 & 2	0.004	0.126	
12	D_A · Severe Disaster Periods 1 & 2	0.003	0.541	
13	Moderate Disaster Periods 1 & 2	0.001	0.412	
14	D_A · Moderate Disaster Periods 1 & 2	0.008	0.114	
15	Moderate Disaster Period 1 & Severe Period 2	-0.001	0.736	
16	D_A · Moderate Disaster Period 1 & Severe Period 2	0.004	0.483	
17	Severe Disaster Period 1 & Moderate Period 2	0.002	0.409	
18	D_A · Severe Disaster Period 1 & Moderate Period 2	0.003	0.569	
19	No Disaster Period 1, Severe Period 2	0.001	0.835	
20	D_A · No Disaster Period 1, Severe Period 2	-0.006	0.489	
21	No Disaster Period 1, Moderate Period 2	-0.004	0.192	
22	D_A · No Disaster Period 1, Moderate Period 2	0.013	0.045	**
23	L Severe Disaster period 1 & 2	0.004	0.174	
24	D_A · L Severe Disaster Periods 1 & 2	0	0.981	
25	L Moderate Disaster Periods 1 & 2	-0.002	0.353	
26	D_A · L Moderate Disaster Periods 1 & 2	0.008	0.171	
27	L Moderate Disaster Period 1 & Severe Period 2	0.009	0.009	***
28	D_A · L Moderate Disaster Period 1 & Severe Period 2	-0.001	0.902	
29	L Severe Disaster Period 1 & Moderate Period 2	0.004	0.074	*
30	D_A · L Severe Disaster Period 1 & Moderate Period 2	0.011	0.015	**
31	L No Disaster Period 1, Severe Period 2	-0.004	0.438	
32	D_A · L No Disaster Period 1, Severe Period 2	-0.008	0.334	
33	L No Disaster Period 1, Moderate Period 2	-0.006	0.004	***
34	D_A · L No Disaster Period 1, Moderate Period 2	-0.002	0.738	
35	Intercept	0.024	0.000	***
	Number of Observations	833		
	Number of Countries	121		
	R Squared	0.4632		
	Adjusted R Squared	0.4403		

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Note: The dependent variable is GDP per capita growth. Period 1 indicates the previous five-year period, and period 2 is the current five-year period. D_A is an interactive variable (see equation (1)) indicating an agricultural sector larger than 23 per cent of value added of GDP, which includes 30 countries (see Appendix A for a complete list). L indicates that the variable is lagged.

5.2.1 Natural Disasters

Few variables for natural disasters show significance, but this comes as no surprise considering previous research. Of the variables comprising all countries, only lagged variables show significance. These include no disaster in period one but a moderate disaster in period two (see row 33), a moderate disaster in period one followed by a severe in period two (see row 27), and the variable representing the events occurring in the opposite order (see row 29).

However, the lag of a severe disaster in period one and a moderate disaster in period two (row 29) only shows significance on a ten per cent level for all countries with a coefficient of 0.004. For countries with a large agricultural sector (row 30), this coefficient is 0.011 on a five per cent significance level. The positive effects are thus significantly more prominent for the latter country group, regardless of whether the coefficient is considered insignificant for the larger country group.

The lag of both no disaster in period one but a moderate disaster in period two (row 33) and a moderate disaster in period one and a severe in period two (row 27) show significance on a one per cent level, with no difference for countries with a large agricultural sector. Furthermore, the coefficients for the different combinations are different, and the most noteworthy dissimilarity is that a single moderate disaster (row 33) has a negative coefficient (-0.006) and a moderate disaster followed by a severe disaster (row 27) has a positive one (0.009). The latter implies that a lagged severe disaster has a positive impact on economic growth if it is following a moderate disaster, but the former suggests that a lagged moderate disaster has a negative impact. The result differs from most previous research in that authors who find positive impacts of severe disasters do not tend to find negative impacts of moderate disasters.

Other instances also stand out from the literature. On the one hand, a moderate disaster followed by a severe disaster (row 15) does not show any significance when it is not lagged, essentially capturing that a lagged moderate disaster and a non-lagged severe disaster, on average, have no impact. On the other hand, a single lagged moderate disaster (row 33) has a coefficient of -0.006. Similarly, the lagged variable of a severe disaster followed by a moderate disaster (row 29) shows significance on a ten per cent level but a coefficient of 0.004. All three variables just mentioned include a lagged moderate disaster but show different coefficients and even different signs on the coefficients. One cannot interpret from the regression results if the coefficients are significantly different from each other, but the results indicate that they might be.

The adverse effects might lessen in combination with a severe disaster, except for the variable for countries with a large agricultural sector representing no disaster in period one and a moderate disaster in period two with a coefficient of 0.013 (row 22).

To summarise, the most meaningful result is that a lagged single moderate disaster is the only natural disaster with a negative coefficient for all countries. This result implies that the effects are more adverse for infrequent moderate disasters than for frequent ones. When two disasters with different degrees of severity (one moderate and one severe) follow each other, the effect on economic growth is positive, which highlights the difference. However, two moderate (or severe) disasters following each other have no significant effect on economic growth. The difference in the effects of the variables suggests that a moderate disaster negatively impacts growth unless the country experiences another disaster within a limited time frame.

Another result that stands out is the positive effects experienced only by countries with large agricultural sectors. The results indicate that a single moderate disaster entails immediate positive effects for countries with large agricultural sectors, but the growth rate then slows down to become negative in the following period. Additionally, the coefficient of the lag of a severe disaster followed by a moderate disaster is greater for countries with large agricultural sectors, implying a higher growth rate in GDP per capita.

5.2.2 Control Variables

Growth in human capital does not show any significance, which might stem from the difficulty of measuring human capital.

The squared variables have two coefficients describing the relationship with GDP per capita growth. The two coefficients should be interpreted as a pair and viewed as a quadratic function, such as $y = ax + bx^2$, where a and b are the two coefficients. The effect will thus change depending on the value of the variable x. If b is negative, the relationship has the shape of an inverted U and vice versa. Taking derivatives and solving for zero will show the turning point.

The regression shows the relationship between growth in GDP per capita and capital per capita to be $g_y = 0.23g_k - 0.342g_k^2$ (rows 1 and 3) for all countries, indicating a relationship with an inverse U shape. Note that g_k is centralised and consequently takes the value zero when the actual value is the mean of the entire dataset. The mean is approximately 4.72 per cent, which implies that if the growth rate in capital is less than 4.72 per cent, the effect will be negative. However, the intercept (row 35) also captures the effects (Enders & Tofighi, 2007, p. 127), suggesting a positive effect of 0.024 when all variables take the value of zero.

Taking derivatives and solving for zero show the maximum effect to take place when g_k has a value of approximately 0.34 (0.3872 when adding the mean). This relationship implies that a more significant growth rate in capital corresponds to a larger effect, although increasing at a diminishing rate. However, if the agricultural sector is more than 23 per cent of the value added to GDP, the relationship is $g_y = 0.065g_k - 0.342g_k^2$ (row 2) if one disregards the second power of the growth in capital per capita (row 4) which is only significant on a ten per cent significance level. Including the latter would change the second term to $-0.047g_k^2$. Either way, the effect is more negligible for countries with a large agricultural sector, but the effect might change at a slower pace with respect to the size of g_k.

The coefficient of the natural logarithm debt (rows 7 and 9) and growth rate in GDP per capita shows a negative relationship according to equation (6).

$$g_y = -0.01 * log(debt) - 0.001 * (\log(debt))^2 \quad \textbf{(6)}$$

There is no statistical difference for countries with a large agricultural sector (rows 8 and 10). Similarly to the capital per capita growth, the log of the debt variable is zero when the debt equals the size of the mean, approximately 42 per cent of GDP. This relationship, in turn, means that for debts less than 42 per cent of GDP, a one per cent increase will have a positive effect, and vice versa. The effect will change depending on the size of the debt at an increasing rate. For a debt larger than 42 per cent, the effect will be more significant, in absolute terms, the larger the debt. The coefficient is divided by 100 to show the effect of a one per cent change in the debt.

6 Analysis and Discussion

The results above show that some coefficients representing different frequencies of events with regard to severity are different, although a majority of the variables are statistically insignificant. Additionally, countries with large agricultural sectors sometimes experience increased positive effects on GDP per capita growth. The following section will compare the results to previous research. After that, with the help of the existing literature, insignificant results and complications of the model will be discussed. A short discussion concerning severeness classification is then made before summarising.

The results are in line with the positive effects regarding frequent climatological events Skidmore and Toya (2007) find, which is the only study considering frequency to the author's knowledge. Nevertheless, the study in this paper includes more observations[11] and subgroups than Skidmore and Toya (2007) and additionally shows that single moderate disasters have adverse effects. Similarly, Skidmore and Toya (2007) do not consider the severity of disasters but only the count of climatological events. However, the results above suggest that frequent severe disasters may not benefit economic growth. Moreover, Skidmore and Toya (2007) do not take the size of the agricultural sector into contemplation.

Loayza et al. (2009) and Lima and Barbosa (2018) do not investigate the effect of frequency but consider the agricultural sector. Both studies find that the agricultural sector tends to be more sensitive. The only exception is moderate flooding, which according to Loayza et al. (2009, p. 20), sometimes results in positive effects on the agricultural sector. The results above do not signal additional sensitivity for countries with larger agricultural sectors. On the contrary, the countries with large agricultural sectors experience increased growth rates compared to the other countries.

Due to this paper not differencing between disaster types, different outcomes in the two country groups may be affected by different disaster types hitting the areas and contributing to the insignificant result. Floodings make up approximately 44 per cent of moderate disasters in the dataset. The positive effect of moderate floodings found by Loayza et al. (2009) might hence

[11] Skidmore and Toya (2007) use 89 observations, compared to 833 observations in the study in this paper (see Table 1).

explain why differences between country groups and significance, in general, seem to occur only when moderate disasters are included in the variable.

It should be noted that the distribution of disaster types and where they occur might change. Similarly, living conditions are changing, and Lustgarten (2022, pp. 166-167) points out that the land too hot and dry for civilisation is estimated to grow from one to 19 per cent by 2070. The author clarifies that scientists expect these changes to cause the number of climate refugees to surge, along with the extinction of animals, pollution in water and air, et cetera. However, the intention is not to model the future economic impacts of climate change and should not be interpreted that way. Thus, applying the results to what the future might entail is problematic.

Furthermore, insignificant results are not interpreted as the disaster in question has no effect; on average, the effect is insignificant for the countries in the sample. Of course, the effects could be insignificant, and the significant results might be effects of social reform, aid, or similar, as Ahlerup (2013, pp. 10, 14-15) argues (see discussion above). Nonetheless, since significance exists in some cases, there is reason to believe that further investigation of the frequency of disasters is a good path forward.

Moreover, the frequency of disasters in this study is simplified as it does not specify what year they occurred or how many disasters are in the period. From this follows that two disasters can occur with one or nine years in between them and be represented with the same dummy variable. Likewise, two periods with one disaster each year have the same dummy variable, assuming that the severity is the same. If one hypothesises that frequent natural disasters put pressure on infrastructure, these three scenarios would likely result in different outcomes. Comparably, one cannot interpret from the results if specific types of disasters are more likely to occur in pairs, especially if the effects are different for different combinations of disasters. These aspects contribute to the uncertainty of the model.

Considering previous research, country-specific characteristics are also probable contributors to how a country is affected by a natural disaster. However, these individual effects can be hard to measure but are assumed to be accounted for in the (fixed effects) error terms. Nevertheless, the economic impact is affected by social and qualitative variables that might change drastically over time, uncorrelated to natural disasters and climate change. Policies, education, income distribution, and general social stability in the country are just a few examples of variables that, according to literature, seem to play an important role – but can either change quickly or vary substantially within the country. Including more control variables could potentially increase the fit of the model but implies a risk of making the coefficients biased if data is only available for countries with certain characteristics (see, for example Ahlerup, 2013, p. 6).

Furthermore, a universal severity classification of natural disasters would presumably benefit economists' ability to compare research and build upon each other's results. Although, due to limitations in historical data, the measurement will most likely have to be based on fatalities and the number of people affected to be applicable in growth theory.

Although the current climate debate and countries exposed to natural disasters could benefit from an answer to what natural disasters' effect on economic growth is, research shows that general conclusions are sensitive to multiple factors. Methods and data, country-specific characteristics, type of disaster, and magnitude seemingly affect the results. Inconclusive or conflicting results might be unsatisfactory, but this does not mean that the impacts will be the same when the frequency and magnitude of disasters increase, nor does it mean that the impact on human suffering is insignificant.

To summarise, the results indicate that frequency is an aspect to consider moving forward, as coefficients sometimes vary depending on what combination of disasters occurs. Nevertheless, the results are not assumed to reflect the whole picture of the effects. Additional research is needed to ensure the effects of frequent natural disasters and why they occur.

7 Suggestions for Further Research

As discussed, this paper aims to investigate how the frequency of natural disasters (climatological, meteorological, and hydrological disasters) affect economic growth, and the general conclusion is that it might have an impact. Although, the model is limited, and further research is thus necessary to draw concrete conclusions.

Further research can be done in a variety of ways. It could be interesting to incorporate frequency in more advanced and specific models, such as methods to split the data into specific combinations of disaster types. One could, for example, choose only to include the two or three most frequent disaster types in the regression to avoid multicollinearity. Easing the assumptions of linear effects of natural disasters could likewise improve the fit.

The severity classification used in this paper only divides the disasters into three groups. A disaster that affects one per cent of the population is subsequently put in the same bracket as a disaster that affects ten per cent of the population. However, these disasters can have fundamentally different effects on the economy. One possible solution could be to exclude outliers or introduce more severity groups.

Even though country-specific effects are assumed to be captured in the error terms, it could be of policymakers' interest to know what decreases the likelihood of adverse effects. Natural disasters can affect isolated regions, and differences in local governments and levels of HDI can cause the effects to vary within the same country, similar to Barone's and Mocetti's (2014) and Asyahid's and Pekerti's (2022) findings in Italy and Indonesia, respectively (discussed in section 3). Thus, country- and region-specific research could further explain why the differences exist and investigate the characteristics needed for the positive effect to occur. Additionally, different sectors are affected differently, and taking more sectors into account could be beneficial.

8 Conclusions

Natural disasters are expected to increase and modifying a model to predict what consequences this has for economic growth seems like a plausible area to research. However, research regarding the effects of natural disasters taking the frequency of events into account is scarce. To the author's knowledge, only one study considers the aspect of frequency. Furthermore, the literature treating natural disasters as isolated events concludes conflicting effects. This paper thus aims to investigate how frequency of events impacts the effects natural disasters have on growth through a linear panel regression. Natural disasters, defined as either severe or moderate, are analysed regarding frequency and the combination of disasters. The regression separates countries with large agricultural sectors, with an interactive term, to determine if the outcomes are different depending on the size of this sector, as the literature suggests this might be the case.

The results indicate that if the country experiences a disaster in the past five-year period, followed by a disaster in the current five-year period, the effect on economic growth is more likely to be positive. Isolated moderate disasters have adverse effects, while the combination of one moderate and one severe disaster have positive effects. However, two moderate (or severe) disasters following each other show no significant effects. Additionally, countries with large agricultural sectors experience immediate positive effects in events of isolated moderate disasters. However, a single moderate disaster has adverse effects in the following five-year period for all countries. It is not sure where these effects stem from, but they can result from moderate floods, sometimes benefiting the agricultural sector, according to literature.

Most of the variables representing natural disasters in the regression show no significance, which according to literature, can be the case when no social reforms take place. Contradictory results from literature imply that conclusions seem challenging to derive and that the future is inherently unpredictable, especially when human factors can make outcomes differ substantially. Kay and King (2021, p. xxii) state that "the proper response to radical uncertainty is not to redouble our efforts to predict an unknowable future, but to develop strategies that are robust and resilient to events which we cannot anticipate."

Conclusively, the frequency of natural disasters could positively impact the economic outcome. It thus exists a reason for furthering this perspective in future research, as frequency of disasters seems to matter. Nevertheless, research on natural disasters' effect on economic growth is contradictory and seemingly complex. The proper response should thus be to avoid natural disasters if one can, and the most efficient way is to minimise climate change and build resilient societies through means such as social and physical infrastructure.

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Appendix A. Additional Statistics

Table 2 Countries in regression (121) and the corresponding average size of the agricultural sector (value added as a percentage of GDP), where the first eleven listed exceeds 23 per cent. Countries with an agricultural sector surpassing 33 per cent of value added in GDP are written in bold font.

	Country	Sector Size	Country	Sector Size
Large Agricultural Sector	**Bangladesh**	**33.83%**	France	3.81%
	Benin	32.82%	Gabon	10.63%
	Burkina Faso	29.00%	Germany	0.89%
	Burundi	**46.71%**	Greece	4.33%
	Cambodia	**33.78%**	Guatemala	20.91%
	Central African Republic	**33.83%**	Haiti	21.58%
	Congo, Dem. Rep.	28.48%	Honduras	22.79%
	Cote d'Ivoire	25.75%	Hong Kong SAR, China	0.07%
	Gambia, The	26.79%	Hungary	4.35%
	Ghana	**39.51%**	Iceland	6.07%
	India	28.27%	Indonesia	17.03%
	Kenya	27.34%	Iran, Islamic Rep.	11.70%
	Kyrgyz Republic	27.54%	Iraq	9.87%
	Lao PDR	30.55%	Ireland	1.77%
	Lesotho	23.92%	Israel	1.48%
	Madagascar	27.89%	Italy	2.37%
	Mali	40.75%	Jamaica	6.28%
	Mauritania	23.33%	Japan	1.26%
	Mozambique	25.71%	Jordan	5.94%
	Nepal	**45.95%**	Kazakhstan	7.97%
	Niger	**45.39%**	Korea, Rep.	13.62%
	Nigeria	22.84%	Latvia	4.03%
	Pakistan	27.31%	Lithuania	4.76%
	Rwanda	**40.54%**	Luxembourg	0.43%
	Sierra Leone	**42.74%**	Malaysia	19.43%
	Sudan	**35.88%**	Mauritius	8.14%
	Syrian Arab Republic	24.61%	Mexico	6.30%
	Tanzania	30.58%	Moldova	16.32%
	Togo	**34.49%**	Morocco	15.28%
	Uganda	**43.45%**	Namibia	8.54%
	Albania	21.32%	Netherlands	3.04%
	Algeria	9.61%	New Zealand	7.15%
	Angola	7.14%	Nicaragua	17.05%
	Argentina	7.53%	Norway	2.63%
	Armenia	16.06%	Panama	6.38%

Australia	2.83%	Paraguay	22.02%
Austria	2.31%	Peru	11.06%
Belgium	0.90%	Philippines	19.12%
Belize	15.40%	Poland	3.14%
Bolivia	14.89%	Portugal	2.59%
Botswana	13.94%	Romania	10.74%
Brazil	8.40%	Russian Federation	5.74%
Brunei Darussalam	1.07%	Saudi Arabia	3.52%
Bulgaria	9.68%	Senegal	19.33%
Cameroon	22.82%	Serbia	9.81%
Canada	1.88%	Slovak Republic	2.03%
Chile	6.41%	Slovenia	2.48%
Colombia	15.17%	South Africa	4.43%
Congo, Rep.	11.22%	Spain	3.06%
Costa Rica	15.11%	Sri Lanka	22.25%
Croatia	4.06%	Sweden	2.68%
Cyprus	5.48%	Switzerland	1.01%
Czechia	2.65%	Thailand	17.46%
Denmark	3.03%	Tunisia	12.95%
Dominican Republic	12.73%	Ukraine	12.85%
Ecuador	18.76%	United Arab Emirates	1.15%
Egypt, Arab Rep.	18.45%	United Kingdom	0.84%
El Salvador	20.06%	United States	1.09%
Estonia	3.35%	Uruguay	8.69%
Eswatini	18.08%	Zimbabwe	14.88%
Finland	4.43%		