The Impact of Natural Disasters on Capital Flows: Preparedness and Exposure Matter

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Abstract

Natural disasters increase economic losses worldwide, with severe weather events now costing $143 billion annually. Although research has examined various macroeconomic impacts of disasters, their relationship with international capital flows has received little attention so far. This paper shows that a country's ability to respond to disasters, rather than the likelihood of physical disasters, drives cross-border investment. In particular, investors react the most in countries that are usually unaffected by disasters and unprepared to handle them when they occur. Portfolio and bank flows show the strongest reactions, with a 0.1 percentage point increase in population exposure leading to changes of between 0.5 and 4.4 percentage points of GDP, up to twice the average size of flows. In contrast, FDI remains stable, suggesting that long-term strategic investments are less sensitive to disaster events. The reaction of portfolio flows goes beyond domestic events. While internal disasters reduce flows, external disasters increase portfolio equity inflows by 3.8 percentage points, suggesting that investors reallocate to safer markets within country groups.

Keywords: Portfolio investment, foreign direct investment, other investment, preparedness, disaster risk, vulnerability, EM-DAT

JEL classification: F21, F3, Q54

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1 Introduction

Climate- and weather-related natural disasters now account for half of all global disasters and over 70% of related economic losses, with an estimated annual cost of US$143 billion (Douris & Kim, 2021; IPCC, 2022; Newman & Noy, 2023). Droughts, extreme temperatures, storms and floods alone affect at least 178 million people every year (Guha-Sapir et al., 2014). Beyond the immediate physical and economic damage they cause, natural disasters also provide information about their future likelihood. Therefore, forward-looking variables, such as financial variables, should react to disasters, as markets price in new information by updating expectations. International capital flows are one example of such variables, as investors base their decisions on expectations of future returns, productivity and growth (Benhima & Cordonier, 2022). Capital flows are also economically important, as they promote growth or even worsen financial instability (Forbes & Warnock, 2012a; Koepke, 2019). Despite extensive research on capital flows, their reactions to natural disasters remain scarcely studied in the literature.

This paper contributes to closing this gap by analysing capital flow responses to natural disasters. The initial analysis of aggregate capital flows reveals no significant reaction to natural disasters. The lack of response suggests that investors are largely indifferent to natural disasters, contradicting the forward-looking nature of capital flows. However, this lack of response masks substantial heterogeneity among countries. To reveal hidden responses, I rely on three approaches. First, I examine whether disaster preparedness and risk affect investment patterns differently. To achieve this, I use a k-means clustering method to classify countries into four groups according to their level of disaster preparedness and risk. Second, I create two complementary disaster measures to distinguish between the human impact and the temporal extent of disasters. These measures allow me to identify the characteristics of disasters that affect investment the most, specifically population exposure and disaster duration. Finally, I estimate how capital flows respond to these measures across country groups, considering both internal disasters within a country and external disasters affecting similar countries.

To comprehensively examine whether natural disasters impact international capital flows, I compare the responses of the three main types of flows: foreign direct investment (FDI), portfolio flows and other investment flows. This framework captures both the long-term strategic commitments of FDI and the more flexible financial positions of portfolio flows, showing how different dimensions of international investment behaviour respond to natural disasters. For a more detailed understanding of investment behaviour, I follow the residency principle of the balance of payments and assess both inflows, representing net purchases of domestic assets by foreign investors, and outflows, representing net purchases of foreign assets by domestic investors (Avdjiev et al., 2022; Forbes & Warnock, 2012a).

I find three main results on the impact of natural disasters on international capital flows. First, an increase in population exposure to disasters leads to significant capital flow responses in countries with low disaster preparedness and low disaster risk. A 0.1 percentage point increase in population exposure reduces portfolio inflows and outflows by 0.5 to 2 percentage points of GDP and other investment outflows by 4.4 percentage points. These responses are up to twice the size of the average quarterly flows in the sample, representing sizable effects. The significant responses are only observed for flows with lower levels of commitment, as FDI remains stable. Second, capital flows are affected by natural disasters differently depending on whether the disaster is internal, i.e. occurring domestically, or external, i.e. occurring in another country of the same country group. While internal disasters affect both inflows and outflows, external disasters affect only portfolio inflows. Specifically, when external disasters hit similar countries in the unprepared low-disaster-risk group, portfolio equity inflows to the unaffected country increase by 3.8 percentage points. This suggests that investors reallocate capital to safer markets within the group. Third, investors react more to disaster severity measured by population exposure than to disaster duration, indicating that investors consider the human impact of disasters to be more important than their length.

These findings are increasingly important as climate change exacerbates the impact of natural disasters and potentially worsens financial stability (Carney, 2015; IPCC, 2022). While capital flows can improve financial conditions, their volatility can increase the vulnerability of financial systems (Forbes & Warnock, 2012a, 2021; Milesi-

Ferretti & Tille, 2011). My results show that capital flows indeed react strongly to natural disasters, particularly in countries that are unprepared for natural disasters. Understanding these effects is important for building resilience and effective disaster preparedness policies, especially in the current climate crisis.

This paper makes three distinct contributions to understanding how natural disasters impact international capital flows. First, I introduce a new conceptual framework that separates a country's ability to manage disasters effectively (preparedness) from the probability of disaster occurrence (risk). While previous studies have considered country "risk" only in a broader sense (Ferriani et al., 2023; Koepke & Paetzold, 2024), my analysis shows the importance of distinguishing between a country's exposure to disasters and its ability to manage them. By explicitly separating preparedness and risk, I find that a high level of disaster risk alone does not change investment behaviour. Rather, what matters to investors is how well countries are prepared to deal with disasters when they occur.

Second, I introduce two new measures of natural disasters that reduce reporting biases and allow meaningful cross-country comparisons. The first measure, population exposure, uses satellite data to calculate the actual population density in disaster-affected areas relative to the country's population. It provides an objective measure of the human impact across different levels of economic development. The second measure assesses disaster duration relative to a country's historical experience, capturing how extreme an event is in the country. Unlike measures based on economic losses or insurance claims, which are biased by property values and countries' reporting incentives, these measures provide standardised metrics that better isolate the true impact of disasters and reveal more reliable patterns in market responses (Guha-Sapir et al., 2014).

Finally, I extend the traditional push-pull framework of capital flows by measuring how internal (pull) and external (push) disasters affect investment decisions. I show that preparedness and risk similarities between countries matter for understanding investment patterns after disasters. This finding extends the traditional view that disasters affect economies only through regional or trade spillovers (Ferriani et al., 2023; Osberghaus, 2019).

The rest of the paper is organised as follows. Section 2 connects the findings of this paper to the literature. Section 3 describes the data. Section 4 explains country grouping and disaster measures. Section 5 outlines the research methodology, Section 6 presents the results. Section 7 discusses findings and policy implications.

2 Related Literature

This paper contributes to three strands of literature. First, my work adds to the growing body of literature analysing the broader economic impacts of natural disasters. Although there is increasing recognition of the economic risks posed by climate change (Tol, 2018), few studies extend this analysis to international finance, in particular, how disasters may drive capital flows (Ferriani et al., 2023; Gu & Hale, 2023). Second, it draws on extensive empirical studies of capital flows and their traditional drivers. Classical models use the push-pull framework to identify global (push) and local (pull) factors that influence capital flows (Calvo et al., 1993; Koepke, 2019). Within this framework, my research focuses on natural disasters. In particular, I am the first in the literature to examine external natural disasters in similar countries as a potential push factor rather than a geographically close one. Finally, my work contributes to the literature on country risk, in particular by considering how disaster preparedness and risk levels affect investor behaviour.

The literature often measures the impact of natural disasters by focusing on specific extreme weather events, such as hurricanes (Batten et al., 2016; Chavaz, 2016; Kruttli et al., 2025; Pelli & Tschopp, 2017; Yang, 2008), droughts (Landon-Lane et al., 2009), temperature changes (Balvers et al., 2017; Deryugina & Hsiang, 2014), floods (Rehbein & Ongena, 2022) and volcanic eruptions (Berg & Schrader, 2012). I further build on this strand of literature by including the most common disasters worldwide to capture the complex and interconnected nature of natural disasters. In this way, I account for the cumulative effects of multiple events and their interactions. For example, floods often occur in conjunction with storms, both of which can disrupt markets. Similarly, extreme temperatures and droughts often coincide. I also use satellite data to measure the exposed population. Economic variables can be influenced by factors such as reporting incentives or local politics, potentially confounding the relationship between climate events and market responses (Yang, 2008).

Although an increasing number of papers look at the impact of weather events on the economy from different angles, it is important to note the difference between weather events and climate change as Tol (2018) highlights. Weather events are short-term events that reflect conditions in the atmosphere at a particular location (IPCC, 2023). Climate, on the other hand, is the long-term average of weather events. Although weather events are very likely to become more intense and frequent in the future as a result of anthropogenic climate change (IPCC, 2023), it is difficult to determine the extent to which global warming contributes to specific disasters. Therefore, looking at events alone is not sufficient to study the impact of climate change. Despite this fundamental difference, many studies claim to analyse the impact of climate change by relying on weather data (Tol, 2018). In my work, I focus on investors' reactions to weather events to understand how they incorporate weather events into their future decisions.

Despite the growing recognition of weather risks, research on the impact of natural disasters on capital flows remains very scarce (Osberghaus, 2019). Existing studies provide mixed evidence on the relationship between disaster risk and investment. While some research suggests that FDI may theoretically decrease in high-risk countries (Gu & Hale, 2023), other findings do not provide conclusive empirical evidence (Yang, 2008). On portfolio flows, Ferriani et al. (2023) find that investments in risky emerging markets are affected by natural disasters. They define riskiness by ranking countries according to their vulnerability to disasters. In their paper, vulnerability combines physical vulnerability and socio-economic vulnerability without further differentiation. My research extends this emerging literature by examining the impact of internal and external disasters on a broader range of capital flows, and by explicitly considering the role of the level of disaster risk and disaster preparedness in mitigating these impacts. This focus on preparedness highlights a previously overlooked dimension in understanding the impact of natural disasters on capital flows and informs the development of more appropriate policies to address the threat of natural disasters.

To better understand the impact of natural disasters on capital flows, I first turn to the literature that assesses their drivers by flow types. Different components of capital flows, such as FDI, portfolio equity, portfolio debt and other investment flows, respond differently to domestic and external shocks. The separation between shocks is based on the push-pull framework, which identifies both domestic and international drivers of capital flows (Calvo et al., 1993; Fernandez-Arias, 1996; Koepke & Paetzold, 2024). In emerging markets, portfolio flows react negatively to global risk aversion, a rise in US interest rates and domestic country risk. Portfolio debt and equity flows are also closely related to asset price and exchange rate movements and therefore have important implications for central bank policy decisions (Bergant & Schmitz, 2018; Koepke & Paetzold, 2024). In emerging markets, banking flows respond most positively to domestic output growth and domestic increases in the rate of return on assets (Koepke, 2019). FDI is the least responsive to global changes. FDI flows depend on investors' long-term strategic decisions, such as where to invest and how to operate, which require more time, effort and information than portfolio investments (Dunning, 1977; Koepke, 2019). However, while this push-pull framework has been widely applied to traditional economic drivers, its application to weather-related events is new. To my knowledge, this is the first study to examine the impact of external disasters by examining how natural disasters affect capital flows in countries with similar risk and preparedness characteristics, rather than focusing solely on geographical proximity or trade ties. This approach provides new insights into how investors reallocate capital in response to disasters by taking into account institutional and risk management similarities between countries.

3 Data and Stylized Facts

I combine multiple datasets to measure the impact of natural disasters on international capital flows. For the dependent variables, I use capital flow data from the 6th edition of the Balance of Payments Statistics (BoP) of the International Monetary Fund (IMF) (2009; 2014). To examine natural disasters, I rely on the geocoded extension (GDIS) of the Emergency Events Database (EM-DAT) from the Centre for Research on the Epidemiology of Disasters (CRED) (Guha-Sapir et al., 2014; Rosvold & Buhaug, 2021a, 2021b). Additionally, I use the Gridded Population of the World (GPW) dataset from NASA (2018) to consider the number of disaster-exposed population. To assess a country's disaster risk and preparedness characteristics, I use data from the IMF RISK INFORM dataset (IMF, 2022). I rely on further information from the World Bank and Forbes and Warnock (2021) to measure country-specific variables.

3.1 Natural Disasters

This analysis focuses on climate and weather-related disasters such as droughts, extreme temperatures, floods and storms, using the geocoded version, GDIS, of EM-DAT (Guha-Sapir et al., 2014; Rosvold & Buhaug, 2021a, 2021b). The EM-DAT, a well-known dataset in various research fields, such as climate science, economics and geomorphology[1], includes disasters if they meet at least one of the following criteria: at least 10 deaths, at least 100 people were affected, the country requested international assistance or declared a state of emergency following a disaster (Guha-Sapir et al., 2014). The GDIS version further provides the exact location of reported disasters with latitude and longitude coordinates from 1960 to 2018 (Rosvold & Buhaug, 2021a, 2021b).

Between 1960 and 2000, the number of recorded disasters in EM-DAT increased sharply (Figure 1). However, this increase does not reflect the actual number of disasters. Instead, it reflects improvements in disaster recording technologies, such as more advanced satellites and national survey systems. Therefore, the sharp increase in reported disasters until 2000 was due to reporting bias rather than an actual increase in disasters (Guha-Sapir et al., 2014). This difference between the actual and reported number of disasters in EM-DAT is often overlooked by researchers, media outlets, and even influential organisations (Ritchie & Rosado, 2024).[2] However, when the period after 2000 is examined, which uses more reliable reporting standards, the data shows no clear increase in the total number of disasters, despite the widespread expectation that climate change would increase the number of extreme weather events. However,

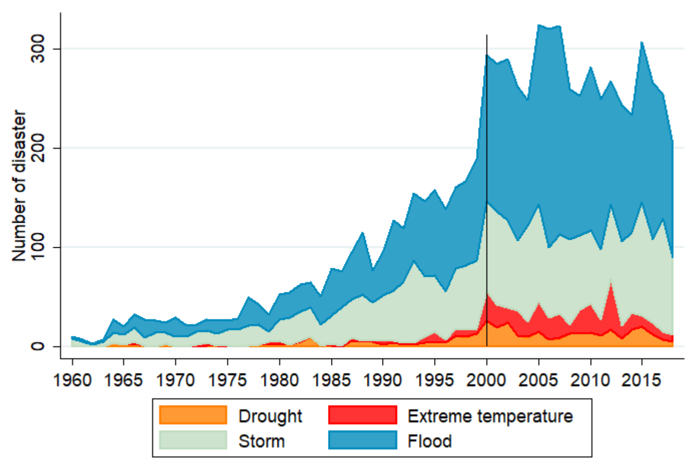
[1] See, for example, Alcántara-Ayala (2002), Gu and Hale (2023), Jones et al. (2022), Kahn (2005), Lesk et al. (2016), Noy (2009), and Toya and Skidmore (2007) among many others.

[2] The United Nations, the World Meteorological Organization and The Economist are a few examples. For further examples, see Ritchie and Rosado (2024).

the apparent stagnation in the total number of disasters in EM-DAT should not be taken as proof that climate change is not affecting disasters, as it may hide changes in the types, regions, and intensity of disasters (Ritchie & Rosado, 2024).

Despite these challenges, EM-DAT provides the most reliable data for examining disasters, as it is the only comprehensive, freely accessible global disaster database. To reduce time bias and control for measurement error, I focus on the period from 2000 to 2018. I also exclude small island developing states (e.g. the Bahamas and Haiti) to avoid including countries whose entire territory is recurrently exposed to potential disasters. The resulting dataset includes 117 countries and shows the locations of disasters, with latitude and longitude coordinates pointing to their centroids (Rosvold & Buhaug, 2021a, 2021b). There is high variation in latitude and longitude, with disasters stretching from Canada to Argentina (north-south) and from Tuvalu to Tonga (east-west). The most affected countries are in Central America (floods and storms), Southern Europe (extreme temperatures and floods), and South-East Asia (floods and storms) (Figure 2).

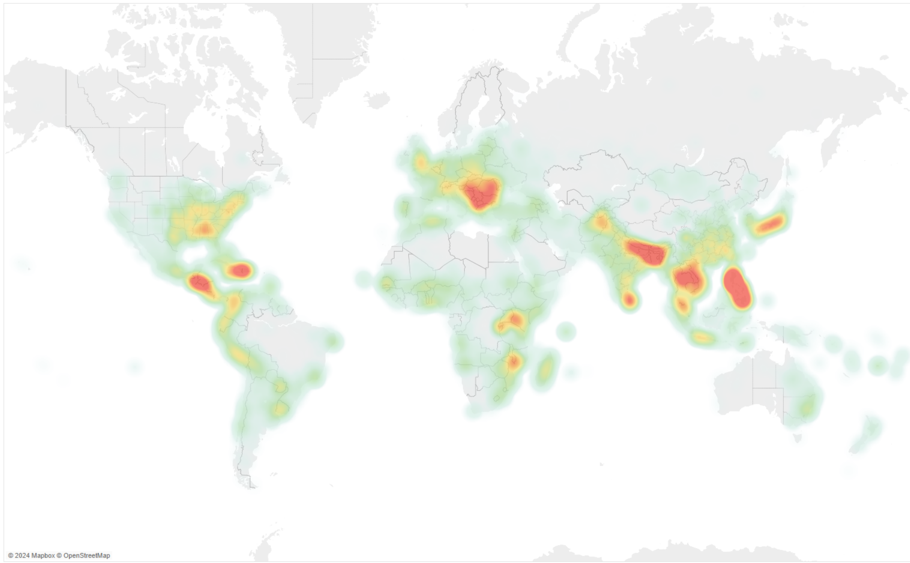
Figure 1: Time Bias in the Number of Disasters before 2000



Source: EM-DAT.

The dataset lists 5,135 different disasters affecting 27,041 areas. Floods are the most common type of disaster (Figure 3). However, there are regional differences. For example, extreme temperatures are the second most frequent disaster in European countries, replacing storms (Figure 14). This result is mainly due to the frequency of

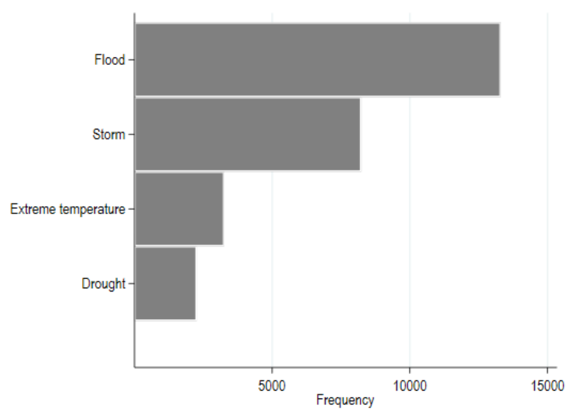
Figure 2: Frequency of Disasters by Location between 2000 and 2018



Source: GDIS and EM-DAT. The author's calculation.

storm events in the Americas and Asia and the under-reporting of extreme temperatures in African countries (Jones et al., 2022, 2023).

Figure 3: Number of disaster-affected locations between 2000 and 2018



Source: EM-DAT. The author's calculation.

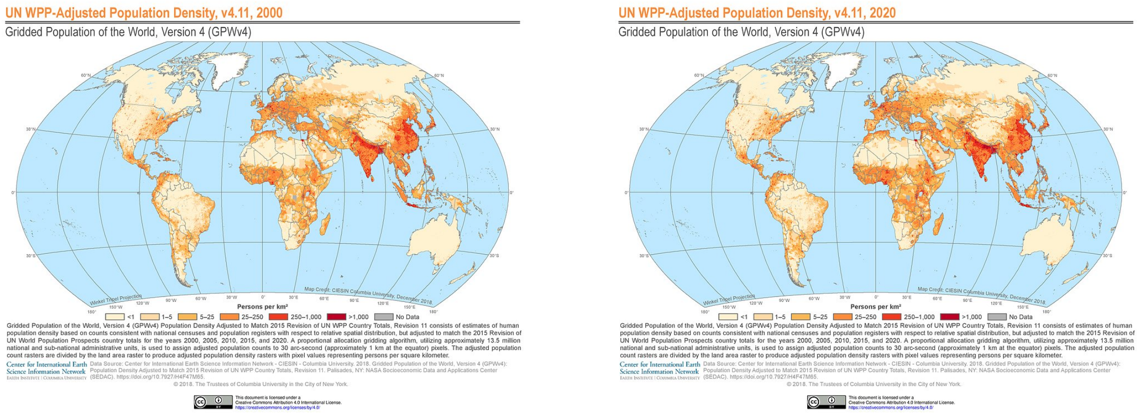
Although its accessibility and global coverage make EM-DAT an important resource for understanding natural hazards, it suffers from known problems other than the previously discussed time bias. These include preferential reporting of large disasters and non-random missing data in variables that measure the impact of disasters, such as the number of people affected (Gall et al., 2009; Jones et al., 2022, 2023). First, although unequal disaster coverage is important locally, as small disasters can have a high cumulative impact on local development (Marulanda et al., 2010), it is not detrimental to the current analysis. This study focuses on the short-term responses of international investors to disasters at the country level. In particular, I focus on the total investment that enters or leaves the country after a major disaster, rather than the adjustment of local investment to small disasters. Second, to address the non-random missing data in variables measuring the impact of disasters, such as population exposure, I rely on satellite data from the Gridded Population of the World (GPW) dataset (2018). This provides a more consistent measure of population exposure than relying solely on the measures from EM-DAT.

3.2 Population

Socio-economic factors often lead to uneven reporting of disaster impact variables in EM-DAT, such as the level of population exposure. Differences in data quality pose a significant challenge, as data are not missing at random. To control for this limitation, I merge the natural disaster data from EM-DAT with the population GPW dataset from NASA (2018). The GPW dataset records population density (number of people per square kilometre) at a resolution consistent with that of EM-DAT's GDIS (e.g. 2.5 arc-minute, equivalent to 5 km at the Equator). I rely on population density rather than population count data because the raster size varies greatly with latitude (2.5 arc-minutes is equivalent to 5 km at the Equator, while it is about 2 km at the 67th degree). By combining these datasets, I match each disaster event with the corresponding population density at its centroid. Thus, the resulting dataset is free of non-random patterns of missing data, since each disaster is associated with a potentially exposed population density figure. This matching, therefore, increases the overall quality and reliability of the dataset.

NASA (2018) provides population estimates every five years from 2000 to 2020, and adjusts them to match the United Nations country totals from 2015. Migration and population growth affect the data, resulting in changing population estimates over time (Figure 4). To control for possible overestimation of the population exposed to

Figure 4: Changing Population Density over Time, GPW.



(a) Population Density in 2000

(b) Population Density in 2020

disasters, I focus on population data from 2000, as most climate and weather-related disasters affect the fastest-growing countries in Central America, Africa, and South Asia (Figure 2 and Figure 4). In Section 4.2, I show how I calculate the population exposure variable to measure the number of people affected by disasters.

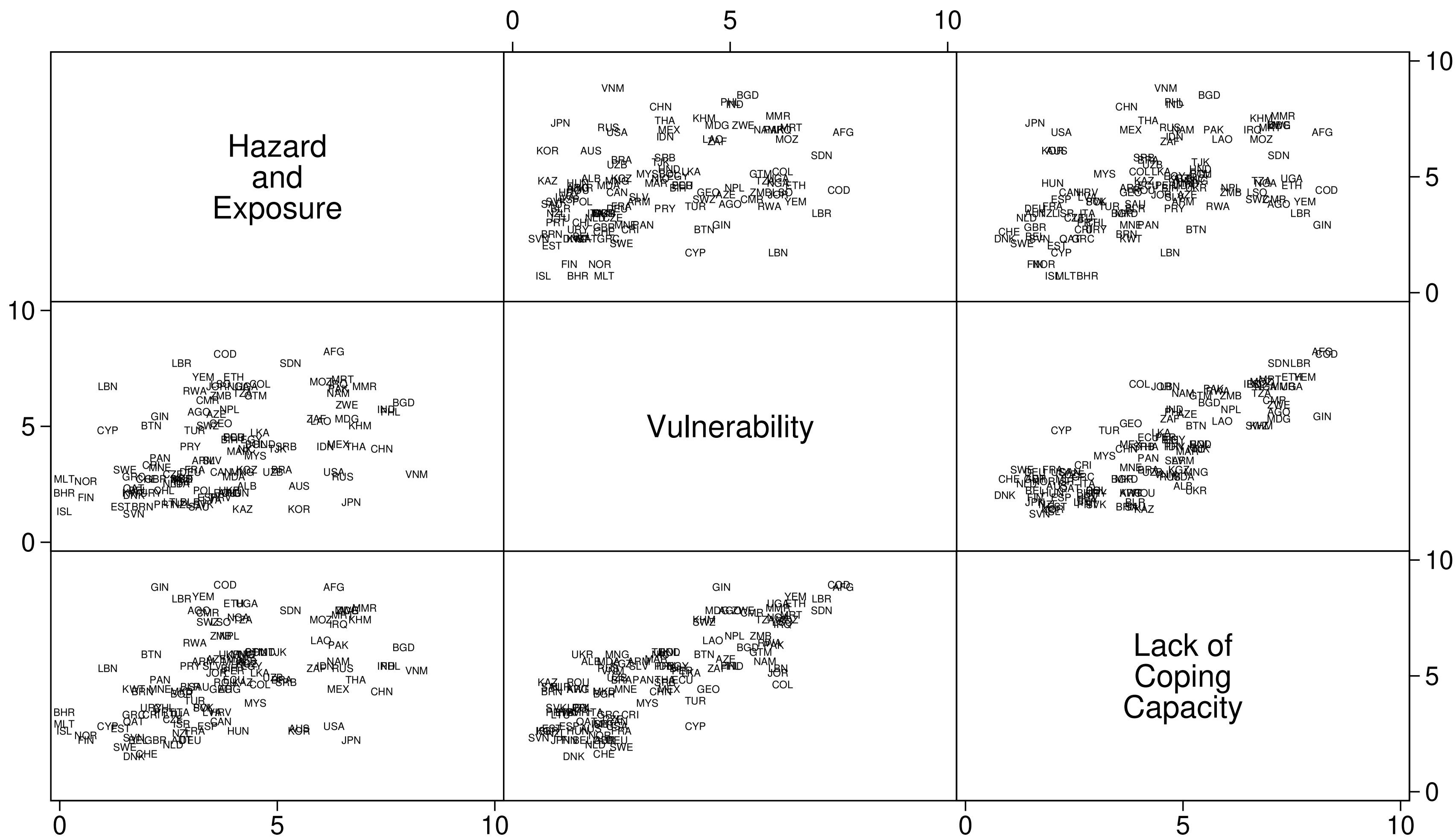
3.3 IMF INFORM Risk

To assess a country's disaster risk and preparedness characteristics, I rely on the IMF INFORM Risk dataset (2022), which publishes three main indicators that rank the level of climate *Hazard and Exposure*, country *Vulnerability*, and *Lack of Coping Capacity* of 191 countries. These three indicators are based on 54 core indicators developed by the Joint Research Centre (JRC) of the European Commission. The only difference between the two INFORM Risk datasets is that the IMF INFORM Risk data includes only climate-related disasters, while the JRC includes epidemics and global conflicts in its risk indicators. The indicators range from 0 to 10, with higher values indicating worse conditions in a country. The standardised scale allows direct comparison between countries. Data are available annually from 2014, and I focus on the earliest data from 2014 for the 117 countries available in my dataset.

The three IMF-aggregated indicators show countries' physical risks and preparedness levels from different dimensions (Figure 5). The first indicator, Hazard and

Exposure, depicts the physical risk of the population to natural disasters. It is calculated by taking the geometric mean of the drought, flood, and tropical cyclone indicators. Theoretically, the Hazard and Exposure indicator could have a value of zero if no citizen is exposed to a climate hazard or the probability of a hazard is zero. The second indicator, Vulnerability, shows how vulnerable communities are to hazards. Individuals and households in countries with high Vulnerability scores are less prepared to cope with disasters. The third indicator, Lack of Coping Capacity, shows whether the country's institutions are prepared to handle disasters. Countries that are not resilient and do not have recovery strategies in place have higher scores. Therefore, Vulnerability indicates socio-economic preparedness, while Lack of Coping Capacity indicates institutional preparedness. The Vulnerability and Lack of Coping Capacity indicators are highly correlated ($\rho = 0.8$). However, the Hazard and Exposure indicators are less correlated with each other ($\rho = 0.3$). In Section 4.1, I show how I construct the four country groups based on the three IMF indicators to control for countries with low or high levels of disaster risk and preparedness.

Figure 5: Country Matrix of the IMF INFORM RISK Indices



Notes: The three main indicators rank the level of physical risk of the population to natural disasters (Hazard and Exposure), socio-economic vulnerability (Vulnerability), and institutional preparedness (Lack of Coping Capacity). The indicators range from 0 to 10, with higher numbers indicating worse conditions.

3.4 Capital Flows

I rely on the sixth edition of the standard Balance of Payments Manual (BPM6) data to study international capital flows from the IMF (2009). I analyse gross capital flows by instrument and focus on foreign direct investment (FDI), portfolio debt and portfolio equity, and other flows. My dataset consists of 117 countries between 2000 and 2018 at a quarterly frequency. Table 6 and 7 in the Appendix show the country list and their time coverage.

The BoP data follows the residency principle and depicts changes in the investment positions of foreigners and domestic investors. Gross capital inflows describe net foreign purchases of domestic assets, while gross capital outflows show how domestic investors change their net foreign asset purchases. I follow the conventions of the current sixth edition of the BoP while handling capital flows. In BPM6, positive gross inflows show that foreign investors buy more domestic assets than they sell, while positive gross outflows represent that domestic investors sell more foreign assets than they purchase. In general, investors from advanced economies (AE) influence the most investments leaving or entering their economy, similar to investments entering emerging economies (EMEs). Therefore, a positive correlation exists between gross in- and outflows from AE and inflows to EMEs, whereas gross outflows from EMEs are less related (Avdjiev et al., 2022).

Different types of flows describe the market from different points of view. FDI represents investments with at least 10% of ownership, showing a tighter relationship and influence. Portfolio debt and equity investment include investments in securities with ownership of less than 10%. Portfolio debt has repayment obligations, whereas equities do not. Debt financing retains full ownership on the debtor side, unlike equity financing. Therefore, debt flows tend to be a more stable investment. Other flows represent investments not included in the previous categories and financial derivatives. Other investment flows show the majority of banking flows as well, especially in advanced economies (Avdjiev et al., 2022).

High volatility and great heterogeneity exist within and between countries. Figure 6 shows that portfolio equity and debt financing in the United States move around 5% and 10% of GDP, respectively. These numbers reach even 1000% in the case of Luxembourg, as shown in Figure 7. To account for the extraordinary amount of capital flows in financial centres, Luxembourg, Ireland, and Mauritius are excluded. These three countries were chosen based on the work of Milesi-Ferretti and Tille (2011), which focuses on countries where capital flows exceed 100% of their GDP.

Figure 6: Gross Portfolio Equity and Debt Flows in the United States

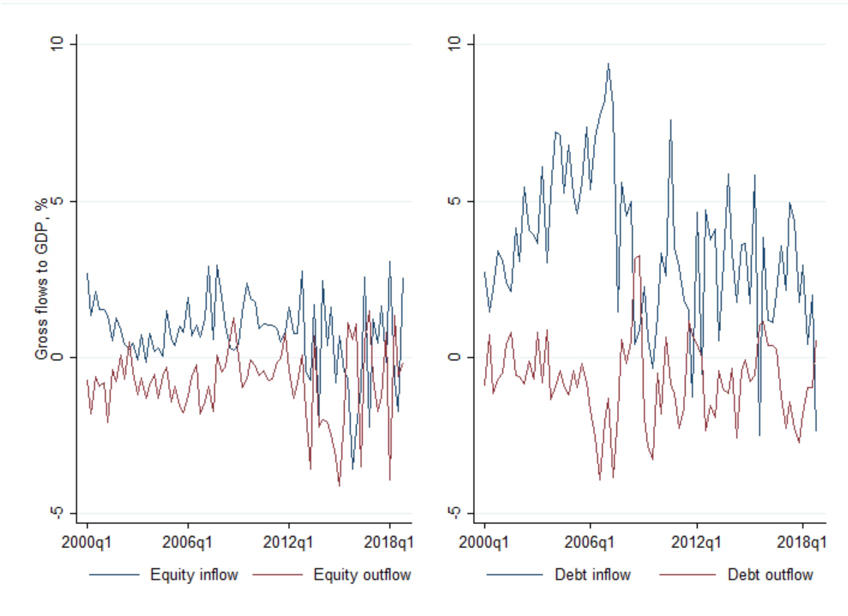
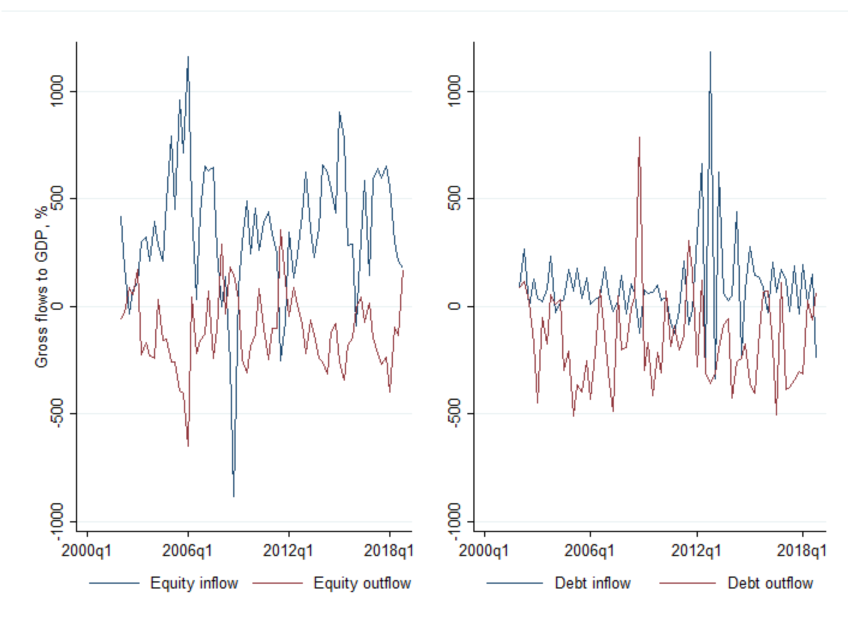


Figure 7: Gross Portfolio Equity and Debt Flows in Luxembourg



3.5 Control Variables

The literature has analysed in depth different factors affecting capital flows. These factors are classified into global and local drivers following the so-called push-pull framework in the literature (Forbes & Warnock, 2012b, 2021; Koepke & Paetzold, 2024). My study follows this framework, relying on the proposed global and local factors as control variables.

For global factors, I count for broadly accessible factors to minimise missing observations (Forbes & Warnock, 2021). I control for global risk measured by changes in VXO relative to four quarters earlier; quarterly global money supply changes measured by the sum of M2 in the euro area, US, UK, and Japan relative to one year earlier; quarterly global long interest rate accounted by the rate on long-term government bonds in the US, Euro area and Japan; quarterly global growth rate relative to one year earlier measured in real GDP; and finally quarterly percent changes in oil prices relative to one year earlier from Forbes and Warnock (2021) and IMF (2009; 2014).

For local factors, I control for quarterly real GDP growth relative to the previous year's value from the IMF and lagged official aid from the IMF (2009; 2014).

4 Country Groups and Disaster Measures

In this section, I first explain how country groups are created using the IMF INFORM risk indicators to account for cross-country similarities. I then present the two measures of natural disasters. The first variable, *Duration*, reflects how long a disaster affects a country relative to its historical average. The second variable, *Population Exposure*, represents the proportion of the population affected by the disaster relative to the total population. I create two versions of both variables to capture disasters that occur domestically within the country, i.e. *internal disasters*, and disasters that affect countries that belong to the same group of countries as the home country, i.e. *external disasters*.

4.1 Country Groups

To account for similarities between countries in terms of physical risk and preparedness levels, I divide countries into four groups. To avoid preferential selection, I use k-means clustering with Euclidean distances to assign the most similar countries to a group. K-means clustering is an unsupervised machine learning algorithm that sorts data into k groups without any prior training on the data. The Euclidean distance is the most common distance measure used in clustering and is especially preferred when data points are continuous, there are no large outliers, and the variables are normally distributed.[3] This method starts by randomly assigning the centroids of the clusters, and then assigning the data points to these clusters according to their distance. This process is repeated until the best clusters are found, represented by the minimised Euclidean distance between the observations and their nearest mean. In my setup, I first classify the groups according to their level of physical risk, measured by Hazard and Exposure, and then according to their level of socio-economic and institutional preparedness, measured by Vulnerability and Lack of Coping Capacity indicators from the IMF INFORM Risk dataset (Section 3.3).

The final groups, therefore, depend on whether the country has a high or low score on the Hazard and Exposure, Vulnerability, and Lack of Coping Capacity indicators, based on the first observations from 2014. Countries with generally low scores on the Hazard and Exposure indicator are classified as low disaster risk countries. Otherwise, they are classified as high disaster risk countries. In addition, if a country scores low on the Vulnerability or Lack of Coping Capacity indicators, it is classified in the Prepared group, otherwise in the Unprepared group.[4] This results in four country groups: low disaster risk & prepared (e.g. Switzerland); low disaster risk & unprepared (e.g. Jordan); high disaster risk & prepared (e.g. United States); and high disaster risk & unprepared (e.g. Bangladesh). Most countries fall into the low disaster risk and prepared groups, while the remaining country groups are balanced: 61, 20, 15, and 21

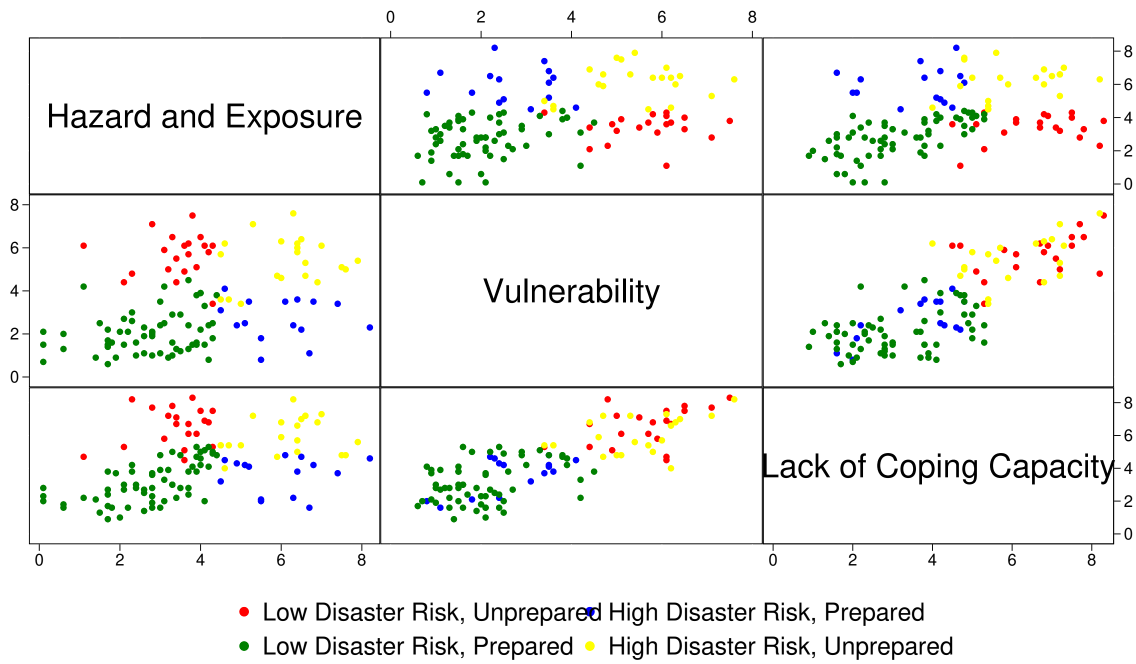
[3] Using a skewness and kurtosis test, I can only reject one of the three indicators, the vulnerability index, that is normally distributed. As a robustness check, I use Manhattan distance as an alternative distance measure. It shows very similar results (Section 6.4).

[4] Information on the exact definition of the variables can be found in Section 3.3.

countries, respectively (Figure 8). Country groups do not match the income groups. For example, although most European countries are in the same group (low disaster risk & prepared), the United States is listed with Brazil (Figure 9).

Countries experience different numbers of natural disasters according to country groups (Figure 10). On average, countries with low disaster risk experience fewer disasters than countries with high disaster risk. High disaster risk and prepared countries experience the most natural disasters due to storms and floods. However, there is not much difference between unprepared and prepared countries when their disaster risk is low.

Figure 8: Country Groups along the IMF INFORM Matrix



4.1.1 Sensitivity to the Clustering Year

To measure whether adaptation matters over time, I look at how the core IMF INFORM Risk indices changed between the first observation in 2014 and the last in 2021 (Figure 11). This analysis is important because a country's level of disaster risk and preparedness can change over time due to a number of factors, including climate change,

Figure 9: Country groups

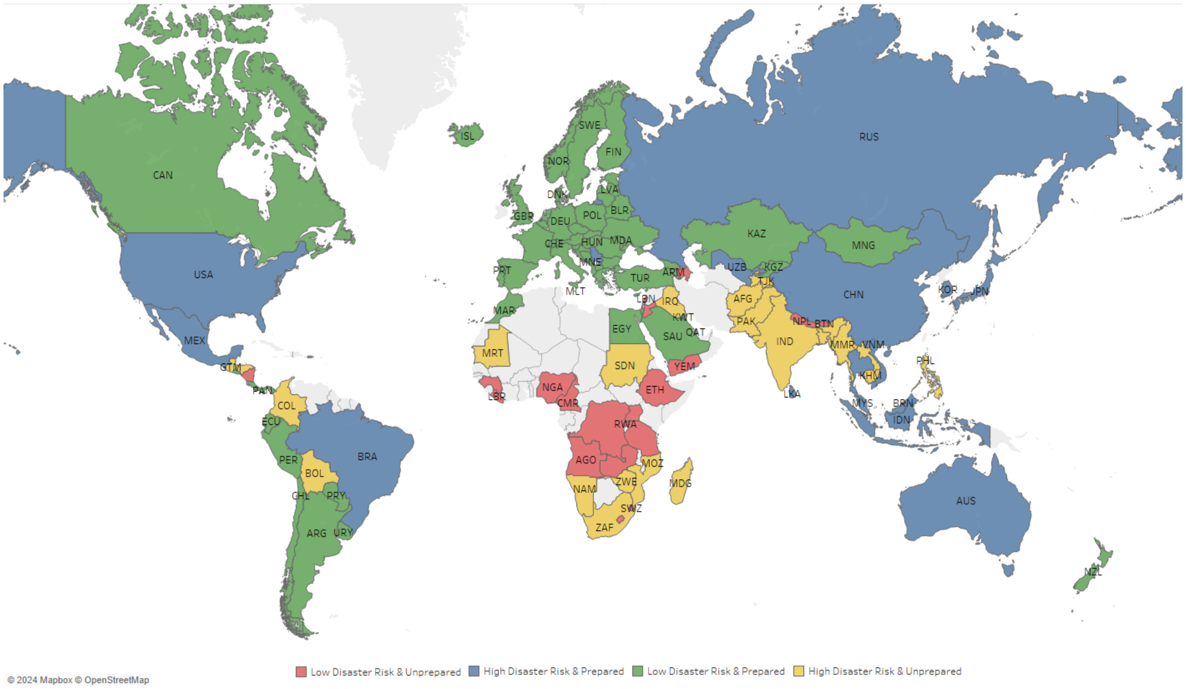
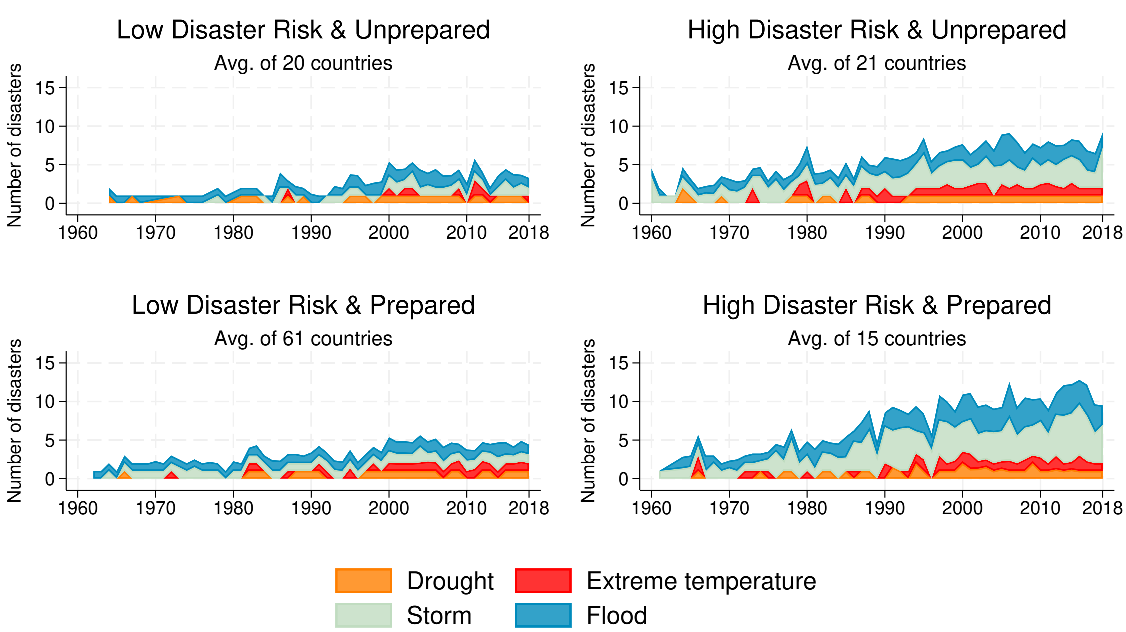


Figure 10: Differences by Country Groups.



Source: CRED and EM–DAT. Author's calculation.

scientific and institutional improvements, and adaptation. Understanding the dynamics of these indices helps to assess the stability of country group classifications and the potential impact of adaptation efforts.

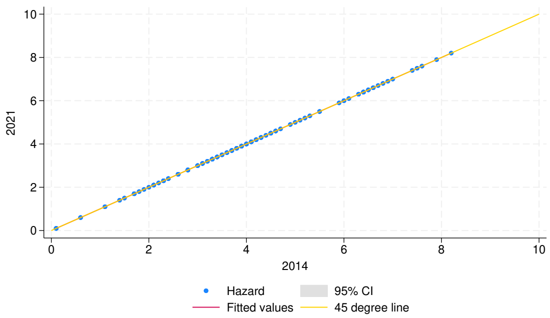
The first indicator, Hazard and Exposure, reflects the likelihood of exposure to natural disasters. It shows no change over time for any country (Figure 11a). This means that between 2014 and 2021, the level of disaster risk neither improved nor worsened for each country. The lack of change may be due to the fact that climate change, whether natural or anthropogenic, is a long-term process that takes time to materialise. Therefore, none of the countries has experienced any change in their disaster risk over time.

The second indicator, Vulnerability, reflects susceptibility to disaster impacts based on socio-economic factors, taking into account the potential for damage due to country characteristics rather than the hazard itself. It shows heterogeneous socio-economic changes over time by country. For example, Honduras experienced the greatest deterioration in its indicator over the period, while the Czech Republic saw the greatest improvement. Overall, however, there was no statistically significant change in the Vulnerability index between 2014 and 2021, at 95% level (Figure 11b).

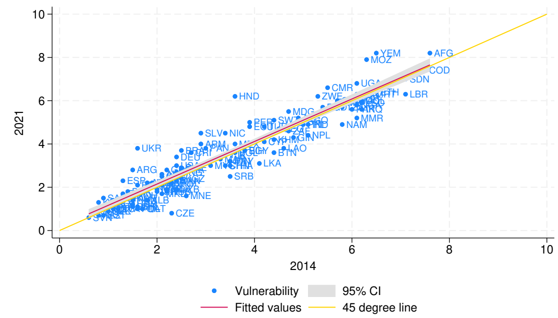
The only indicator that has improved over time at the 95% level is the Lack of Coping Capacity index (Figure 11c). The fitted line has a slope below the 45-degree line, indicating that, on average, countries' governments have increased their resilience over time. This implies that countries have improved their institutional preparedness to deal with disasters, possibly through better institutional and infrastructural management. Only fourteen countries worsened their scores, almost half of which were European countries: Belgium, Croatia, Cyprus, Denmark, Hungary, and Sweden scored higher in 2021 than in 2014, indicating a worsening situation.

To control for possible endogeneity due to changes in the country indicators, I rerun my estimates in a subsample after 2014 (Section 6.4). Thus, the subsample uses country groups based on 2014 values, but the effect of natural disasters is measured only on observations from 2015 onwards. This ensures that the country group classifications are not affected by changes in the core indices over time, and that the results are robust to potential endogeneity concerns. Indeed, the results remain similar, with small changes in the estimated coefficients but consistent signs.

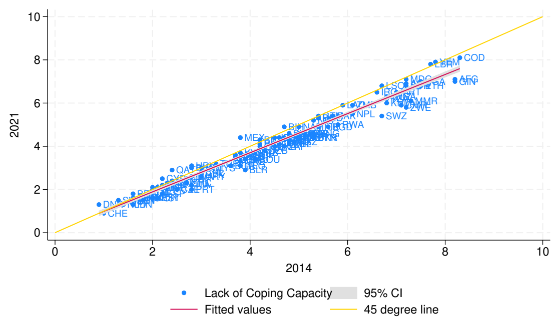
Figure 11: Changes in IMF INFORM Risk indicators between 2014 and 2021



(a) Hazard and Exposure



(b) Vulnerability



(c) Lack of Coping Capacity

4.2 Natural Disaster Measures - Duration and Population Exposure

4.2.1 Internal Natural Disasters

To test whether climate- and weather-related natural disasters can be new drivers of capital flows, I estimate the responses of gross capital inflows and outflows to extreme events. I quantify natural disasters using two newly constructed measures. First, I assess the duration of internal disasters relative to the climate history of countries using the variable *Duration*. Second, I examine the exposure of the population to disasters relative to the country's population through the variable *PopExposure*. The distinction between the two measures of natural disasters indicates whether capital flows are more sensitive to disasters that may be prolonged but remote events, or to those with greater human impact. For natural disasters, I use data from the NASA geocoded (GDIS) version of EM-DAT (2021a, 2021b) and the geocoded population of the world (2018) datasets between 2000 and 2018 (Section 3.1 and 3.2). The most common natural disasters, such as droughts, extreme temperatures, floods, and storms, are included in the analysis (Section 3.1). By including a wide range of disasters rather than focusing on a single event, I reduce the risk of omitted variable bias, as certain disasters, such as droughts and extreme temperatures, or floods and storms, may affect each other.

The first measure of natural disasters, $Duration_{it}$, captures how extreme the duration of the disaster is compared to the country's historical average in a given quarter. It shows the number of disaster-affected months in country i at time t relative to the country average on a quarterly basis, expressed as a percentage. Specifically,

$$Duration_{it} = \frac{Month_{it}}{AVGMonth_i} \times 100 \tag{1}$$

where $Month_{it}$ gives the monthly duration of disasters per quarter. $AVGMonth_i$ shows the average monthly duration per country. For example, if a flood occurred in March and lasted until April, I count two months in the first quarter and zero in the second, and divide this amount by the country's average. For events of short duration, such as storms, I divide by the average number of days per month to control for overestimation. This standardisation allows me to compare countries that experience disasters at different frequencies, and to observe whether an event was particularly extreme compared to the past. Thus, for an event to be considered above average, it must have had a longer-lasting impact in some countries, such as the US, compared to others, like Sweden, where the average duration of disasters is shorter (Figure 12). To handle eventual missing information on the duration of disasters, I used text-based sources by searching for disaster events online. Online data represent only a small fraction, less than 0.1% of the whole sample. In the case of unavailable data, I calculated the length of the duration, while controlling for overestimation. For example, if the last month of a disaster was missing, I calculated the duration of the disaster up to January of the previous year of the disaster. If the end year and month were missing, I counted only one month for the disaster.

My second measure, $PopExposure_{it}$, shows a country's exposure to disasters relative to its population, expressed as a percentage on a quarterly basis. Specifically,

$$PopExposure_{it} = \frac{ExposedPeople_{it}}{CountryPop_{it}} \times 100 \tag{2}$$

where $ExposedPeople_{it}$ represents the density of people affected by the disaster. In particular, it shows the number of people per square kilometre within the grid cells of the disasters with a resolution of 2.5 arc minutes (five kilometres at the equator) using the GPW data (2018). $CountryPop_{it}$ is the population of the country. The subscript i refers to the country, while t refers to the quarter. To control for possible migration, $ExposedPeople_{it}$ is constructed using the same weight of the 2000 population size throughout the sample. Therefore, any increase in the measure $PopExposure_{it}$ is due to an increase in the number of disasters or a decrease in $CountryPop_{it}$. Countries in Europe, Japan, and Russia experienced a decrease in population during my sample period. These countries tend to be well prepared for disasters, so obtaining insignificant coefficients for these countries further supports my argument that capital flows are not responsive to disasters in prepared countries (Section 6).

Figure 12 and Figure 13 show the differences between the duration and exposure measures. Although the United States has experienced several longer natural disasters (darker blue in Figure 12), the population is not as affected (lighter blue in Figure 13). A similar pattern is observed in Russia. The correlation between the two indices is positive but low ($\rho = 0.175$), suggesting that the measures capture climate impacts from different angles.

4.2.2 External Natural Disasters

Following the push-pull framework from the literature, local factors are typically considered internal, while global factors are external, reflecting broader global changes (Koepke & Paetzold, 2024). Consistent with this framework, my analysis distinguishes between internal and external disasters. Until now, disasters were considered to happen internally, referring to events that directly affected the home country within its borders. I now introduce external disaster measures, which capture events that occur in the country group of the home country. Specifically, I examine how external disasters in the country group affect capital flows in the home country. I calculate the average number of months that foreign countries in the country group are affected (External

Figure 12: Average Duration of Disasters, in months, 2000-2018.

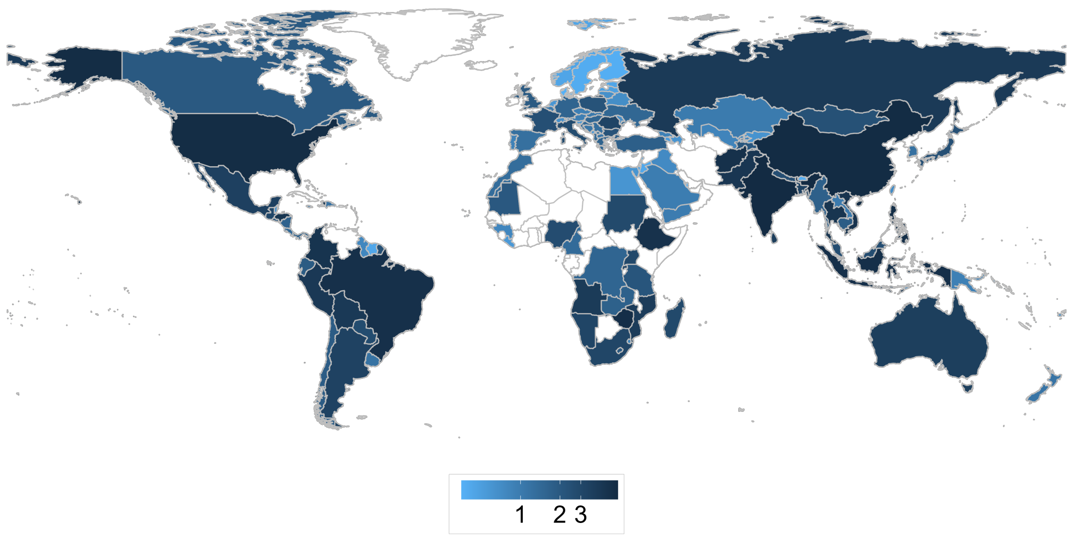
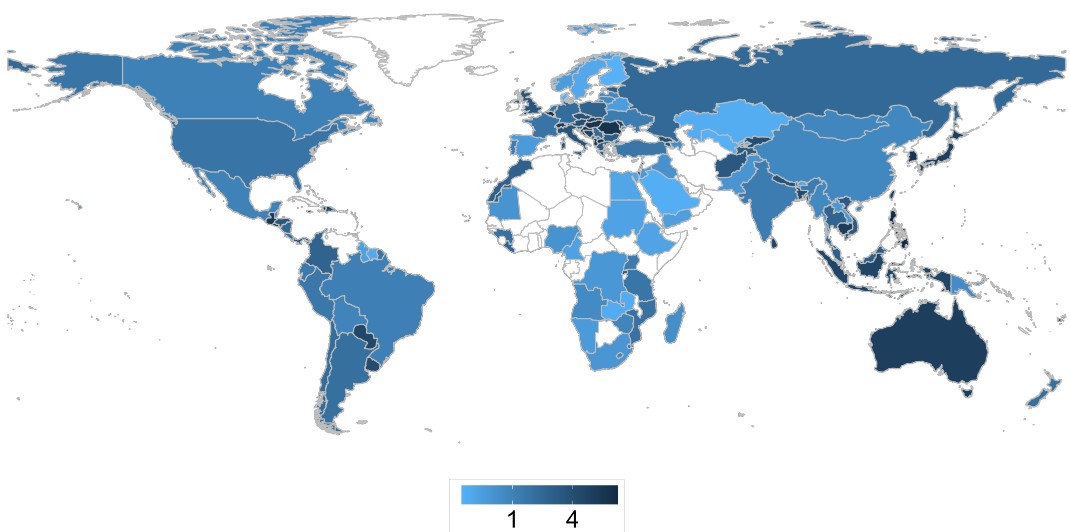


Figure 13: Population Exposure to Disasters, per thousand, 2000-2018



Duration) and assess the average share of the population affected (External Population Exposure). To ensure a clear distinction between internal and external effects, internal natural disasters are excluded from the calculation of external disaster measures.

For example, in the case of Switzerland, I measure how an increase in the average number of affected months, External Duration, or exposed population, External Population Exposure, in similar countries, such as the United Kingdom, affects Swiss capital flows. Internal disasters, i.e. Swiss disasters in this example, are excluded.

To measure external natural disasters, I first calculate the average number of months of disasters and the total exposed population in the complementary country group of the country i:

$$\sum_{l \in \text{CountryGroup}(i) \backslash \{i\}} Duration_{l,t}$$
$$\sum_{l \in \text{CountryGroup}(i) \backslash \{i\}} PopExposure_{l,t}$$

where $Duration_{l,t}$ and $PopExposure_{l,t}$ show the internal measure of duration and exposed people in country l from the country group of country i at time t (Equation 1 and Equation 2).

Second, I count the set size of the complementary set of countries in the country group of country i:

$$|\text{CountryGroup}(i) \backslash \{i\}|$$

I then divide the average measures by the size of the complementary set to obtain the external disaster measures. Specifically,

$$Duration_{i,t}^{External} = \frac{\sum_{l \in \text{CountryGroup}(i) \backslash \{i\}} Duration_{l,t}}{|\text{CountryGroup}(i) \backslash \{i\}|} \tag{3}$$

$$PopExposure_{i,t}^{External} = \frac{\sum_{l \in \text{CountryGroup}(i) \backslash \{i\}} PopExposure_{l,t}}{|\text{CountryGroup}(i) \backslash \{i\}|} \tag{4}$$

These newly constructed external disaster measures, $Duration_{i,t}^{External}$ and $PopExposure_{i,t}^{External}$, show how severely disasters hit the remaining countries in the country group of country i, measured by duration and population exposure.

The internal disaster measures, $Duration_{i,t}$ and $PopExposure_{i,t}$, with the external measures, $Duration_{i,t}^{External}$ and $PopExposure_{i,t}^{External}$, will serve as the main regressors to evaluate the effect of natural disasters on capital flows. The Table 1 shows the summary statistics of the disaster measures. We observe that the observations are right-skewed, which is typical of disaster data. The external measures show a much lower standard deviation because we are averaging across all the countries in a given group.

Table 1: Descriptive Statistics

Variable	Mean	SD	Min	25th pct	Median	75th pct	Max	Obs.
$PopExposure$	0.0063	0.1351	0	0	0	0	9.4612	13,559
$Duration$	90.48	457.03	0	0	0	0	7,600	13,559
$PopExposure^{External}$	0.0063	0.0165	0	0.0012	0.0027	0.0052	0.1383	13,559
$Duration^{External}$	92.05	94.49	0	29.85	61.19	129.34	842.23	13,559

Notes: $PopExposure$ measures the population affected by natural disasters as a percentage of the country's total population. $Duration$ shows disaster length relative to the country's historical average as a percentage. $PopExposure^{External}$ and $Duration^{External}$ represent the same metrics for external disasters, averaged across countries with similar risk and preparedness profiles, excluding home country disasters. Country classifications are based on the IMF INFORM Risk indicators using k-means clustering.

5 Empirical Strategy

This section outlines an empirical framework to test whether capital flows react heterogeneously to natural disasters depending on the country group, and whether disasters are internal or external drivers of capital flows. The framework relies on a two-way fixed effects panel regression with country and time fixed effects, leveraging the exogenous nature of disasters conditional on a country's underlying disaster characteristics. Finally, I discuss further points to address any remaining concerns about endogeneity.

5.1 Natural Disasters as Internal Driver

To measure the possibly heterogeneous internal effects of natural disasters on capital flows, I interact the newly created natural disaster variables, *Duration* and *PopExposure*, with the newly created country groups from Section 4. Specifically, I estimate the following equations:

$$K_{it} = \alpha_i + year_t + \beta Duration_{it} + \theta Duration_{it} \times CountryGroup_i + \\ + \sum_{j=1}^{6} \gamma_j Global_{jt} + \sum_{k=1}^{2} \delta Local_{kit} + \epsilon_{it} \tag{5}$$

$$K_{it} = \alpha_i + year_t + \beta PopExposure_{it} + \theta PopExposure_{it} \times CountryGroup_i + \\ + \sum_{j=1}^{6} \gamma_j Global_{jt} + \sum_{k=1}^{2} \delta Local_{kit} + \epsilon_{it} \tag{6}$$

where K_{it} measures capital in- and outflows to GDP, in country i in time t, in percentage. The parameters α_i and $year_t$ measure country and year-time fixed effects. $Duration_{it}$ and $PopExposure_{it}$ measure internal natural disasters. $Duration_{it}$ exhibits the number of disaster-affected months to the country average in percentage terms, quarterly. $PopExposure_{it}$ shows the affected country's population in percentage. $CountryGroup$ stands for country groups based on the IMF indicators of natural disaster risk and preparedness levels, and are classified into four groups: low disaster risk & prepared, low disaster risk & unprepared, high disaster risk & prepared, and high disaster risk & unprepared. For further information on the variables, see Section 4.

The remaining variables, *Global* and *Local*, show control variables from the literature. I count for global risk changes measured by VXO, global money supply growth, long-term government bond rates, changes in oil prices, global commodity prices, and global inflation. All variables are measured quarterly using data from Forbes and IMF (Forbes & Warnock, 2021; IMF, 2009). *Global* variables are not included if time fixed effects are at the quarter level instead of the year level. For the two *Local* variables, I count quarterly domestic real GDP growth from the IFS and lagged official aid described in Section 3.

5.2 Natural Disasters as External Driver

To assess how capital flows react to external natural disasters, I estimate the effect of a disaster that happened in the country group of the home country on capital flows. These measures capture the duration and population exposure of disasters in the country groups (Section 4.2.2). This method isolates the impact of external disasters on investor decisions, as the measures explicitly exclude any internal disasters experienced by the home country.

Equation 7 and Equation 8 estimate the effects of external natural disasters on capital flows measured by external duration and external population exposure, respectively.

$$K_{it} = \alpha_i + year_t + \beta^E Duration_{it}^{External} + \theta^E Duration_{it}^{External} \times CountryGroup_i + \\ + \beta Duration_{it} + \theta Duration_{it} \times CountryGroup_i + \\ + \sum_{j=1}^{6} \gamma_j Global_{jt} + \delta Local_{it} + \epsilon_{it} \tag{7}$$

$$K_{it} = \alpha_i + year_t + \beta^E PopExposure_{it}^{External} + \theta^E PopExposure_{it}^{External} \times CountryGroup_i + \\ + \beta PopExposure_{it} + \theta PopExposure_{it} \times CountryGroup_i + \\ + \sum_{j=1}^{6} \gamma_j Global_{jt} + \delta Local_{it} + \epsilon_{it} \tag{8}$$

Specifically, $Duration_{it}^{External}$ and $PopExposure_{it}^{External}$ measure the external natural disasters calculated in Equation 3 and Equation 4, respectively. They show if the country group of country i experiences a greater duration or population exposure to the group's average without the disasters of country i.

Global exhibits the same factors as before if time fixed effects are at the year level and are excluded at the quarter level. *Local* only includes real GDP growth and excludes the variable aid to focus solely on external natural disasters.

5.3 Addressing Endogeneity

To account for omitted variable bias, I created country groups to control for unobserved similarities in disaster risk and preparedness. While disaster risk captures physical risk, the preparedness level may depend on hidden factors. For example, corruption or public debt can also impact capital flows and preparedness levels. Country groups control for these issues, as countries belonging to the same country group tend to have comparable disaster exposure and solving strategies, or lack thereof. This makes it possible to consider the exogenous nature of natural disasters conditional on country groups and minimise endogeneity concerns further.

Many studies assess the severity of climate events using economic variables such as insurance costs or damage reports, but this approach is often biased. Developing countries may underreport damage due to a lack of resources, while emerging economies may overreport to attract aid. In contrast, advanced economies tend to report higher costs due to higher-valued assets. These inconsistencies undermine the reliability of economic measures of disaster severity. To account for measurement error, I create new variables, duration and population exposure, that focus on the disaster itself based on satellite data rather than economic outcomes. I used NASA data to calculate population exposure, which helps reduce inconsistencies in data reporting. Although socio-economic factors may still influence weather data, country groups again control for these.

It is also possible that capital flows influence the impact of disasters. For example, increased investment may increase the risk of heat waves due to pollution or help reduce flood risks through infrastructure improvements. Similarly, higher levels of urbanisation can increase the incidence of flash floods if urban planning is poor. However, no effect of capital flows on the severity of climate events has been found in the literature. This may be because capital flows cover many sectors and sources, including central banks, governments and private companies, across industries such as agriculture and transportation. Their aggregate effect, therefore, may cancel each other out.

Moreover, climate adaptation flows, those most likely to change the impact of disasters, represent only a small fraction of global capital. For example, according to Tall et al. (2021), US$30 billion was spent on adaptation in 2017 and 2018, of which only US$500 million came from private investment. This amount is negligible compared to portfolio capital flows, which often exceed $500 billion per quarter.

Finally, the estimation accounts for simultaneity by assessing how individual economies respond to external natural disasters. Based on the small open economy framework, global variables such as external natural disasters are treated as exogenous to a country's domestic conditions.

6 Results

To examine the impact of natural disasters on international capital flows, I estimate the responses of different types of flows, including portfolio equity and debt, FDI, and other flows.[5] First, I examine whether capital flows react heterogeneously to natural disasters across country groups based on disaster risk (high or low) and disaster preparedness (prepared or unprepared). Second, I contrast the impact of internal disasters in the home country with that of external disasters occurring within the home country's group, revealing whether disasters act as push or pull factors of capital flows. Finally, I assess whether the two different measures of natural disasters, duration of disasters and population exposure, affect capital flows differently.

6.1 Heterogeneous Capital Flow Responses - Population Exposure Measure

To establish a baseline for comparison, I first estimate how capital flows respond to natural disasters at the aggregate level. I find that capital flows tend not to react to internal disasters without distinguishing among country groups (Table 2). Specifically, portfolio equity, debt and other investment flows do not respond to an increase in the impact of disasters as represented by population exposure. Only FDI shows a statistically significant reaction to disasters at the 5% level. However, the estimated effects are small, at around 2% of the mean FDI flows. These results are similar to previous findings in the literature, which suggest that capital flows are not particularly sensitive to natural disasters at the aggregate level (Gu & Hale, 2023).

To test whether capital flows react heterogeneously to natural disasters depending on country characteristics, I interact country groups with the population exposure measure. I use low disaster risk (low DR) and unprepared countries (UP) as the reference group, meaning the estimated coefficients show how other country groups differ from this baseline (Equation 6 with quarterly fixed effects). In contrast to the lack of aggregate flow reaction (Table 2), investors now react significantly (Table 3). In the reference group of low disaster risk and unprepared countries, a 0.1 percentage point increase in population exposure leads to decreases of 0.6 pp in portfolio equity

[5] I follow the residency principle from the balance of payments data, where inflows represent the net holdings of domestic assets by foreign investors. Outflows represent the net holdings of foreign assets by domestic investors. Therefore, negative values represent a decrease in domestic and foreign holdings, respectively (Avdjiev et al., 2022; IMF, 2009).

inflows (p<0.001), 1.9 pp in equity outflows (p<0.001), 0.5 pp in debt inflows (p<0.05), and 4.4 pp in other outflows (p<0.001) (Table 3, row 1). FDI flows, on the other hand, do not react to an increase in population exposure.[6]

Other country groups show significantly different responses compared to the reference group of low disaster risk and unprepared countries (Table 3, col. 1, 2, 8). For example, in column 1 in Table 3, countries with low disaster risk and high preparedness show a 0.4 pp larger increase in portfolio equity inflows (p<0.05). Countries with high disaster risk and low preparedness also show a 0.6 pp larger increase (p<0.001). However, these coefficients represent differences from the reference group, instead of total effects. After estimating the total effects for these groups by adding the interaction coefficients to the estimated reference group effect, the values are no longer statistically significant, indicating that the overall responses of these countries to disasters are not significantly different from zero. The same findings are true for column 8 in Table 3, where significant differences from the reference country groups exist, but the effect of population exposure is only significant in countries with a low level of disaster risk that are unprepared. The only exception to this is foreign debt investment in countries with high disaster risk and preparedness, such as the United States, which reacts significantly to natural disasters. Specifically, foreign investors increase their net debt investment following a natural disaster (Table 3, col. 3). This may indicate the "build-back-better" phenomenon, where investors anticipate the demand for new sources of investment after a disaster. They are inclined to make new investments knowing that the country is prepared to deal with the aftermath of disasters.

The estimated strong reactions of inflows and outflows in the reference group suggest that the level of disaster risk and a country's disaster preparedness influence the reactions of foreign and domestic investors to natural disasters. First, foreign investors faced with natural disasters in unprepared countries with low disaster risk reassess their investment strategies in these mainly emerging and developing countries, where disasters are a relative surprise. They leave the country by divesting. These changes in perception can have long-term effects on the country. If investors no longer

[6]The previously found significant negative FDI response in the aggregate analysis was driven by the large number of low disaster risk and prepared countries in the sample, 61 out of 117 countries (Table 2).

trust the country, countries not only experience a sudden stop in investment, but also face a decline in future investment in an environment where natural disasters are expected to become more frequent. Net foreign investment usually comes from advanced economies (Avdjiev et al., 2022), meaning that countries in the low disaster risk and unprepared group are exposed to a lull in foreign investment from advanced economies following a natural disaster. A stop in investment can have a negative impact on countries' growth expectations. However, different investors are affected in different ways. Disasters have less of an impact on debt than on equities, possibly due to a relatively higher level of confidence in the country's government than in its markets. However, foreign investors with higher investment and fixed costs, represented by FDI flows, do not react. Even if the country is hit by a disaster, investors' decision is not affected, presumably caused by the long-term strategic nature of FDI.

Second, domestic investors reduce their net foreign holdings even more compared to foreign investors. The significant 1.9 and 4.4 percentage points drop in equity and other outflows indicates that domestic investors retrench and reduce their net foreign investment after a natural disaster strikes. In emerging markets, corporates account for the bulk of portfolio flows and banks and corporates account for the majority of other investment flows (Avdjiev et al., 2022). This means that banks are especially exposed to domestic natural disasters in unprepared countries with low disaster risk.

For prepared countries and those with high disaster risk, the overall impact is close to zero, except for financing possible reconstruction needs through debt inflows. Investors do not change their behaviour in countries with a high disaster risk or in countries that are prepared for disasters in general. This suggests that investors have already priced in the higher probability of disasters in countries that regularly experience natural disasters. In addition, investors have confidence in prepared countries, and therefore do not need to change their investment strategies.

Overall, these findings reveal the heterogeneous impact of natural disasters on capital flows, highlighting the importance of considering country-specific factors such as disaster risk and preparedness levels. The results suggest that unprepared countries with low disaster risk are particularly vulnerable to sudden stops in investment following natural disasters, while prepared countries and those with high disaster risk experience less disruption.

Table 2: Portfolio, FDI, and Other Flows without Country Groups

	(1) Equity in b/se	(2) Equity out b/se	(3) Debt in b/se	(4) Debt out b/se	(5) FDI in b/se	(6) FDI out b/se	(7) Other in b/se	(8) Other out b/se
Pop. Exposure	-0.056	-0.013	-0.027	0.018	-0.179*	-0.137*	0.010	-0.078
	(0.04)	(0.02)	(0.03)	(0.03)	(0.07)	(0.06)	(0.09)	(0.11)
Received aid	0.003	0.079	0.222	0.160	0.426	0.284	0.824	0.701
	(0.17)	(0.16)	(0.24)	(0.20)	(0.61)	(0.62)	(0.61)	(0.47)
Real GDP growth	0.354	0.102	0.126	0.282	-0.103	-0.250	0.363	0.460
	(0.25)	(0.10)	(0.08)	(0.20)	(0.31)	(0.30)	(0.24)	(0.30)
Obs.	7642	7721	7651	7724	8873	8327	8908	8847
Adjusted R^2	0.572	0.301	0.148	0.300	0.326	0.319	0.058	0.228
Mean of Dep. Var	3.931	2.824	2.358	3.043	9.938	6.542	3.946	4.909

Notes: The dependent variables are capital inflows and outflows as a share of nominal GDP in quarter t. Pop. Exposure is the relative exposure of the domestic population to natural disasters compared to the country's population. All regressions include country and quarter fixed effects and are estimated by OLS. Pull factors are aid and GDP growth. Push factors are absorbed by quarter-time fixed effects. Standard errors clustered at the country level are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6.2 Disasters in Similar Countries - External Population Exposure

In this section, I further examine the impact of disasters on capital flows from an external perspective. Specifically, I compare the impact of natural disasters as external drivers with that of internal drivers. Internal disasters, as defined previously, are those that directly affect the home country. External disasters, on the other hand, are those that occur in countries within the same group of countries as the home country, but not in the home country itself. Examining external disasters provides information on whether investors take external disasters into account when making an investment decision in their home country, and not just internal disasters.

Building on the existing literature on the drivers of capital flows, I follow the

Table 3: Portfolio, FDI, and other Investment Flows with Country Groups

	(1) Equity in b/se	(2) Equity out b/se	(3) Debt in b/se	(4) Debt out b/se	(5) FDI in b/se	(6) FDI out b/se	(7) Other in b/se	(8) Other out b/se
Pop. Exposure in Low DR & UP	-0.606***	-1.927***	-0.515*	-0.285	1.172	-0.815	-6.564	-4.395***
	(0.11)	(0.24)	(0.24)	(0.25)	(2.98)	(0.45)	(7.70)	(0.83)
Pop. Exposure × High DR & P	0.152	2.669***	3.078**	1.050*	-1.138	1.062	7.520	4.894***
	(0.38)	(0.55)	(0.99)	(0.49)	(3.21)	(0.92)	(7.76)	(1.05)
Pop. Exposure × Low DR & P	0.379*	1.866***	0.182	-0.136	-1.526	0.298	6.273	4.319***
	(0.16)	(0.27)	(0.43)	(0.46)	(3.06)	(0.52)	(7.78)	(1.11)
Pop. Exposure × High DR & UP	0.618***	2.057***	0.730**	0.240	-1.401	0.994	7.314	4.636***
	(0.10)	(0.29)	(0.26)	(0.33)	(3.04)	(0.55)	(7.74)	(0.85)
Received aid	-0.045	0.038	0.256	0.115	0.468	0.224	0.448	0.396
	(0.05)	(0.11)	(0.23)	(0.12)	(0.49)	(0.39)	(0.38)	(0.32)
Real GDP growth	0.006	-0.030	0.040	0.024	-0.187	-0.371	0.104	-0.015
	(0.03)	(0.08)	(0.06)	(0.09)	(0.35)	(0.36)	(0.16)	(0.09)
Obs.	6959	6818	6768	6900	7535	7080	7560	7507
Adjusted R2	0.032	0.490	0.099	0.064	0.264	0.186	0.079	0.096
Mean of Dep Var	0.339	1.539	1.556	1.129	6.215	2.959	3.066	2.503

Notes: The dependent variables are capital inflows and outflows as a share of nominal GDP in quarter t. Pop. Exposure is the relative exposure of the domestic population to natural disasters compared to the country's population. Pop. Exposure is interacted with the created country groups from Section 4.1. The base country group is "Low Disaster Risk (Low DR) and Unprepared (UP)". All regressions include country and quarter fixed effects and are estimated by OLS. Pull factors are aid and GDP growth. Push factors are absorbed by quarter-time fixed effects. Standard errors clustered at the country level are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

push-pull framework to examine whether natural disasters act as internal or external drivers. The negative coefficients observed for portfolio and other investment flows in Table 3 in Section 6.1 indicate that foreign investors exit the market by divesting, and domestic investors reduce their foreign assets when disasters hit their home country, acting as an internal driver. This suggests that internal disasters have a "pull" effect, discouraging both foreign and domestic investment. To see if natural disasters also act as possible "push" drivers, I focus on natural disasters that occur in the country group of the home country. Specifically, I construct an external disaster measure that counts all disasters that affect any country in the home country group, while excluding those that directly affect the home country itself. This approach allows me to control for both internal drivers (disasters in the home country) and external drivers (disasters in other countries in the country groups).

The results show that capital flows only react to natural disasters in unprepared countries with low disaster risk. Specifically, portfolio equity in response to external disasters increases by 3.8 percentage points in the home country for every 0.1 percentage point increase in population exposure in the low disaster risk but unprepared country group (Table 4). The positive coefficient associated with external disasters on portfolio equity inflows suggests that in the low disaster risk but unprepared country group, foreign investors increase their equity investment in unaffected countries when other countries suffer natural disasters. This observation is consistent with the findings of Ferriani et al. (2023), who show that capital flows tend to "fly" to safer countries. However, unlike their methodology, which groups all "risky" countries together, my research takes into account differences in disaster risk exposure and preparedness, and considers both internal and external disasters.

Meanwhile, the coefficients for the internal population exposure remain similar. This implies that external and internal natural disasters are not linked in my methodology. This result is expected as country groups are created to reflect similarities in disaster risk and preparedness rather than geographical proximity.

6.3 Heterogeneous Capital Flows Responses - Duration Measure

I have created different measures of natural disasters to indicate whether investors are more concerned about the duration of disasters or the exposure of a country's population (Section 4.2). The duration measure, calculated as the number of disaster-affected months relative to a country's historical average, is standardised to allow comparisons between countries with different frequencies of natural disasters. For example, an event affecting the US for a longer period of time would be considered less extreme than a similar event in Sweden, as the average duration of disasters in Sweden is shorter. Duration, therefore, only measures how long a disaster lasted in a country, without focusing on the human component.

To measure the effect of disaster duration, I estimate how capital flows re-

Table 4: Portfolio, FDI, and Other Investment Flows with Country Groups and External Population Exposure

	(1) Equity in b/se	(2) Equity out b/se	(3) Debt in b/se	(4) Debt out b/se	(5) FDI in b/se	(6) FDI out b/se	(7) Other in b/se	(8) Other out b/se
External Pop. Exposure in Low DR & UP	3.806*	-0.360	6.253	-1.752	-22.164	-13.988	-16.577	-12.513
	(1.65)	(3.59)	(4.99)	(6.60)	(13.29)	(8.90)	(9.50)	(12.35)
External Pop. Exposure × High DR & P	-3.289	0.997	-3.364	1.206	25.065	19.751	15.965	15.206
	(2.11)	(4.81)	(5.81)	(7.07)	(14.68)	(11.21)	(10.60)	(14.04)
External Pop. Exposure × Low DR & P	-2.499	6.896	-6.281	0.593	28.712	16.973	7.035	6.096
	(1.74)	(4.72)	(6.35)	(7.40)	(15.39)	(14.29)	(10.50)	(12.07)
External Pop. Exposure × High DR & UP	-2.871*	2.678	-3.829	1.143	23.882	19.488	21.677	20.559
	(1.42)	(5.48)	(5.18)	(7.52)	(15.99)	(12.19)	(11.81)	(13.13)
Pop. Exposure in Low DR & UP	-0.566***	-1.861***	-0.437	-0.300	1.037	-0.902*	-6.798	-4.533***
	(0.11)	(0.25)	(0.26)	(0.29)	(2.95)	(0.45)	(7.65)	(0.82)
Pop. Exposure × High DR & P	0.165	2.698***	3.003**	1.045*	-0.867	1.218	7.669	5.095***
	(0.36)	(0.57)	(1.02)	(0.49)	(3.18)	(0.98)	(7.71)	(1.07)
Pop. Exposure × Low DR & P	0.352*	1.821***	0.098	0.080	-1.416	0.397	6.785	4.455***
	(0.17)	(0.29)	(0.43)	(0.41)	(3.04)	(0.55)	(7.72)	(1.12)
Pop. Exposure × High DR & UP	0.565***	2.020***	0.612*	0.284	-1.312	1.059	7.720	4.828***
	(0.11)	(0.33)	(0.28)	(0.38)	(3.01)	(0.59)	(7.71)	(0.84)
Received aid	-0.043	0.026	0.244	0.131	0.420	0.225	0.454	0.361
	(0.05)	(0.11)	(0.23)	(0.12)	(0.49)	(0.40)	(0.38)	(0.32)
Real GDP growth	0.007	-0.039	0.042	0.020	-0.193	-0.377	0.103	-0.008
	(0.03)	(0.09)	(0.06)	(0.10)	(0.36)	(0.36)	(0.16)	(0.09)
Obs.	6750	6612	6568	6698	7290	6864	7315	7264
Adjusted R2	0.028	0.490	0.094	0.065	0.261	0.185	0.078	0.092
Mean of Dep Var	0.333	1.561	1.543	1.128	6.249	3.007	3.069	2.473

Notes: The dependent variables are capital inflows and outflows as a share of nominal GDP in quarter t. Pop. Exposure is the relative exposure of the domestic population to natural disasters compared to the country's population. Pop. Exposure is interacted with the created country groups from Section 4.1. The base country group is "Low Disaster Risk (Low DR) and Unprepared (UP)". All regressions include country and quarter fixed effects and are estimated by OLS. Pull factors are aid and GDP growth. Push factors are absorbed by quarter-time fixed effects. Standard errors clustered at the country level are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

act to duration across country groups. Looking at different capital flows, including portfolio equity and debt, FDI, and other flows, I find that the duration measure does not significantly affect capital flows, and the magnitude of the effects is small in all specifications. For example, a one-unit increase in the duration measure leads to less than a 0.001% change in all flows (Table 5). Similarly, none of the other specifications show significant results. In contrast, population exposure significantly affects portfolio and other investment flows. A 0.1 pp increase in population exposure reduces portfolio equity inflows and outflows by 0.6 pp and 1.9 pp, respectively, debt inflows by 0.5 pp, and Other outflows by 4.4 pp.

The results imply that investors are more concerned about the number of people affected by disasters than the duration of the disaster. This finding is consistent with the idea that financial market participants give priority to human impact and potential economic disruption when assessing risk.

Table 5: Portfolio, FDI, and Other Investment Flows with Country Groups, Duration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Equity in	Equity out	Debt in	Debt out	FDI in	FDI out	Other in	Other out
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Duration in Low DR & UP	-0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Duration × High DR & P	0.000	-0.000	0.000*	-0.000	-0.000	-0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Duration × Low DR & P	-0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Duration × High DR & UP	0.000	-0.000*	-0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Received aid	-0.045	0.036	0.254	0.116	0.469	0.219	0.442	0.391
	(0.05)	(0.11)	(0.23)	(0.12)	(0.49)	(0.39)	(0.38)	(0.32)
Real GDP growth	0.006	-0.029	0.041	0.025	-0.187	-0.371	0.106	-0.014
	(0.03)	(0.08)	(0.06)	(0.09)	(0.35)	(0.36)	(0.16)	(0.09)
Obs.	6959	6818	6768	6900	7535	7080	7560	7507
Adjusted R2	0.031	0.489	0.099	0.064	0.264	0.186	0.078	0.096
Mean of Dep Var	0.339	1.539	1.556	1.129	6.215	2.959	3.066	2.503

Notes: The dependent variables are capital inflows and outflows as a share of nominal GDP in quarter t. Duration shows the relative duration of natural disasters compared to the country's average. Duration is interacted with the created country groups from Section 4.1. The base country group is "Low Disaster Risk (Low DR) and Unprepared (UP)". All regressions include country and quarter fixed effects and are estimated by OLS. Pull factors are aid and GDP growth. Push factors are absorbed by quarter-time fixed effects. Standard errors clustered at the country level are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6.4 Robustness Checks

I carry out several robustness checks to confirm the results. In particular, I change the construction of the country groups, the estimation methods, and introduce new independent variables. I also run further regressions to determine whether the estimated effects are due to a country's preparedness for climate and weather events, rather than other factors, such as income level.

Subsample after 2014. My current country groups are based on the three core indices of the 2014 IMF INFORM Risk dataset. Because of possible endogeneity, I rerun my estimates on the post-2014 subsample. The results are reassuring. The signs of the coefficients remain the same at higher levels of significance (Table 8).

Income levels. Instead of using countries' levels of preparedness and disaster risk, I create country groups according to income level. Although country wealth is an important driver of capital flows, it should not explain differences in the impact of natural disasters. Instead, preparedness and disaster risk should modify the impact. As expected, income groups show no effect when interacting with disaster indicators (Table 9).

Institutional quality. I also control for institutional quality measured by regulatory quality from the Worldwide Governance Indicators. The estimated coefficients are similar (Table 10).

Random effects model instead of fixed effects. I also run a random effects model, assuming that the specific effects are now random. I do this for both technical and conceptual reasons. Computationally, I have to estimate 117 fixed effects for each country. This reduces the degrees of freedom in the fixed effects model, which weakens the results. Theoretically, I have information on 117 of the 193 countries recognised by the UN. Missing countries tend to be small islands, developing countries or other small countries. Therefore, if my large sample accurately reflects the population distribution, I can assume that individual effects are random draws of specific effects in the population. The effects do not disappear and even show a higher significance (Table 11).

Earthquakes. Earthquakes are usually caused by tectonic processes. They can occur anywhere, but usually near fault lines.[7]. They are widely believed to be unaffected by climate change, and predictions of future earthquakes depend on the location of the country. To see if my results are robust, I test my country groups interacting with earthquake disasters. I find that they have no significant effect on capital flows (Table 12).

New country groups. I explore different methods for creating my country groups. First, while using k-means clustering, I switched to using Manhattan distances instead of Euclidean distances. When using Euclidean distances, outliers can have a greater effect on the results. Although I see some differences in the structure of the groups, the results are similar using Manhattan distances. Second, I divide countries into four equal groups according to their disaster and preparedness levels, rather than clustering them, in order to remove randomness from my model. The new methods do not change my results; unprepared countries with low disaster risk are the most exposed to sudden changes in capital flows following a natural disaster. Results are not shown.

Bootstrapping. I re-test my results using bootstrapping; the results remain significant at the 5% level. Results are not shown.

Smaller nations. I also include islands and then small island developing states as defined by the UN. In both cases, my regressions remain robust. Results are not shown.

7 Conclusion and Discussion

This paper reveals that natural disasters affect capital flows heterogeneously. Only countries with low disaster risk and low disaster preparedness react to extreme events. I construct two disaster measures to assess the severity of extreme events and interact them with country characteristics, measuring preparedness and disaster risk levels. I find that the number of people affected by disasters matters to investors, not the duration of disasters. To place natural disasters as a driver of capital flows in the push-pull framework of the literature, I examine the effects of domestic and foreign disasters. I find that climate disasters act as an internal factor for portfolio and other investment

[7] Michigan Technological University

flows and as an external factor for portfolio equity inflows.

The striking difference across country groups suggests that financial markets are responding to the unexpected news component of disasters, represented by the generally high and significant reactions of capital flows in unprepared countries with a low probability of disaster. If a country experiences frequent disasters, investors have already priced in the increased risk of climate disasters and are not surprised by an extreme event. Similarly, if a climate event occurs but the country is prepared to deal with it and, therefore, absorb any negative impact, markets will not react. On the other hand, if the country does not normally experience disasters, investors will react strongly when one does occur. The significant reaction in low-disaster-risk and unprepared countries implies that financial markets have not yet fully priced in climate change in these countries. This potential market failure may have important policy implications. Countries that are unprepared for a future with more climate disasters may suffer more from volatile market reactions threatening their financial stability. This finding is important because the probability of achieving net zero by 2050 is rapidly decreasing, while the frequency of climate- and weather-related disasters is increasing. Countries need to prepare to signal their well-established coping mechanisms for an increased frequency of natural disasters. In doing so, they can shield their economies from additional risks posed by sudden changes in capital flows.

For future research, greater use of satellite data can further reduce endogeneity problems. A sectoral view of investment could disentangle aggregate effects. The response of capital flows may depend on whether they originate from corporations, banks, or governments. In addition, tourism and agriculture may experience negative impacts, while construction may even benefit from climate disasters. It would also be interesting to examine whether there are differences in climate impacts between urban and rural areas. If climate events affect cities, the market may react differently than in the same scenario in rural areas. Furthermore, disaggregated capital flows, such as fund flows from the Emerging Portfolio Fund Research (EPFR), could reveal different sensitivity levels to global factors.

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A Appendix

B Data

Table 6: Country Groups of 117 countries and their availability

Country Group	**ISO3**	**Country**	**Start**	**End**	**Country Group**	**ISO3**	**Country**	**Start**	**End**
Low DR & UP	AGO	Angola	2000q1	2018q4	High DR & P	RUS	Russian Federation	2000q1	2018q4
Low DR & UP	AZE	Azerbaijan	2000q1	2018q4	High DR & P	SRB	Serbia	2000q1	2018q4
Low DR & UP	BTN	Bhutan	2000q1	2018q4	High DR & P	THA	Thailand	2000q1	2018q4
Low DR & UP	CMR	Cameroon	2000q1	2018q4	High DR & P	TWN	Taiwan Province of China	2000q1	2018q4
Low DR & UP	COD	Congo, Dem. Rep.	2000q1	2018q4	High DR & P	USA	United States	2000q1	2018q4
Low DR & UP	ETH	Ethiopia	2000q1	2018q4	High DR & P	UZB	Uzbekistan	2000q1	2018q4
Low DR & UP	GIN	Guinea	2000q1	2018q4	High DR & P	VNM	Vietnam	2000q1	2018q4
Low DR & UP	JOR	Jordan	2000q1	2018q4	High DR & UP	AFG	Afghanistan	2000q1	2018q4
Low DR & UP	LBN	Lebanon	2000q1	2018q4	High DR & UP	BGD	Bangladesh	2000q1	2018q4
Low DR & UP	LBR	Liberia	2000q1	2018q4	High DR & UP	BOL	Bolivia	2000q1	2018q4
Low DR & UP	LSO	Lesotho	2000q1	2018q4	High DR & UP	COL	Colombia	2000q1	2018q4
Low DR & UP	NGA	Nigeria	2000q1	2018q4	High DR & UP	GTM	Guatemala	2000q1	2018q4
Low DR & UP	NIC	Nicaragua	2000q1	2018q4	High DR & UP	HND	Honduras	2000q1	2018q4
Low DR & UP	NPL	Nepal	2000q1	2018q4	High DR & UP	IND	India	2000q1	2018q4
Low DR & UP	RWA	Rwanda	2000q1	2018q4	High DR & UP	IRQ	Iraq	2000q1	2018q4
Low DR & UP	SWZ	Eswatini, Kingdom of	2000q1	2018q4	High DR & UP	KHM	Cambodia	2000q1	2018q4
Low DR & UP	TZA	Tanzania	2000q1	2018q4	High DR & UP	LAO	Lao PDR	2000q1	2018q4
Low DR & UP	UGA	Uganda	2000q1	2018q4	High DR & UP	MDG	Madagascar, Rep. of	2000q1	2018q4
Low DR & UP	YEM	Yemen, Rep.	2000q1	2018q4	High DR & UP	MMR	Myanmar	2000q1	2018q4
Low DR & UP	ZMB	Zambia	2000q1	2018q4	High DR & UP	MOZ	Mozambique, Rep. of	2000q1	2018q4
High DR & P	AUS	Australia	2000q1	2018q4	High DR & UP	MRT	Mauritania	2000q1	2018q4
High DR & P	BRA	Brazil	2000q1	2018q4	High DR & UP	NAM	Namibia	2000q1	2018q4
High DR & P	CHN	China	2000q1	2018q4	High DR & UP	PAK	Pakistan	2000q1	2018q4
High DR & P	IDN	Indonesia	2000q1	2018q4	High DR & UP	PHL	Philippines	2000q1	2018q4
High DR & P	JPN	Japan	2000q1	2018q4	High DR & UP	SDN	Sudan	2000q1	2018q4
High DR & P	KOR	Korea, Rep.	2000q1	2018q4	High DR & UP	TJK	Tajikistan	2000q1	2018q4
High DR & P	LKA	Sri Lanka	2000q1	2018q4	High DR & UP	ZAF	South Africa	2000q1	2018q4
High DR & P	MEX	Mexico	2000q1	2018q4	High DR & UP	ZWE	Zimbabwe	2000q1	2018q4
High DR & P	MYS	Malaysia	2000q1	2018q4					

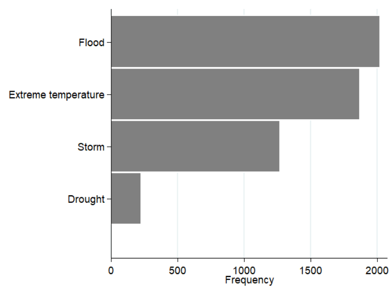
Notes: DR stands for disaster risk. UP stands for unprepared. P stands for prepared. Countries are sorted by country group, by ISO 3 country codes.

Table 7: Country Groups of 117 countries and their availability, Cont.

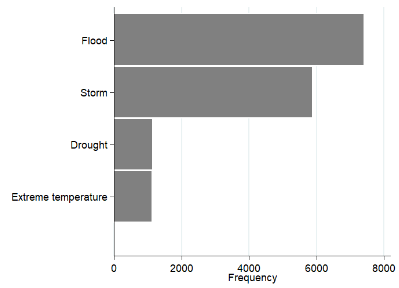
Country Group	ISO3	Country	Start	End	Country Group	ISO3	Country	Start	End
Low DR & P	ALB	Albania	2000q1	2018q4	Low DR & P	ITA	Italy	2000q1	2018q4
Low DR & P	ARG	Argentina	2000q1	2018q4	Low DR & P	KAZ	Kazakhstan	2000q1	2018q4
Low DR & P	ARM	Armenia	2000q1	2018q4	Low DR & P	KGZ	Kyrgyz Republic	2000q1	2018q4
Low DR & P	AUT	Austria	2000q1	2018q4	Low DR & P	KWT	Kuwait	2000q1	2018q4
Low DR & P	BEL	Belgium	2000q1	2018q4	Low DR & P	LTU	Lithuania	2000q1	2018q4
Low DR & P	BGR	Bulgaria	2000q1	2018q4	Low DR & P	LVA	Latvia	2000q1	2018q4
Low DR & P	BHR	Bahrain	2000q1	2018q4	Low DR & P	MAR	Morocco	2000q1	2018q4
Low DR & P	BIH	Bosnia and Herzegovina	2000q1	2018q4	Low DR & P	MDA	Moldova	2000q1	2018q4
Low DR & P	BLR	Belarus	2000q1	2018q4	Low DR & P	MKD	North Macedonia	2000q1	2018q4
Low DR & P	BRN	Brunei Darussalam	2000q1	2018q4	Low DR & P	MLT	Malta	2000q1	2018q4
Low DR & P	CAN	Canada	2000q1	2018q4	Low DR & P	MNE	Montenegro	2000q1	2018q4
Low DR & P	CHE	Switzerland	2000q1	2018q4	Low DR & P	MNG	Mongolia	2000q1	2018q4
Low DR & P	CHL	Chile	2000q1	2018q4	Low DR & P	NLD	Netherlands	2000q1	2018q4
Low DR & P	CRI	Costa Rica	2000q1	2018q4	Low DR & P	NOR	Norway	2000q1	2018q4
Low DR & P	CYP	Cyprus	2000q1	2018q4	Low DR & P	NZL	New Zealand	2000q1	2018q4
Low DR & P	CZE	Czech Republic	2000q1	2018q4	Low DR & P	PAN	Panama	2000q1	2018q4
Low DR & P	DEU	Germany	2000q1	2018q4	Low DR & P	PER	Peru	2000q1	2018q4
Low DR & P	DNK	Denmark	2000q1	2018q4	Low DR & P	POL	Poland	2000q1	2018q4
Low DR & P	ECU	Ecuador	2000q1	2018q4	Low DR & P	PRT	Portugal	2000q1	2018q4
Low DR & P	EGY	Egypt, Arab Rep. of	2000q1	2018q4	Low DR & P	PRY	Paraguay	2000q1	2018q4
Low DR & P	ESP	Spain	2000q1	2018q4	Low DR & P	QAT	Qatar	2000q1	2018q4
Low DR & P	EST	Estonia	2000q1	2018q4	Low DR & P	ROU	Romania	2000q1	2018q4
Low DR & P	FIN	Finland	2000q1	2018q4	Low DR & P	SAU	Saudi Arabia	2000q1	2018q4
Low DR & P	FRA	France	2000q1	2018q4	Low DR & P	SLV	El Salvador	2000q1	2018q4
Low DR & P	GBR	United Kingdom	2000q1	2018q4	Low DR & P	SVK	Slovak Republic	2000q1	2018q4
Low DR & P	GEO	Georgia	2000q1	2018q4	Low DR & P	SVN	Slovenia	2000q1	2018q4
Low DR & P	GRC	Greece	2000q1	2018q4	Low DR & P	SWE	Sweden	2000q1	2018q4
Low DR & P	HRV	Croatia	2000q1	2018q4	Low DR & P	TUR	Turkey	2000q1	2018q4
Low DR & P	HUN	Hungary	2000q1	2018q4	Low DR & P	UKR	Ukraine	2000q1	2018q4
Low DR & P	ISL	Iceland	2000q1	2018q4	Low DR & P	URY	Uruguay	2000q1	2018q4
Low DR & P	ISR	Israel	2000q1	2018q4					

Notes: DR stands for disaster risk. UP stands for unprepared. P stands for prepared. Countries are sorted by country group, by ISO 3 country codes.

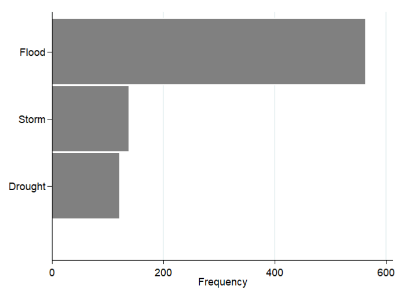
Figure 14: Number of disaster-affected locations by Country groups, 2000-2018.



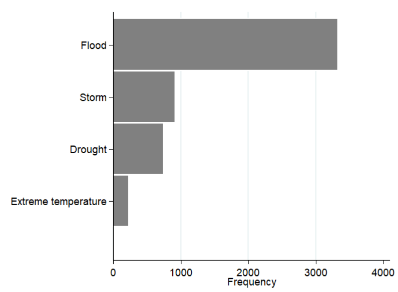
(a) Prepared & Low disaster risk



(b) Prepared & High disaster risk



(c) Unprepared & Low disaster risk



(d) Unprepared & High disaster risk

C Results

Table 8: Portfolio, FDI, and Other Investment Flows with Country Groups, Post-2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Equity in	Equity out	Debt in	Debt out	FDI in	FDI out	Other in	Other out
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Pop. Exposure in Low DR & UP	-0.269***	-1.918***	-1.539***	-0.271	-0.589*	-0.314	-0.479	-5.124***
	(0.07)	(0.20)	(0.18)	(0.15)	(0.23)	(0.20)	(0.98)	(0.48)
Pop. Exposure × High DR & P	-0.477	2.397	2.890	1.665	-0.408	-0.266	3.508	5.917**
	(1.37)	(1.40)	(2.89)	(2.16)	(1.70)	(1.13)	(3.32)	(2.24)
Pop. Exposure × Low DR & P	0.087	1.714***	1.486***	-0.314	-0.093	0.165	0.278	6.005***
	(0.20)	(0.23)	(0.42)	(0.74)	(0.86)	(0.46)	(1.72)	(1.25)
Pop. Exposure × High DR & UP	0.404	2.190***	1.262	0.680	-0.625	0.324	0.303	1.823
	(0.22)	(0.36)	(0.93)	(0.45)	(1.21)	(1.24)	(1.78)	(2.20)
Received aid	0.035	-0.055	-0.867	0.073	-0.136	-0.484	-0.345	-0.436
	(0.06)	(0.06)	(0.61)	(0.12)	(0.45)	(0.33)	(0.44)	(0.40)
Real GDP growth	-0.004	0.083	0.014	0.071	0.019	-0.379	-0.057	-0.276
	(0.02)	(0.06)	(0.06)	(0.09)	(0.26)	(0.33)	(0.23)	(0.16)
Obs.	1592	1551	1542	1557	1701	1608	1701	1701
Adjusted R2	0.064	0.873	0.067	0.185	0.233	0.301	0.057	0.108
Mean of Dep Var	0.175	1.389	0.762	0.392	4.128	1.568	1.621	1.231

Notes: The dependent variables are capital inflows and outflows as a share of nominal GDP in quarter t. Pop. Exposure is the relative exposure of the domestic population to natural disasters compared to the country's population. All regressions include country and quarter fixed effects and are estimated by OLS. Pull factors are aid and GDP growth. Push factors are absorbed by quarter-time fixed effects. Subsample with observations after 2014. Standard errors clustered at the country level are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: Portfolio, FDI, and Other Investment Flows with Income Groups

	(1) Equity in b/se	(2) Equity out b/se	(3) Debt in b/se	(4) Debt out b/se	(5) FDI in b/se	(6) FDI out b/se	(7) Other in b/se	(8) Other out b/se
Pop. Exposure in Low income	0.689	-0.449	-1.069	0.665	-0.769	-2.028	-4.007	-2.745
	(0.84)	(0.46)	(1.39)	(0.69)	(1.77)	(2.23)	(4.09)	(2.19)
Pop. Exposure × Lower middle income	-0.252	0.326	1.237	-0.504	0.485	1.497	4.404	3.161
	(0.58)	(0.45)	(1.49)	(0.71)	(1.73)	(2.02)	(4.16)	(2.41)
Pop. Exposure × Upper middle income	-0.746	0.442	1.054	-0.672	0.573	1.895	4.070	2.749
	(0.88)	(0.46)	(1.43)	(0.70)	(1.77)	(2.21)	(4.09)	(2.19)
Pop. Exposure × High income	-0.757	0.432	1.030	-0.624	0.576	1.877	3.973	2.569
	(0.88)	(0.46)	(1.39)	(0.71)	(1.76)	(2.20)	(4.06)	(2.13)
Received aid	-0.026	-0.000	0.220	0.124	0.114	-0.024	0.670	0.596
	(0.18)	(0.11)	(0.25)	(0.19)	(0.53)	(0.57)	(0.58)	(0.47)
Real GDP growth	0.387	0.169*	0.126	0.331	0.139	-0.042	0.467*	0.553
	(0.26)	(0.08)	(0.08)	(0.20)	(0.19)	(0.22)	(0.23)	(0.30)
Obs.	7502	7502	7511	7528	8670	8171	8689	8628
Adjusted R2	0.573	0.261	0.148	0.307	0.329	0.326	0.054	0.231
Mean of Dep Var	3.975	2.157	2.399	2.927	9.273	6.491	3.715	4.648

Notes: The dependent variables are capital inflows and outflows as a share of nominal GDP in quarter t. Pop. Exposure is the relative exposure of the domestic population to natural disasters compared to the country's population. All regressions include country and quarter fixed effects and are estimated by OLS. Pull factors are aid and GDP growth. Push factors are absorbed by quarter-time fixed effects. Standard errors clustered at the country level are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: Portfolio, FDI, and Other Investment Flows with Country Groups and Institutional Quality

	(1) Equity in b/se	(2) Equity out b/se	(3) Debt in b/se	(4) Debt out b/se	(5) FDI in b/se	(6) FDI out b/se	(7) Other in b/se	(8) Other out b/se
Pop. Exposure in Low DR & UP	-0.605***	-1.931***	-0.415	-0.226	1.191	-0.807	-6.517	-4.289***
	(0.10)	(0.24)	(0.26)	(0.27)	(3.01)	(0.45)	(7.74)	(0.81)
Pop. Exposure × High DR & P	0.045	2.779***	3.358***	1.052*	-1.403	0.962	7.670	5.064***
	(0.33)	(0.51)	(0.85)	(0.52)	(3.23)	(0.89)	(7.80)	(1.01)
Pop. Exposure × Low DR & P	0.392*	1.876***	-0.008	-0.194	-1.476	0.335	6.082	3.849***
	(0.16)	(0.27)	(0.47)	(0.42)	(3.08)	(0.51)	(7.81)	(1.12)
Pop. Exposure × High DR & UP	0.614***	2.071***	0.643*	0.169	-1.417	0.935	7.283	4.480***
	(0.10)	(0.30)	(0.26)	(0.34)	(3.06)	(0.58)	(7.77)	(0.81)
Received aid	-0.051	0.069	0.340	0.195	0.493	0.227	0.589	0.566
	(0.05)	(0.10)	(0.26)	(0.13)	(0.49)	(0.40)	(0.41)	(0.36)
Real GDP growth	0.002	-0.064	0.029	0.014	-0.219	-0.378	0.085	-0.037
	(0.03)	(0.11)	(0.06)	(0.10)	(0.39)	(0.37)	(0.18)	(0.11)
Institutional quality	0.003	0.016	0.111*	0.060*	-0.010	-0.014	0.103	0.109*
	(0.01)	(0.02)	(0.05)	(0.03)	(0.04)	(0.05)	(0.06)	(0.05)
Obs.	6667	6530	6486	6608	7203	6774	7224	7175
Adjusted R2	0.034	0.519	0.104	0.066	0.275	0.195	0.085	0.105
Mean of Dep Var	0.341	1.564	1.561	1.111	6.333	3.033	3.125	2.544

Notes: The dependent variables are capital inflows and outflows as a share of nominal GDP in quarter t. Pop. Exposure is the relative exposure of the domestic population to natural disasters compared to the country's population. All regressions include country and quarter fixed effects and are estimated by OLS. Pull factors are aid and GDP growth. Push factors are absorbed by quarter-time fixed effects. Standard errors clustered at the country level are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 11: Portfolio, FDI, and Other Investment Flows with Country Groups, Random Effects

	(1) Equity in b/se	(2) Equity out b/se	(3) Debt in b/se	(4) Debt out b/se	(5) FDI in b/se	(6) FDI out b/se	(7) Other in b/se	(8) Other out b/se
Pop. Exposure in Low DR & UP	-0.599***	-1.896***	-0.481**	-0.597***	1.282	-0.632**	-5.995	-3.971***
	(0.05)	(0.22)	(0.18)	(0.06)	(3.16)	(0.20)	(7.48)	(0.77)
High DR & P	0.261	0.044	0.582	0.282	-3.572	-0.219	-1.566*	-0.689
	(0.15)	(0.18)	(0.41)	(0.19)	(2.20)	(0.91)	(0.71)	(1.53)
Low DR & P	0.257*	1.858	1.427***	1.360***	1.275	2.575	0.995	0.607
	(0.11)	(1.16)	(0.40)	(0.32)	(2.67)	(1.38)	(1.32)	(1.76)
High DR & UP	0.075	0.089	-0.184	0.224	-2.048	-0.796	-0.838	-1.493
	(0.13)	(0.27)	(0.23)	(0.19)	(2.36)	(0.97)	(0.76)	(1.45)
Pop. Exposure × High DR & P	0.200	2.493***	2.944**	1.450***	-1.586	0.519	6.505	3.764***
	(0.37)	(0.68)	(1.12)	(0.37)	(3.21)	(0.39)	(7.55)	(0.84)
Pop. Exposure × Low DR & P	0.376**	1.888***	0.078	-0.020	-1.479	0.193	5.721	3.857***
	(0.12)	(0.24)	(0.42)	(0.29)	(3.18)	(0.33)	(7.56)	(1.09)
Pop. Exposure × High DR & UP	0.585***	1.904***	0.497*	0.453***	-1.646	0.556**	6.530	4.000***
	(0.06)	(0.22)	(0.20)	(0.08)	(3.15)	(0.19)	(7.48)	(0.80)
Received aid	-0.054	-0.119*	-0.167	-0.277***	-0.256	-0.370*	-0.177	-0.289
	(0.03)	(0.05)	(0.11)	(0.08)	(0.24)	(0.15)	(0.22)	(0.22)
Real GDP growth	0.008	0.023	0.077	0.052	0.035	-0.179	0.366**	0.287***
	(0.01)	(0.03)	(0.06)	(0.05)	(0.25)	(0.29)	(0.12)	(0.08)
Constant	0.139	0.261	0.367	0.131	6.217**	2.360	1.067	1.130
	(0.10)	(0.21)	(0.33)	(0.25)	(2.26)	(1.44)	(0.85)	(1.63)
Obs.	6959	6819	6768	6900	7535	7080	7560	7507
Mean of Dep Var	0.339	1.539	1.556	1.129	6.215	2.959	3.066	2.503

Notes: The dependent variables are capital inflows and outflows as a share of nominal GDP in quarter t. Pop. Exposure is the relative exposure of the domestic population to natural disasters compared to the country's population. All regressions include country and quarter fixed effects and are estimated by OLS. Pull factors are aid and GDP growth. Push factors are absorbed by quarter-time fixed effects. Standard errors clustered at the country level are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 12: Portfolio, FDI, and Other Investment Flows with Country Groups, Earthquakes and Volcanic Eruptions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Equity in	Equity out	Debt in	Debt out	FDI in	FDI out	Other in	Other out
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Pop. Exposure in Low DR & UP	-18.325	-7.240	64.029	27.477	-67.611	-205.380	-3.687	-404.418
	(16.25)	(13.10)	(39.42)	(24.69)	(70.37)	(115.90)	(62.72)	(264.88)
Pop. Exposure × High DR & P	35.555	7.857	-75.650	-23.475	8.264	174.249	-35.513	357.860
	(19.89)	(22.74)	(59.95)	(41.27)	(96.83)	(121.69)	(115.85)	(274.76)
Pop. Exposure × Low DR & P	18.616	10.745	-70.296	-14.628	103.237	229.538	33.530	437.837
	(15.79)	(14.30)	(38.91)	(31.08)	(68.60)	(117.93)	(62.64)	(264.77)
Pop. Exposure × High DR & UP	21.138	10.387	-44.588	-24.878	68.660	229.411	36.786	459.307
	(17.71)	(13.07)	(42.53)	(28.37)	(80.66)	(123.76)	(58.73)	(263.63)
Received aid	-0.046	0.036	0.253	0.116	0.472	0.225	0.444	0.398
	(0.05)	(0.11)	(0.23)	(0.12)	(0.49)	(0.39)	(0.38)	(0.31)
Real GDP growth	0.006	-0.030	0.041	0.024	-0.187	-0.371	0.106	-0.014
	(0.03)	(0.08)	(0.06)	(0.09)	(0.35)	(0.36)	(0.16)	(0.09)
Obs.	6959	6818	6768	6900	7535	7080	7560	7507
Adjusted R2	0.031	0.489	0.099	0.064	0.264	0.186	0.078	0.096
Mean of Dep Var	0.339	1.539	1.556	1.129	6.215	2.959	3.066	2.503

Notes: The dependent variables are capital inflows and outflows as a share of nominal GDP in quarter t. Pop. Exposure is the relative exposure of the domestic population to earthquakes compared to the country's population. All regressions include country and quarter fixed effects and are estimated by OLS. Pull factors are aid and GDP growth. Push factors are absorbed by quarter-time fixed effects. Standard errors clustered at the country level are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.