International Development

Prizewinning Dissertation 2024

No.24-CFM

Climate-related Disasters and Firm Location: Geospatial Evidence from India

Constantin Freiherr von Mengersen

Published: April 2025

Department of International Development

London School of Economics and Political Science

Houghton Street

London

WC2A 2AE UK

Tel: +44 (020) 7955 7425/6252

Fax: +44 (020) 7955-6844

Email: d.daley@lse.ac.uk

Website: http://www.lse.ac.uk/internationalDevelopment/home.aspx

Abstract

This paper explores how firms adapt to climate-related disasters through their location decisions, using the 2018 floods in Kerala (India) as a natural experiment. By combining geo-referenced firm-level administrative data and satellite imagery of the inundation zones, I analyze the impact of the floods on the subsequent location choices of newly formed and existing companies. Employing a variety of different models, I find that flood-affected villages experienced a significant and temporally persistent decline in new firm registrations following the disaster. Likewise, affected firms seem to be more likely to relocate after the flood, although this effect is only evident under certain empirical specifications. Finally, I find that among relocating firms, those affected by the flood systematically choose locations with lower underlying flood risk. This suggests that these relocations are a deliberate measure to reduce future risk exposure, reflecting an experience-driven adjustment in firms' risk assessments.

Abbreviations

API	Application Programming Interface
CIN	Corporate Identification Number
CWC	Central Water Commission
FDI	Foreign Direct Investment
IPCC	Intergovernmental Panel on Climate Change
MNE	Multinational Enterprise
R&D	Research & Development
UNEP	United Nations Environment Program
USD	US-Dollar
WESR	World Environment Situation Room

Table of Contents

1 Introduction

Climate change fundamentally threatens societies and economic growth in many parts of the world. Despite increasing global attention to the need to limit greenhouse gas emissions, current mitigation efforts are almost certainly insufficient to prevent most of the predicted damages and costs (IPCC 2023). One significant channel through which climate change harms societies and economies is by increasing the occurrence and intensity of extreme weather events (Ibid). Due to their greater exposure and vulnerability, developing countries have been particularly affected by the rising frequency of such climate-related disasters. Given these considerations, it is crucial for researchers and policymakers to understand how these disasters impact economic activity and how economic actors respond to their occurrence in these countries.

This paper investigates how firms, as key drivers of economic activity and essential to a country's development, adapt to disasters. Existing research has shown that disasters can raise firms' risk awareness, prompting them to take measures to reduce their exposure to future disasters (see Pankratz and Schiller 2022; Vincenzi-Castro et al. 2024). While adaptation to climate change, i. e. reducing future exposure or vulnerability to climate risk, can take many forms (Grover and Kahn 2024), this paper focuses on the spatial dimension of firm-level adaptation, specifically how disasters influence where existing and newly formed companies choose to locate. Consequently, it seeks to answer the following research question:

How do climate-related disasters impact firm location decisions?

Given the substantial damages that disasters can inflict on firm operations (see Zhou and Botzen 2021; Vu and Noy 2018), there is a clear theoretical rationale for firms to consider climate risk in their location decisions (Linnenluecke et al. 2011). However, empirical research on this issue is extremely sparse and has produced inconclusive results (Balboni et al. 2023; Alves et al. 2024). Yet, the locational response of companies has wide-raging implications: If firms continue to operate in risky areas, the rising frequency and intensity of climate-related disasters will result in significant future costs for them and the country as a whole. Conversely, if firms choose to avoid or abandon disaster-prone locations, this can have severe adverse effects on the already vulnerable populations residing in these areas.

To investigate the research question, I analyze the case of the 2018 floods in Kerala, India. Floods constitute the most widespread type of climate-related disaster (Tellman et al. 2021), and India is among the countries with the highest flood risk in the world (Rentschler et al. 2022). The 2018 Kerala floods were the most destructive in the state in the last 100 years (Walia and Nusrat 2020). The unprecedented and unexpected nature of the floods makes them an exogenous event, allowing me to investigate their causal effect on firm entry and relocation. I geo-reference firm-level administrative data and combine them with shapefiles of satellite images of the inundation zones to assign treatment and control groups. To assess the effect on firm entry, I construct a yearly panel on firm registration at the village level and employ a negative binomial model event study approach to estimate dynamic effects over time. To investigate the effect on firm relocation, I exploit different rounds of administrative data collection and estimate a logit model assessing the probability of relocation at the firm level. Finally, I employ a linear model to determine if flood-affected relocating firms reduce their locational risk exposure by moving to areas with lower underlying flood risk.

I find that the flood had a statistically significant and robust negative effect on firm entry in affected villages in the year of its occurrence, and that this effect persists until today. Regarding relocation, the results are more ambiguous and suggest an increased likelihood of relocation for affected firms only under certain treatment specifications. However, among relocating firms, those affected by the flood seem to systematically choose areas with lower flood risk.

This paper contributes to the existing literature in several ways: first, it is the first to investigate locational adaptation to climate risk by Indian firms, adding a valuable case to the literature. Second, it is the first to demonstrate strongly negative, enduring effects of climate-related disasters on firm entry, using a highly robust methodological approach. Lastly, its findings on relocation add nuance to the inconclusive results of the extant empirical literature and align with evidence from other studies suggesting that disasters can trigger experience-based, rational updating and induce firms to consciously reduce their future exposure to climate risk (Balboni et al. 2023; Pankratz and Schiller 2022).

The rest of the paper is organized as follows: Section 2 reviews the empirical literature on firm-level responses to disasters, with an emphasis on adaptation; Section 3 outlines the theoretical rationale for why disasters should affect firm location decisions; Section 4 describes the data sources and methodology; Section 5 presents the results of the analysis; Section 6 discusses implications and limitations, and Section 7 concludes.

2 Firm-level Responses to Climate-Related Disasters

The literature on firm responses in the aftermath of extreme weather events highlights two main types of responses. The first type focuses on measures that seek to mitigate the economic losses incurred from these events through an adjustment of expenditures. For instance, Indaco et al. (2021) found that affected establishments in New York City significantly reduced employment and wages after Hurricane Sandy. Similarly, Li et al. (2020) demonstrated how heatwaves in the US led to substantial reductions in employment and the closure of establishments, directly linking these effects to a decline in local consumer demand. Gramlich et al. (2020) showed that financial constraints caused by disasters discourage corporate innovation by reducing spending on R&D.

The second type of response, and the most pertinent to this paper, encompasses *adaptive* strategies. While adaptation to climate change broadly refers to "the process of adjustment to actual or expected climate and its effects" (IPCC 2014, 1758), firm-level adaptation usually involves strategies aimed at reducing exposure or vulnerability to climate risk (Linnenluecke et al. 2013). Among the various adaptation measures a firm can implement (Grover and Kahn 2024), this paper focuses on the spatial (locational) dimension of adaptation. A key focus within this area is on the diversification of production across locations. The rationale here is that even if firms themselves are not directly exposed to climate risk, climate change-induced disruptions in their suppliers' operations can significantly harm their own operations, thus propagating climate risk exposure along the supply chain (Inoue and Todo 2019; Altay and Ramirez 2010). Using a cross-country dataset on supplier-customer relationships, Pankratz and Schiller (2022) found that firms are 6-11% more likely to end existing supplier relationships when the supplier is exposed to higher-than-expected risks of flooding and heatwaves. Moreover, firms replace such suppliers with others located in regions less exposed to climate disasters, indicating that firms update their risk assessments following large-scale weather shocks. Similarly, Vincenzi-Castro et al. (2024) found that firms in India diversify their supplier base if their existing suppliers were exposed to flooding. In the aftermath of floods, firms source products from locations that are further away and less exposed to flooding, thus reducing their supply-chain exposure to floods even at the expense of higher input prices. Comparable findings are reported by Balboni et al. (2023), who found that flood-affected firms in Pakistan increased their number of suppliers in the aftermath and systematically shifted their supplier composition towards regions with lower flood risk. They further demonstrated that firms select new suppliers that can be reached via infrastructure and roads less prone to floods, aiming to minimize future logistical disruptions. Most significantly, these changes are not merely short-term responses to floods but enduring, long-term adjustments of production networks. While supply chain management seems to be the focal point of the empirical literature on spatial firm-level adaptation, a growing number of studies are examining how firms can adapt to the impacts of climate change through their location decisions.

On the one hand, this literature investigates the effect of climate risk on location decisions of *multinational* enterprises (MNEs), specifically how the risk and the occurrence of natural disasters affect foreign direct investment (FDI). Most of these studies evaluate the effect of disasters on FDI at the country-level (Escaleras and Register 2011; Neise et al. 2022), which raises significant concerns about the credibility of their counterfactual due to potential omitted variables. Others shift the unit of analysis to more granular levels. For instance, using panel data on approximately 6000 firms in 66 different countries, Gu and Hale (2023) found no robust evidence that the overall FDI patterns of MNEs are responsive to extreme weather events. Conversely, Friedt and Toner-Rodgers (2022) explored how natural disasters alter the within-country allocation of FDI in India, revealing that MNEs significantly reduce their investments in disaster-affected regions, with these effects persisting for up to six years post-disaster. They also observed substantial positive spillover effects for unaffected regions, indicating a reallocation of FDI to these areas. A limitation of their study is the assignment of treatment at the regional level – considering entire regions treated if any part was affected by a disaster, thereby overlooking the variation in disaster severity and extent within regions. In this paper, treatment assignment is conducted at the much more precise village and firm levels. By focusing on the impacts of the disaster at these specific units of analysis, my research design seeks to establish a more credible counterfactual than the above-mentioned regional and cross-country analyses.

On the other hand, the effect of climate-related disasters on *domestic* firm location decisions has been much less explored. Yasuyuki et al. (2014) studied the aftermath of the 2011 floods in central Thailand using survey data from 314 firms. They found that firms were significantly less likely to choose flood-affected regions for new establishments. However, the firms in their sample were predominantly large in terms of size and financial performance. Consequently, their disaster response might not be representative of the average firm's response, which this paper seeks to investigate. To the best of my knowledge, only two papers, yet to be published, have assessed the impact of disasters on firm location using geocoded microdata on the entire universe of firms within the affected geographical area. Alves et al. (2024) investigated how the 2008 Santa Catarina Flash Flood in Brazil affected business closure, entry and relocation. Using an event-study, they found that affected areas experienced significant reductions in firm entry only in the fourth year after the floods. Moreover, firms affected by the disaster did not exhibit a higher likelihood of relocating to other areas. Since the authors detected a positive and significant effect of the flood on business closure, they concluded that affected firms were more likely to terminate operations than relocate to less flood-prone areas. Conversely, Balboni et al. (2023) analyzed the impacts of flood events in Pakistan and found that flood-affected firms were significantly more likely to relocate than unaffected firms. Moreover, firms that did relocate systematically chose areas with a significantly lower risk of flood occurrence, implying that relocation was undertaken as a deliberate risk management measure rather than as a response to general economic dynamics, such as changes in factor prices. However, a limitation of their empirical approach is the combination of observing company locations at only two points in time (2011 and 2019) and the considerable time gap between the baseline address data and most of the flood events they investigate. Consequently, their analysis likely includes relocations that occurred before the floods, introducing a form of measurement error. Depending on the nature of these unrelated relocations, this error could either attenuate the estimated effect of the flood on relocation, leading to an underestimation or create a spurious relationship, resulting in an overestimation of the effect. The temporal mismatch between baseline data and event occurrence can also lead to erroneous treatment assignment. Since treatment is assigned according to the baseline data, any relocations between the baseline and the event are not captured, potentially leading to non-affected firms being mistakenly categorized as treated and/or affected firms being incorrectly classified as part of the control group. In contrast, my study seeks to mitigate these limitations as the timing of my baseline address data is very close to the occurrence of the floods, thus minimizing the likelihood of falsely classifying pre-flood relocations and treatment status, ensuring a more precise estimation of the impact of the flood.

All in all, this paper aims to overcome the methodological shortcomings of the existing empirical literature by utilizing geocoded microdata at the firm and village levels, with precise timing relative to flood events, to investigate the effect of flooding on firm entry and relocation. By focusing on the 2018 Kerala floods in India, this study adds a valuable case to the limited empirical literature on this topic, seeking to provide greater clarity in light of the ambiguous findings presented above.

3 Why Should Climate-Related Disasters Influence Firm Location Decisions?

It is useful to outline why firms should be expected to incorporate climate-related disasters into their location decision. Destructive disasters like floods and storms can profoundly impact firm performance, adversely affecting output, labor productivity, and operating income (see Zhou and Botzen 2021; Hu et al. 2019; Pankratz et al. 2023). These impacts can manifest through both temporary and more permanent location-specific mechanisms. This section reviews the mechanisms most prevalent in the literature and subsequently integrates disaster risk into a simplified profit-maximization model of location choice.

a) Temporary effects

The damages caused by climate-related disasters can impose significant costs on both directly and indirectly affected firms (Rentschler et al. 2021). Primarily, these disasters can inflict substantial damage to firms' physical capital, including buildings, machinery, and inventories. Especially in developing countries, where these assets are often less resilient to climate shocks, disasters have been found to destroy a substantial share of physical capital (Pelli et al. 2023; De Mel et al. 2012). The subsequent need for repair and replacement can considerably increase firms' costs in the short run. Additionally, significant damage to machinery or inventory typically results in a temporary reduction in production capacity, thus diminishing their revenues.

However, even if firms' premises are not directly impacted by the disaster, firms located in the broader disaster area can incur costs indirectly due to infrastructure disruptions. Large-scale disasters frequently disrupt electricity, transport, and water infrastructure in the wider area (Rentschler et al. 2019b; 2021). The monetary costs of these disruptions, particularly in developing countries, are substantial and have been found to lead to significant reductions in capacity utilization, thereby negatively affecting revenues (Rentschler et al. 2019a).

Additionally, if firms use alternative transport routes in response to infrastructure disruptions, their operating costs may also increase.
Lastly, firms not directly hit by the disaster can be negatively affected by such climate shocks through a reduction in consumer demand. The damage caused by large-scale disasters creates a negative income shock for affected households. This shock is then partially passed on to firms, as consumer demand for most goods and services tends to decrease significantly in the aftermath, with households redirecting funds to basic needs and reconstruction efforts (Beyer et al. 2022; Li et al. 2020).

b) *Permanent effects*

Beyond these temporary effects, climate-related disasters can also trigger more enduring adverse impacts on firm operations. These rely mainly on the fact that the location of past disasters is a significant predictor of where future disasters may occur (Dilley et al. 2005; Amei et al. 2012; Friedt and Toner-Rodgers 2022). Consequently, past disasters can reshape economic actors' beliefs about the likelihood of future disasters in a particular location, and their perceptions of that location's susceptibility to such events (Ibid.).
Firstly, climate-related disasters and increased climate vulnerability are priced in financial markets, increasing affected firms' cost of capital and restricting their access to finance. The occurrence of disasters can prompt lenders and investors to update their risk assessments of a firm's locational exposure to climate risk, inducing them to demand higher returns. This can result in higher costs of debt (Kling et al. 2021) and equity (Chu and Xu 2022). Notably, the occurrence of disasters can cause lenders to reassess the risk and financing terms not only for directly affected firms, but also for unaffected firms located in areas of high climate risk (Correa et al. 2022). In addition to higher costs, firms subject to increased climate vulnerability also face restricted access to finance, as lenders become reluctant to extend credit even at higher interest rates (Kling et al. 2021; Cevik and Miryugin 2023).
Moreover, not only lenders and investors, but also insurance companies update their risk assessment and charge higher insurance premia in response to climate-related disasters (Grover and Kahn 2024; Friedt and Toner-Rodgers 2022). Unless firms take measures to reduce their exposure or increase their resilience to climate risk, these effects are likely to be sustained in the long-run.
Lastly, there is substantial evidence that people adapt to climate-related disasters through (internal) migration (Berlemann and Steinhardt 2017). Climate-induced migration can

adversely affect firm operations in two ways. First, disasters can cause significant and permanent outmigration and deter in-migration to affected areas (Boustan et al. 2020), leading to a permanent reduction in local market size and thus lower revenues. Second, migration responses to climate risk also include permanent labor migration (Gröger and Zylberberg 2016; Li 2024). The reduced labor supply in affected areas can result in increased costs for firms, as they may need to offer higher wages to attract workers, and labor scarcity can delay hiring new employees.

3.1 Location Choice in Light of Climate Risks

The common denominator of the above-discussed effects is that they are all location-specific, meaning their severity and extent strongly depend on the proximity of firms to the affected areas. Neoclassical location theory, a commonly used framework for analyzing firm location decisions, posits that firms are rational and perfectly informed agents, choosing their optimal locations based on profit maximization (Pellenbarg and van Dijk 2000; Arauzo-Cardo et al. 2010). While various profit-driving factors, such as market size, infrastructure quality, and agglomeration economies, impact location decisions, the previous section demonstrated that disasters can adversely affect both the revenue and cost components of a firm's profit function, both in the immediate aftermath and in the long-run. This makes (current and future) disaster risk and the exposure to its adverse effects a similar profit-driving factor that firms should consider when choosing their optimal location.

a) Firm entry

Following and simplifying the approach by Friedt and Toner-Rodgers (2022), the profit π_{ij} of a newly formed firm i when choosing location j can thus be expressed as[1]:

$$\pi_{ij}^{New} = \mathrm{R}_{ij}(\mathrm{r}_j) - \mathrm{C}_{ij}(\mathrm{r}_j)$$

where R represents revenues, C denotes costs and r_j symbolizes the disaster "risk-factor" at location j.

[1] The following expressions are for illustrative purposes only and do not aim to give a holistic account of firm location decisions.

In addition to disaster risk, potential revenues are a function of the potential quantity firm i can sell and the price level P in location j and can thus be written as:[2]

$$\mathrm{R}_{ij} = \mathrm{P}_j \times \mathrm{Q}_{ij} - \alpha_i \mathrm{r}_j$$

with α_i indicating the susceptibility of the firm's revenues to the disaster risk r_j. The potential cost function can be written as:

$$\mathrm{C}_{ij} = \mathrm{F}_{ij} + \mathrm{c}_{ij} \times \mathrm{Q}_{ij} + \beta_i \mathrm{r}_j$$

where F_{ij} represents fixed costs, $\mathrm{c}_{ij} \times \mathrm{Q}_{ij}$ variable costs and β_i the susceptibility of the firm's costs to the disaster risk.

For newly formed firms, the optimal location is the location j that maximizes their profit π_{ij}^{New}. Based on the above considerations, I expect decision-makers considering to register a firm to avoid affected locations in the aftermath of a disaster.

H_1: *In the aftermath of a disaster, newly formed firms should avoid affected areas.*

b) Firm relocation

On the other hand, existing firms seeking to relocate to location j face a similar optimization problem as above but incur a relocation cost γ_i, which can be substantial and may deter relocation even if the current location is suboptimal (Brouwer et al. 2004). These costs include *direct* expenses such as searching for and acquiring new real estate, relocating physical capital, and hiring new labor (Ibid.; McCann 2001), as well as *indirect* costs, like investments in infrastructure and buildings at the current location (Pellenbarg and van Dijk 2000) and the loss of location-bound benefits such as buyer and supplier networks (Linnenluecke et al. 2011).

Consequently, their profit function can be expressed as

$$\pi_{ij}^{Existing} = \mathrm{R}_{ij}(\mathrm{r}_j) - \mathrm{C}_{ij}(\mathrm{r}_j) - \gamma_i$$

[2] For simplicity, the effect of risk on revenues and costs is assumed to be linear.

and their optimal location choice will be location j that maximizes their profit $\pi_{ij}^{Existing}$.

Despite the potential magnitude of relocation costs, I expect a large-scale disaster with significant damages to incentivize existing firms to relocate since the current and expected future damages in their current location can make another location more profitable:

H_{2A}: *In the aftermath of a disaster, affected firms should be more likely to relocate than unaffected firms.*

However, the mere fact that affected firms are more likely to relocate does not necessarily imply that they undertake this action to reduce their exposure to disaster risk. To classify the relocation as a forward-looking response to reduce future exposure, these firms should systematically relocate to less disaster-prone locations (Balboni et al. 2023):

H_{2B}: *Among relocating firms, firms affected by a disaster should relocate to less disaster-prone locations.*

It is important to specify the type of disaster under investigation. Since the implicit assumption of the stated hypotheses is an ex-post update in economic actors' risk assessment, the disaster must be sufficiently unpredictable and unexpected to induce this update. In the case of more predictable (seasonal) disasters, firms might undertake ex-ante adaptive measures. For instance, existing firms might have already considered the effects of seasonal disasters in their initial location decision, making it unlikely to detect an ex-post locational adjustment.

Moreover, as reflected in the terms α_i and β_i in the revenue and cost functions, not all firms' operations are equally vulnerable to the adverse effects of disasters and climate change (see Addoum et al. 2019). For instance, manufacturing firms, whose location is crucial to their operations and whose activities are highly capital-intensive, are likely to be more affected by the direct damages of destructive events like floods and storms compared to less capital-intensive firms, such as those in the service sector (Hossain 2020). Likewise, some firms may be less capable of relocating due to their dependence on specific ecosystems and resources, such as agricultural or mining firms (Linnenluecke et al. 2011). Therefore, it is crucial to consider the potential for heterogeneous effects by sector when investigating the impact of disasters on relocation decisions.

Lastly, it is essential to acknowledge that the neoclassical assumptions of perfect rationality and information are highly stylized. If firms lack information about the future potential of climate risk in different locations, their responses to disasters might not align with the abovementioned predictions. Beyond neoclassical theory, other frameworks highlight additional determinants of industrial location choice. For example, behavioral location theory recognizes that location decisions are often constrained by limited information, leading firms to choose suboptimal rather than profit-maximizing locations (Brouwer et al. 2004). Specifically, this theory posits that firms consider only a limited set of options and evaluate them sequentially, often selecting the first alternative that meets a predefined standard (Pellenbarg and van Dijk 2000). It also notes that firms only occasionally re-evaluate the profitability of their present location and that relocation often turns out to be too costly (Ibid.). In contrast, institutional location theory emphasizes the importance of the institutional environment of a firm's location, particularly the role of taxes, regulations and incentive programs set by governments (Arauzo-Cardo et al. 2010). In the context of disasters, the latter could encompass, for instance, recovery programs and compensation schemes for affected firms.

Consequently, various determinants beyond purely profit-driving factors can influence firms' location decisions, potentially leading to different outcomes than those theorized above. The validity of my hypotheses largely depends on whether rational, profit-driven factors prevail over alternative considerations, and whether firms possess accurate information about the riskiness of their current and prospective locations. To test these hypotheses, I will conduct a case study analyzing the effects of the 2018 Kerala floods on firm entry and relocation. One advantage of studying floods over other climate-related disasters, such as storms or heatwaves, is the availability of precise data. Satellite imagery provides highly detailed information on the geographical extent of floods, allowing for a granular measurement of their impact. The following section will provide a more detailed description of the case, outline the data sources employed, and detail the empirical specification used.

4 Methodology

4.1 Case Selection

India figures among the most disaster-prone countries in the developing world and has been particularly subject to prolonged episodes of monsoonal rains, triggering large-scale floods. This makes it a popular case for investigating the impacts of flood events on economic outcomes (Friedt and Toner-Rodgers 2022; Vincenzi-Castro et al. 2024; Rabano and Rosas 2023). Moreover, to the best of my knowledge, India is the only developing country with comprehensive, publicly available microdata on company locations.

The particular flood event under investigation is the 2018 Kerala floods. Kerala experienced unusually high rainfall during the southwest monsoon season from June to July of that year (Beyer et al. 2022). However, the situation escalated in early August when rainfall surged to more than 700% above normal levels (Ibid.). The resulting floods and landslides caused widespread devastation, including 433 fatalities and the destruction and heavy damage of more than 17,000 houses (Walia and Nusrat 2020). Additionally, there was significant damage to the road, water, and electricity infrastructure. The economic effects were also profound: Beyer et al. (2022) demonstrate that economic activity proxied by nighttime lights was reduced by approximately 8%. Likewise, they identified significant, though temporally limited, negative impacts on household income and consumer demand. The Kerala floods were selected as a case study for several reasons:

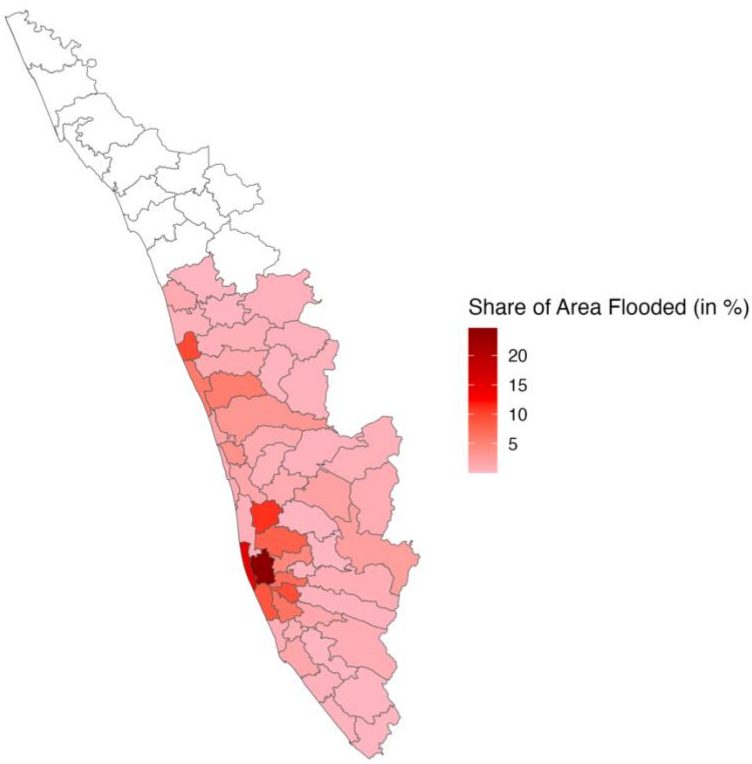
Firstly, the nature of the Indian company data and the timing of the data collection restricted the possible event period for the analysis of relocations. The Kerala flood is the major flood event in India that occurred closest to the baseline company data, with only approximately three months between the two. To estimate the impact of the flood on the probability of relocation accurately, this time period should be as short as possible. As previously explained, since the relocation analysis relies on address information from only two points in time (pre- and post-flood), a larger temporal distance between the baseline data and the flood could result in misclassifications of both the outcome (by including pre-flood relocations) and the predictor variable (by incorrectly assigning treatment status), potentially biasing the estimation.

Secondly, the Kerala floods were selected due to their exogeneity. Floods are common in many parts of India, particularly in Central and East India, including states like Bihar, Odisha, and West Bengal, which have also experienced floods of similar magnitude in recent years.

However, research has shown that economic actors incorporate frequent (seasonal) floods into their decision-making and adjust their behavior accordingly (Kocornick-Mina et al. 2020). For my purpose, this could mean that the occurrence of the flood might be correlated with certain company characteristics. For example, more productive firms might anticipate the seasonal floods and locate further away from flood-prone areas, implying that less productive firms, which might have a different probability of relocating, will be more exposed to the floods.

In contrast, the 2018 floods were the worst flood event in Kerala in over a hundred years, occurring in a region where the incidence of rainfall had been much lower than in the aforementioned states (CWC 2018). The unprecedented nature of the Kerala floods thus makes them a truly exogenous event, underpinning my identification strategy (Beyer et al. 2022). Figure 1 shows the extent of the floods, illustrating that large parts of the state, particularly the districts of Alappuzha, Ernakulam and Kottayam, were affected.

Figure 1: Magnitude of the Kerala Floods



Own elaboration

4.2 Dataset Creation[3]

The company data used in the analysis was taken from administrative records of the Government of India, which contain information on the entirety of Indian firms registered with the Registrar of Companies. The dataset includes detailed firm-level information such as addresses, exact registration dates, and several other firm characteristics. Notably, the data was collected and updated at distinct points in time—2015, 2018, 2021, and 2023—enabling tracking of changes in firm locations over time. To the best of my knowledge, this is the first contribution to use this data for research purposes.

a) Entry dataset

The dataset to investigate the registration of new firms over time was built by combining the four rounds of administrative data, using the 2023 data as a starting point. A limitation of the 2023 version is that it only contains the most recent address information (as of 2023). For example, if a firm registered in 2015 and relocated subsequently, the 2023 dataset would only contain the firm's latest address, not the one at the time of registration. To address this, I utilized the address information from the administrative record closest to the firm's registration date for any firm that potentially relocated during the period of analysis. Company addresses were geolocated with the help of the ArcGIS geocoding API. To enhance the accuracy of geocoding, several manipulations involving regular expressions and pattern detection were applied to the (initially very messy) address strings.

b) Relocation dataset

The dataset examining firm relocation decisions between 2018 and 2023 was constructed from the 2018 (pre-flood) data. The 2023 addresses were matched based on the Corporate Identification Number (CIN), a unique firm-level identifier. In cases where firms had changed their CIN—typically due to changes in their industry classification—matching was performed based on company names. As with the entry dataset, addresses were geocoded using ArcGIS. Geocoding operations in ArcGIS are a paid service, and thus, the number of addresses to be geocoded as part of this project was limited. As a result, potential address changes between 2018 and 2023 were assessed with the help of a self-created function measuring the similarity

[3] More details about the data cleaning, processing, and geocoding in the appendix.

between a firm's address information over time, considering variations in punctuation, spelling, and special characters in the data entry process. Addresses with more than 75% string concordance were considered unchanged and thus matched with their geolocations determined in (a). Addresses below this threshold were geocoded again to accurately determine relocation based on exact coordinates. Upon closer investigation, a minimum threshold for relocation was set at 1km, as many cases where the 2018 and 2023 geocodes were less than 1km apart involved only minor differences in address strings (for example, the same street with and without building number) and firms did not actually relocate. To account for similar potential misclassifications that resulted in geocodes further than 1km apart, all firm relocation specifications are presented with different relocation thresholds between 1 and 10km distance between the 2018 and 2023 address coordinates.

c) Administrative boundaries, flood shapefile, and flood risk data

The shapefile on administrative boundaries of villages, subdistricts, and districts in Kerala was taken from The Shrug. It was spatially intersected with the company coordinates to assign them to their respective administrative units. Data on the Kerala flood was obtained from the Dartmouth Flood Observatory, which provides satellite images of the inundation zones. Lastly, flood hazard maps were taken from the UNEP WESR to assess the change in flood risk among relocating firms. Based on a probabilistic approach, these maps estimate the expected depth of flood events for several return periods at a 1km $\times$ 1km resolution. Following Balboni et al. (2023), I used a hazard map of a 100-year return period (indicating a 1% likelihood of flood occurrence in any given year) and spatially matched it with the geocoded locations of firms' addresses from 2018 and 2023.

4.3 Treatment Assignment

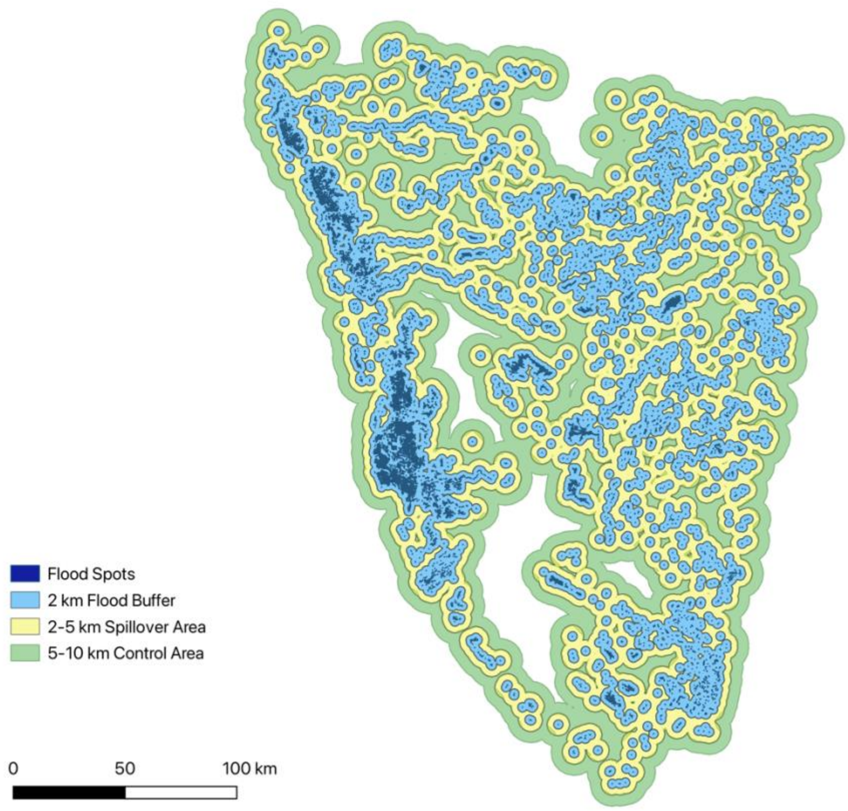
a) Entry dataset

To assess the effect of the Kerala floods on firm entry, I spatially matched the shapefile on village boundaries with the inundation zones, creating a continuous variable that indicates the share of the village area that was flooded. The company data was aggregated at the village-year level to create a balanced panel dataset of firm entry for each village v in year t, spanning from 2000 to 2023.

b) Relocation dataset

For the relocation data, I implemented the "inner-and-outer-ring" approach of treatment assignment, a method proposed, among others, by Alves et al. (2024). This technique establishes buffer zones of varying radii around the flooded spots, creating an inner and outer ring of the disaster coverage area. Companies located within the inner ring are the most strongly affected and constitute the treatment group. In contrast, those in the outer ring are less affected, and may potentially serve as control units.

Figure 2: Illustration of the "Inner-and-Outer-Ring Approach"[4]



Own elaboration

As recognized by Alves et al. (2024), choosing the geographical boundaries of the outer (control) ring area is subject to a trade-off: On the one hand, if the control ring is geographically too distant from the treatment group, the control group might potentially include firms subject to a different economic environment. On the other hand, situating the control ring too close to

[4] The figure shows rings for Kerala and the neighboring state Tamil Nadu, which is included for illustrative purposes.

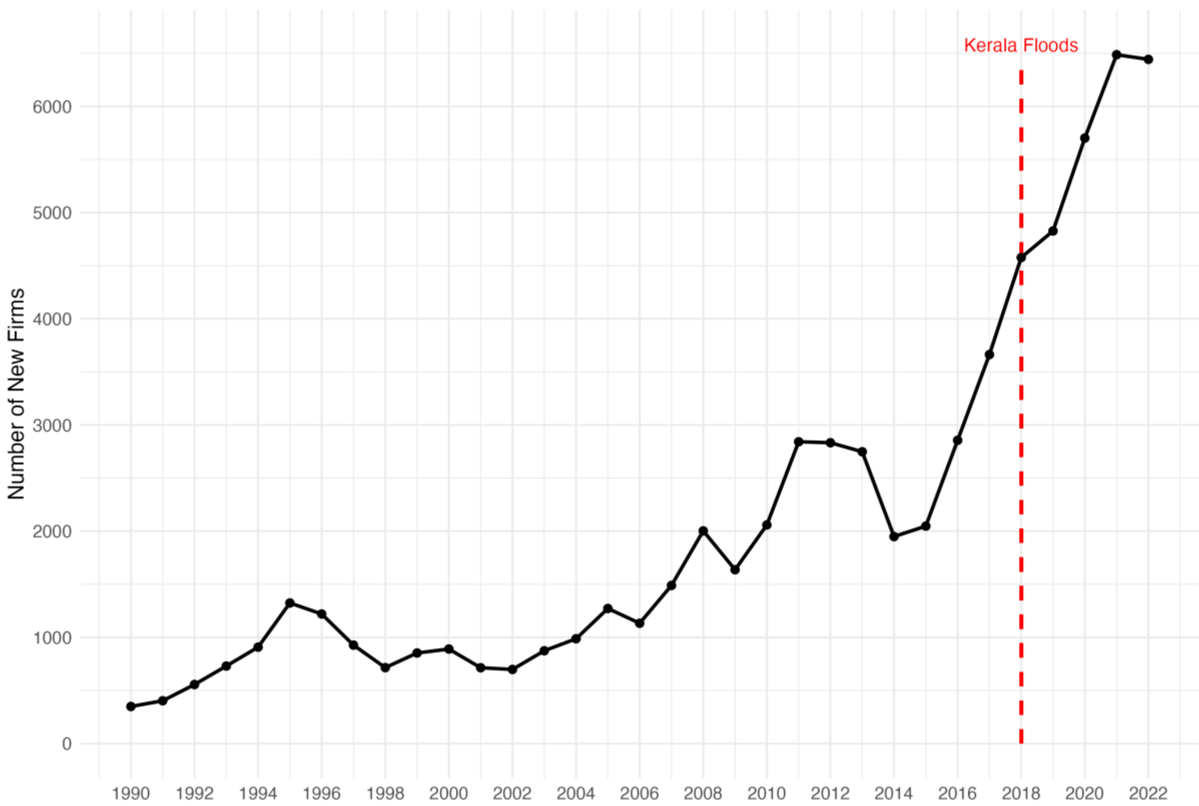
the treated ring might imply the inclusion of firms that were indirectly affected by the flood, leading to an underestimation of the impact of the flooding (Ibid.). Recognizing the need to minimize spillover effects, the outer ring is situated geographically close but not adjacent to the inner ring. One limitation of this approach in the context of the Kerala floods is the state's comparatively small and narrow geography. Thus, applying treatment bands of more than 10km (as done by the authors) is unfeasible, given that these bands will encompass large parts of the entire state and significantly reduce the size of the control group. Additionally, using firms from neighboring states as control units could introduce bias because some important determinants of location choice, such as tax incentives, are frequently set at the state-level in India (see Chaurey 2017). Therefore, I adjusted the size of the treatment bands to better suit these geographical constraints. Accordingly, in my main specification, the inner (treatment) ring is situated within a 2km radius of the flooded spots, while the outer (control) ring encompasses all firms that are between 5 to 10km away from the flooded spots (Figure 2).

Nevertheless, it is important to emphasize that there is no guarantee that the firms in the control area did not suffer some residual impact from the flooding. It is challenging to assert with certainty how far the previously discussed indirect effects, such as infrastructure disruptions, reach, making these thresholds ultimately arbitrary. Therefore, in addition to using control and treatment bands of varying radii, I adopted the methodology described by Balboni et al. (2023) as robustness check. This approach involves creating buffer zones of a 2km radius around each *company* location. These zones were then spatially intersected with the inundation zones, yielding a continuous treatment indicator that quantifies the share of the buffer impacted by flooding.

4.4 Dataset Presentation

The number of registered firms in Kerala has substantially increased since the turn of the millennium. Figure 3 shows that the annual number of registrations has more than sextupled between 2000 and 2022. There is a slight bend in the increasing trend in the year after the floods. Figure 4 shows that firms are concentrated in the middle of the state around the district of Ernakulam. However, firms also agglomerate in the northern district of Kozhikode and the Southern district of Thiruvananthapuram. Comparing this with Figure 1, there is a significant overlap between company locations and the flood inundation zones. Indeed, using the treatment definition outlined above, around 35% of firms and 31% of villages were flood-affected.

Figure 3: Annual Firm Entry in Kerala

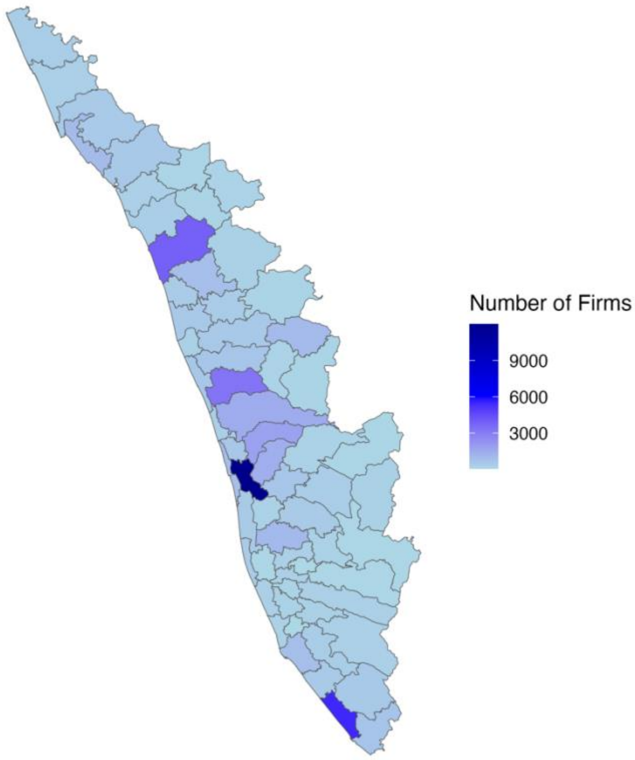


Own elaboration

In terms of industries, as with the rest of the country, Kerala is strongly dominated by service-oriented firms. In fact, services constitute the largest industry in every single subdistrict. Besides services, manufacturing and commerce are likewise important sectors in Kerala, with the former concentrating in the middle and the latter in the south-western part of the state (Figure A1).

Regarding relocation, around 11.5% of firms changed their location between 2018 and 2023. Mostly, these did not relocate very far. The average relocation distance amounts to 32.8km (Table A1). In addition, around 75% of relocations happened within the same district and around 58% within the same subdistrict. Figure A2 shows firm relocations between districts, illustrating that most relocations happen from and to Ernakulam, the district with the highest degree of firm agglomeration.

Figure 4: Geographical Distribution of Firms in Kerala



Own elaboration

4.5 Empirical Model

To assess the impact of floods on firm entry, I estimate an event study specification to capture dynamic effects over time. Since the dependent variable, the number of newly formed firms, is count data, linear models are unsuitable due to their assumptions of normally distributed errors and homoskedasticity. Among count data models, I selected the negative binomial regression over the Poisson regression. As noted by Arauzo-Cardo (2010), firm location data often violate the "equidispersion" assumption (equality of conditional variance and mean) inherent to the Poisson model. The negative binomial model relaxes this assumption. Indeed, the Pearson dispersion test confirmed the presence of significant overdispersion in my data, justifying my choice of model. Nonetheless, I also estimate a Poisson model as a robustness check. Accordingly, I use the following event study specification:

$$E(Entry_{vt}|\boldsymbol{Z}_{vt}) \; = \exp\left(\sum_{k=-5}^{5} \beta_k FloodExtent_v \times Post_{t+k} + \boldsymbol{X}_{vt}\beta + \delta_v + \vartheta_t + \epsilon_{vt}\right) \quad (1)$$

where $E(Entry_{vt}|\boldsymbol{Z}_{vt})$ indicates the expected number of new firms entering village v at time t given the independent variables $\boldsymbol{Z}_{vt}$; $FloodExtent_v$ is a continuous variable measuring the share of the village that was flooded; $Post_{t+k}$ are dummy variables indicating each specific year relative to the year of the floods, with $k = 0$ being the year of the flood; $\boldsymbol{X}_{vt}$ represents time-variant village-level controls. In particular, this includes the number of existing firms in village v at time t, which strongly impacts the entry of new firms due to agglomeration economies. δ_v are village fixed effects controlling for all time-invariant characteristics specific to each village; ϑ_t are time fixed effects that account for all unobserved factors that affect all villages in a particular year; finally, ϵ_{vt} constitute the error terms. Unfortunately, the count data models failed to converge when district × year fixed effects, that account for shocks that affect villages in a particular district in a particular year, were included. Therefore, I also estimate a linear model that includes these fixed effects as another robustness check. The key identifying assumption is that in the absence of the flooding, treatment and control villages would have followed similar trends. If this assumption is met, β_k constitutes the causal effect of the floods on firm entry. To test the parallel trends assumption, I estimate the model for the five years before the occurrence of the flood ($k = -5$). Table A2 gives an overview of the composition of treatment and control villages.

To assess the impact of the flood on the probability of firm relocation between 2018 and 2023, the following logit specification is used:

$$\Pr(Relocation_i = 1) = F(\beta_0 + \beta_1 Flooded_i + \beta_2 \boldsymbol{X}_i + \gamma_s + \delta_d + \epsilon_i) \quad (2)$$

where $Relocation_i$ indicates whether firm i relocated during the specified period; and $Flooded_i$ is a dummy variable equal to one if company i is located within the 2km inner ring of the flood. In addition, $\boldsymbol{X}_i$ is a vector of company characteristics, and γ_s and δ_d denote sector and district-level fixed effects, respectively. The fixed effects ensure that I am only comparing firms that are located in the same district and operating in the same sector. The vector $\boldsymbol{X}_i$ includes firm age, a widely used proxy for indirect relocation costs, as older firms are generally more embedded in their spatial networks (Brouwer et al. 2004). It also includes paid-up capital, which proxies the financial size of a company, as firms with greater financial resources have a higher capacity to undertake relocation. The primary identifying assumption of this model is that the flood is completely exogenous and uncorrelated with unobserved factors that also affect relocation. While the flood was indeed an unpredicted, exogenous event, it is difficult to rule out with certainty that it is entirely uncorrelated with all observed and unobserved factors affecting relocation. For instance, Table A3 shows that the treatment and control groups seem to have slight imbalances regarding average firm age and financial size. Therefore, a caveat of this model is the lack of more comprehensive firm-level control variables affecting relocation, such as measures of financial performance, physical size and supply chain dependencies.

Lastly, to investigate if among relocating firms, those that were affected by the flood locate towards areas subject to lower flood risk, I estimate the following linear model:

$$\Delta FloodRisk_i = \beta_0 + \beta_1 Flooded_i + \beta_2 \boldsymbol{X}_i + \gamma_s + \delta_d + \epsilon_i \tag{3}$$

where $\Delta FloodRisk_i$ indicates the change in the UNEP WESR flood risk measure between firm i's 2023 and 2018 location in units of expected flood depth under a 1-in-100-year flood; and all other terms are specified as above.

5 Results

Table 1 presents the results of the firm entry model for the year of the flood and the subsequent five years (testing H_1). The flooding has an immediate and statistically significant negative impact on the number of new firm registrations in the year of the flood. This adverse effect persists over the following five years across both model specifications. The coefficients are highly significant, with five out of six being significant at the 0.1% level for the negative binomial model. As expected, this model fits the data slightly better due to the overdispersion in the dependent variable. The magnitude of the coefficients is substantial. In 2023, five years after the flood, the expected number of new firm entries in the mean treated village—with 5.6% of its area flooded—is about 89.43% ($e^{-1.994 \times 0.056} \approx 0.8943$) of the number of new firms in non-flooded villages. This is equivalent to a 10.57% decrease in the expected number of firm entries, ceteris paribus. Figure A3 gives an overview of this more intuitive interpretation of the coefficients over time.

Table 1: Impact of Flooding on Firm Entry

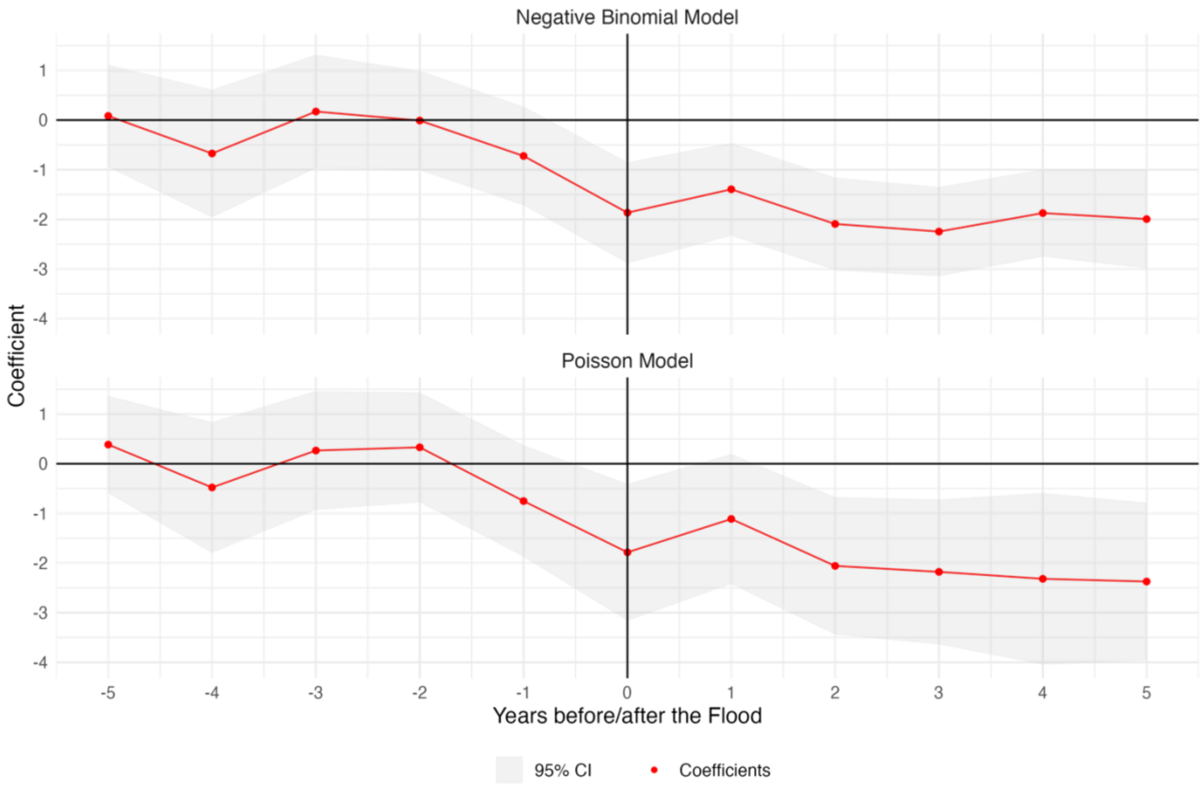
	Dependent variable: Number of New Firms	
	Negative Binomial	Poisson
Flood 2018	-1.865****	-1.785**
	(0.519)	(0.703)
Flood 2019	-1.394***	-1.113*
	(0.478)	(0.668)
Flood 2020	-2.093****	-2.058***
	(0.475)	(0.706)
Flood 2021	-2.246****	-2.178***
	(0.459)	(0.745)
Flood 2022	-1.873****	-2.318***
	(0.448)	(0.881)
Flood 2023	-1.994****	-2.373***
	(0.507)	(0.812)
Village FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
Conditional / Pseudo R^2	0.822	0.821
Number of Observations	30,624	30,624

Standard errors clustered at the village-level in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; $^{****}p < 0.001$

As previously mentioned, to be confident that these coefficients represent the causal effect of the floods on firm entry, it is crucial to ensure that there are no diverging pre-trends between treatment and control group that could be mistakenly interpreted as the effect of the flood. Therefore, both models were also estimated for the five years preceding the floods. Figure 5 plots the coefficients from this estimation. As shown in the graph, none of the coefficients prior to the event are statistically significant across both models, as indicated by the confidence intervals intersecting with zero. Only in the year of the flood the coefficients become significant and remain negative and significant throughout. This underlines that there are no significant pre-trends in the data.

Figure 5: Check for Pre-Trends in Entry Model



Own elaboration

To further check the robustness of the results, I also estimated a linear model with district-year fixed effects (Table A4). The results remain unchanged under this specification.

To determine if existing firms also adjust their location decisions in response to the flood (testing H_{2A}), I estimated the model specified in equation (2). The results of this logistic regression are displayed in Table 2, with different columns showing estimations for different relocation thresholds. Firstly, consistent with the theory presented earlier, the coefficient for firm age is highly significant and negative, while the coefficient for paid-up capital is highly significant and positive. As expected, younger firms and those with greater financial resources are more likely to relocate. The coefficients of primary interest are presented in the first row. For relocations over distances of more than one and two kilometers, respectively, firms located within the 2km buffer of the flood are significantly more likely to have relocated thereafter. Both coefficients are statistically significant at the 1% level. In terms of magnitude, the coefficient in column 1 represents an increase in the log-odds of relocation for flooded firms by 0.22. Transforming this into the odds ratio, the odds of relocating are approximately $e^{0.22} \approx 1.246$ times higher (24.6% higher) for affected firms compared to unaffected ones. However, the coefficients in columns 3 and 4, which examine relocations over distances of more than 5 and 10 km, respectively, are statistically insignificant. This suggests that while affected firms are indeed significantly more likely to relocate in response to the flood, they tend to relocate over shorter distances.

Table 2: Impact of Flooding on Firm Relocation

	Dependent variable: Relocation Dummy			
	(1)	(2)	(3)	(4)
Firm within 2km buffer	0.220***	0.261***	0.120	-0.015
	(0.079)	(0.083)	(0.094)	(0.109)
Firm Age	-0.041****	-0.041****	-0.044****	-0.041****
	(0.004)	(0.004)	(0.005)	(0.006)
Paid-up Capital	0.112****	0.111****	0.103****	0.109****
	(0.013)	(0.013)	(0.015)	(0.018)
Constant	-3.590****	-3.660****	-3.590****	-3.765****
	(0.263)	(0.274)	(0.306)	(0.348)
District FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Relocation Threshold	1km	2km	5km	10km
Control Band	5-10km	5-10km	5-10km	5-10km
Observations	14,816	14,816	14,816	14,816

Logistic Regression Model. Standard errors in parentheses.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; **** $p < 0.001$

To investigate which types of firms drive these relocations, I estimated the model for subsamples of different sectors. The results of this estimation, using the 1km relocation threshold, are presented in Table 3. While the coefficient for firms in the construction sector is positive and significant at the 10% level, it becomes evident that the results in Table 2 are primarily driven by the manufacturing sector. Converting the coefficient, which is significant at the 1% level, into the odds ratio reveals that the odds of relocating among manufacturing firms are approximately 94% higher when the firm is affected by the flood. This seems plausible, given that manufacturing firms are highly capital-intensive and particularly reliant on infrastructure for their production process, making them especially vulnerable to flood damage (Hossain 2020).

Table 3: Impact of Flooding on Firm Relocation by Sector

	Dependent variable: Relocation Dummy				
	Services	Manufacturing	Commerce	Construction	Agriculture
	(1)	(2)	(3)	(4)	(5)
Firm within 2km buffer	0.133	0.662***	0.099	0.598*	0.704
	(0.109)	(0.223)	(0.203)	(0.323)	(0.491)
Firm Age	-0.040****	-0.041****	-0.051****	-0.029*	-0.004
	(0.006)	(0.007)	(0.011)	(0.018)	(0.011)
Paid-up Capital	0.097****	0.098***	0.160****	0.134***	0.243***
	(0.019)	(0.032)	(0.028)	(0.042)	(0.082)
Constant	-3.037****	-3.271****	-4.237****	-3.841****	-21.278
	(0.299)	(0.527)	(0.496)	(0.657)	(750.966)
District FE	Yes	Yes	Yes	Yes	Yes
Relocation Threshold	1km	1km	1km	1km	1km
Control Band	5-10km	5-10km	5-10km	5-10km	5-10km
Observations	7,450	2,475	2,352	1,060	489

Logistic Regression Model. Standard errors in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; $^{****}p < 0.001$

To analyze whether these odds change significantly across different relocation thresholds, Table A5 shows the estimation for the manufacturing sector with the four thresholds used in Table 2. The coefficients are all positive and statistically significant, at least at the 5% level, indicating that within the manufacturing sector, flood-affected firms are indeed more likely to relocate over both shorter and longer distances.

While these results largely remain robust to the modification of treatment and control bands (Tables A6 – A9), they do not hold under the specification using a continuous independent variable to represent the share of a company's 2km buffer that was flooded, as per the approach outlined by Balboni et al. (2023) (Table A10).
Whereas the “inner-and-outer-ring” approach of treatment assignment might better isolate the effects on significantly affected firms by excluding firms potentially subject to spillover effects, the impact of the flood on the likelihood of relocation remains ambiguous. There is evidence suggesting that firms within a 2km buffer of the flood are more likely to relocate over shorter distances, and particularly manufacturing firms seem to be inclined to move across both shorter and longer distances. However, the variability of these findings under alternative specifications makes it difficult to definitively determine whether floods increase firms' propensity to relocate, particularly given the drawbacks of the "inner-and-outer-ring" approach discussed in the previous section.

Lastly, Table 4 shows the results of the specification investigating the change in locational flood risk exposure among relocating firms (testing H_{2B}), using both the binary and the continuous treatment indicator and the same relocation thresholds as before.
The coefficients are statistically significant at the 1% and 5% levels for the binary indicator, and at the 0.1% level for the continuous indicator, consistently across all relocation thresholds.[5]
Specifically, firms located within the 2km radius of the flood that relocated beyond 1km, experienced a 7.48cm reduction in expected 1-in-100-year flood depth at their new location. Using the continuous treatment indicator, the mean treated firm that moved more than 1km—having 2.3% of its 2km buffer flooded—experienced a reduction of 4.66cm (0.023×202.719) in expected flood depth. Therefore, while there remain some doubts regarding whether flood-affected firms are indeed more likely to relocate than their unaffected counterparts, the evidence suggests that *when* such firms do relocate, they systematically choose locations with lower flood risk.

[5] Except for the binary indicator under a 10km threshold, likely because the sample size is too low.

Table 4: Impact of Flooding on UNEP Flood Risk of Firms' Location

	Dependent variable: Change in Flood Risk							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm within 2km buffer	-7.476^{***}		-7.304^{**}		-8.956^{**}		-6.336	
	(2.790)		(2.964)		(3.489)		(4.278)	
Share of 2km Buffer Flooded		-202.719^{****}		-205.502^{****}		-248.278^{****}		-232.581^{****}
		(21.982)		(23.198)		(31.482)		(38.844)
District & Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relocation Threshold	1km	1km	2km	2km	5km	5km	10km	10km
Control Band	5-10km		5-10km		5-10km		5-10km	
R^2	0.042	0.038	0.044	0.040	0.050	0.047	0.058	0.055
Observations	2,206	3,591	1,977	3,202	1,482	2,285	1,073	1,577

Linear Regression Model. Standard errors in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; $^{****}p < 0.001$

6 Discussion

6.1 Synthesis and Limitations

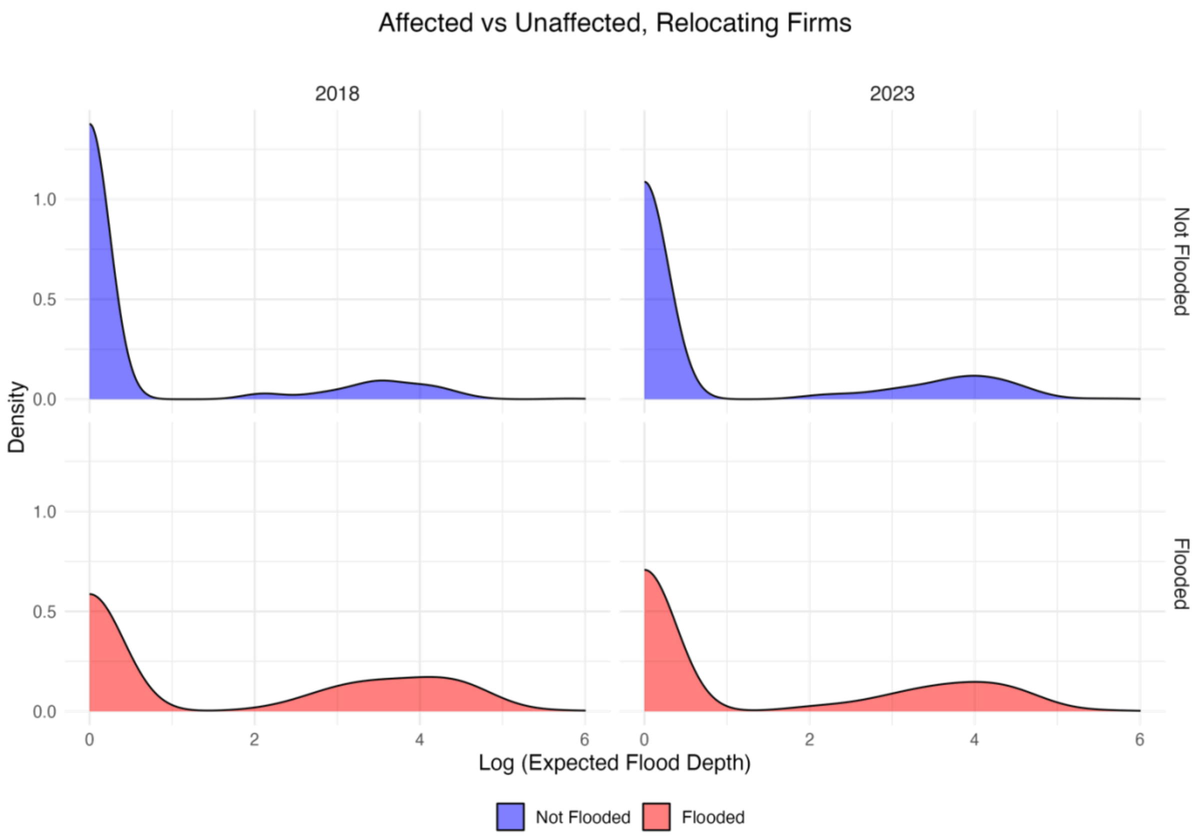
Regarding the firm entry model, it is important to note that, while there is robust evidence of a significant reduction in firm entries in flood-affected villages, the data and model cannot give insights into the underlying mechanisms of this outcome. Although the aforementioned theory suggests that actors should update their risk assessment of disaster-affected locations, the presented evidence cannot conclusively establish if this was really the case. For instance, firms could simply be responding to immediate, temporary post-disaster effects and may start to enter affected villages once these effects fade. Conversely, the reduction might not stem from an active decision by firms but could be due to a lack of administrative capacity to register firms in affected villages after the flood. The persistence of the negative effect on firm entry until today, however, suggests that the behavior might reflect more than just short-term disruptions. If firms avoid disaster-hit areas in the long-run, this is arguably more likely to be driven by ongoing risk considerations rather than temporary effects, which would have faded over time.[6] While the outcome still reflects adaptive behavior—new firms factually reduced their risk exposure compared to a counterfactual scenario where they entered affected villages—it is crucial to investigate its underlying drivers, for example by collecting survey data and conducting interviews with company officials. This would help ensure that it indeed reflects a permanent, deliberate change in firms' risk perceptions rather than merely a temporary response.

In case of the relocation model, on the other hand, the finding that flood-affected firms seem to systematically relocate to locations with lower underlying flood-risk indeed suggests an update in risk assessment consistent with the idea of experience-induced learning after the flood (see Moore 2017). This aligns with the theoretical predictions of neoclassical (rational) location choice, and with the empirical findings of Balboni et al. (2023) for Pakistan. However, a limitation not considered by the authors is that the initial locations of flood-affected firms are naturally more likely to be at the higher end of the flood risk distribution, whereas the locations of unaffected firms, on average, are more towards the lower end.[7] Consequently, when flood-

[6] However, the lack of reliable information about the progress of the reconstruction efforts in Kerala makes it challenging to determine how long these temporary effects really last.
[7] This is because the hazard map is not an annual measure, but measures locational risk based on the most recent information available.

affected firms choose new locations, they are selecting from a set of options that predominantly have lower flood risk than their original locations. In contrast, unaffected firms choose from a much broader set of options in terms of flood risk. Despite this, affected firms still could have relocated to areas with similar or even higher flood risk, even though they had fewer such options compared to non-affected firms. Moreover, Figure 6 illustrates that the initial distribution of flood risk does not vary as significantly by treatment status as one might have expected. Nevertheless, the results in Table 4 should be interpreted as suggestive evidence in favor of an update in risk assessment. To conclusively determine that the observed behavior reflects a deliberate strategy to reduce risk, a more direct measurement of firms' underlying motivations is needed.[8]

Figure 6: Distribution of Flood Risk in 2018 and 2023



Own elaboration

Regarding the ambiguous results on relocation probability, several potential explanations for why affected firms might not be more likely to relocate after the flood merit further discussion:

[8] Additionally, it is important to note that this analysis only considers flood risk, and not overall climate risk.

For instance, it could be that instead of relocating, affected firms decide to end their operations entirely. Thus, if affected firms are more likely to exit the market, this could account for the inconclusive evidence on relocation, as outlined by Alves et al. (2024). To investigate this, I created an exit dummy based on company status information from 2018 and 2023. Using this new outcome variable, I estimated the same logit model as in (2). However, the results indicate that affected firms, under both treatment specifications, are not significantly more likely to terminate their operations (Table A11).

Another possibility is that relocation costs are much more important than presumed, aligning more with the expectations of behavioral rather than neoclassical location theory. Unfortunately, data on more precise indicators of relocations costs are not available at a sufficiently granular level. Likewise, research on relocation costs in India is virtually non-existent. Nevertheless, this remains a plausible explanation and needs further research.

Moreover, government measures to reduce future disaster vulnerability may have prompted firms to stay. In the aftermath of the flood, the state of Kerala received more than half a billion USD in support from the World Bank under the First Resilient Kerala Program. These funds were aimed at increasing flood resilience in vulnerable areas through measures such as elevating flood-prone sections and improving the state's capacity for disaster and climate risk management (World Bank 2022). These measures may have influenced firms' decisions of whether or not to relocate.

Lastly, limitations of the company data used could account for the inconclusive results. First, the administrative data only contains information on firms' registered headquarters location, rather than information on all their locations of operation. Therefore, the data might not capture all relocations if firms moved some of their operations but kept their headquarters in the original location. Likewise, the data only allows the tracing of relocations within the state of Kerala. Firms that change their location beyond state borders receive a new CIN, making it very difficult to trace their relocation path. Finally, the administrative records naturally only comprise formal firms, and thus, given the size of India's informal economy, potentially disregard a considerable number of informal firms that relocated in response to the disaster.

6.2 External Validity and Policy Implications

Since my findings are based on a single case, there naturally are challenges to their external validity. Nevertheless, I am cautiously optimistic that they can be extrapolated to other instances of climate-related disasters with levels of destructiveness and unpredictability similar to the Kerala floods. This includes not only floods but also other disasters with comparable impacts, such as cyclones, hurricanes or typhoons. Moreover, the lack of appropriate disaster preparedness and the inadequate resilience of infrastructure, which significantly contributed to the severity of the impacts of the Kerala floods (Walia and Nusrat 2020), is a common issue in many other developing countries. Regarding relocation, it is noteworthy that the results under the binary specification were primarily driven by manufacturing firms, which constitute around 16% of firms in Kerala. Therefore, it is plausible that these findings could be even more pronounced in the context of regions or countries with larger manufacturing sectors. Nevertheless, it should be highlighted that relocation costs can vary significantly within and across countries and thus pose a significant barrier to the mobility of firms. Therefore, it is important to replicate this analysis in other countries and contexts.

Assessing the broader implications of this paper, my findings indicate that firms indeed undertake measures to adapt to climate change through their location decisions. This presents a dilemma: while locational adaptation can significantly reduce the economic damages associated with future disasters, it can also have substantial ramifications for the people living in the affected areas. While investigating these consequences was outside the scope of this paper, it is plausible that the permanent reduction in firm entry and the relocation of existing firms may result in unemployment, lower product or service variety, and increased prices in affected areas. This could severely impact the welfare of people already burdened with the immediate disaster effects. Thus, from a policy perspective, it is crucial to find a balanced approach. Most importantly, governments in flood-prone, and, more generally, disaster-prone regions need to limit the extent of future disaster damages by investing heavily in in-situ adaptation, thus enhancing the disaster resilience of buildings and critical infrastructure such as transport and electricity. Additionally, monitoring of high-risk areas through continuous data collection needs to improve, and appropriate dissemination systems need to be implemented to continuously share information with all parts of society. However, the recent experience in Kerala, where another large-scale flood in July 2024 caused devastating landslides (The Guardian 2024), demonstrates the limitations of in-situ adaptation measures such as the First Resilient Kerala Program. Despite its investment volume and being classified as highly successful in increasing overall disaster resilience (World Bank 2022), its measures were insufficient to prevent repeated large-scale damages.

This underlines that in developing countries like India, broader adaptation measures, including the migration of both people and companies from the most disaster-prone areas, will become inevitable to limit the effects of future disasters, despite the adverse consequences these forms of adaptation entail. Importantly, this locational adaptation should not occur ex-post but be incentivized ex-ante by sharing accurate information about disaster risk throughout the country.

7 Conclusion

With the continuous intensification of extreme weather events due to a changing climate, comprehending how economic actors respond and adapt to these events is crucial. This paper aimed to examine the extent to which climate-related disasters influence firm location decisions, using the 2018 Kerala floods as a case study. The findings show that location choice is indeed an important dimension of firm-level adaptation to disasters. In the aftermath of the floods, there is a significant and temporally persistent reduction in firm entry in affected villages. Although the impact on the location decisions of existing firms is less conclusive, some empirical specifications suggest an increased probability of relocation among affected firms, particularly in the manufacturing sector. Notably, among relocating firms, those affected by the flood tend to move to areas with lower flood risk, suggesting that relocation is a deliberate measure to reduce future exposure. These findings constitute a significant contribution to the nascent empirical literature on spatial firm-level adaptation.

Beyond addressing the limitations of this paper and exploring the underlying mechanisms of its findings, several avenues for future research merit consideration. First, complementing the analysis of firm relocations with comprehensive data on firm performance and size could provide valuable insights into whether relocation is dependent on these factors and whether it involves long-term benefits in terms of performance. Unfortunately, data from popular sources such as Orbis is highly incomplete for developing countries like India. Second, it is imperative to investigate the broader implications of firm relocations and reductions in entry for local development and labor market outcomes in disaster-affected regions, as well as the potentially positive implications for unaffected/less risky regions. Finally, it is important to underscore that examining adaptation to sharp climate shocks represents only one side of the coin. Climate change also implicates more gradual phenomena, such as rising average temperatures and sea levels. Consequently, it is equally important to investigate how such gradual changes influence location decisions and induce other forms of firm-level adaptation.

Firms are the engines of a country's development and prosperity. Understanding the effects of the growing threat of climate change on their operations and how they are already adjusting is crucial for designing effective policy interventions that enhance their resilience. This, in turn, is paramount for strengthening the resilience of the economy and society as a whole.

8 Bibliography

Addoum, Jawad M., David T. Ng, and Ariel Ortiz-Bobea. "Temperature Shocks and Industry Earnings News." *SSRN Electronic Journal*, 2019. https://doi.org/10.2139/ssrn.3480695.

Altay, Nezih, and Andres Ramirez. "Impact of Disasters on Firms in Different Sectors: Implications for Supply Chains." *Journal of Supply Chain Management* 46, no. 4 (September 28, 2010): 59–80. https://doi.org/10.1111/j.1745-493X.2010.03206.x.

Alves, P., P. Ehrl, and R. Lima. "The Impact of Flash Floods on the Spatial Distribution of Businesses and Workers." *Mimeo*, 2024.

Amei, Amei, Wandong Fu, and Chih-Hsiang Ho. "Time Series Analysis for Predicting the Occurrences of Large-Scale Earthquakes." *International Journal of Applied Science and Technology* 2, no. 7 (2012).

Arauzo-Carod, Josep-Maria, Daniel Liviano-Solis, and Miguel Manjón-Antolín. "Empirical Studies in Industrial Location: An Assessment of Their Methods and Results." *Journal of Regional Science* 50, no. 3 (August 5, 2009): 685–711. https://doi.org/10.1111/j.1467-9787.2009.00625.x.

Balboni, C., J. Böhm, and M. Waseem. "Firm Adaptation in Production Networks: Evidence from Extreme Weather Events in Pakistan." *Mimeo*, 2023.

Berlemann, Michael, and Max Friedrich Steinhardt. "Climate Change, Natural Disasters, and Migration—a Survey of the Empirical Evidence." *CESifo Economic Studies* 63, no. 4 (December 1, 2017): 353–85. https://doi.org/10.1093/cesifo/ifx019.

Beyer, R., A. Narayanan, and G. Thaler. "Natural Disasters and Economic Dynamics: Evidence from the Kerala Floods," Vol. *10084*. *Policy Research Working Paper Series*. The World Bank, 2022.

Boustan, Leah Platt, Matthew E. Kahn, Paul W. Rhode, and Maria Lucia Yanguas. "The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data." *Journal of Urban Economics* 118 (July 2020): 103257. https://doi.org/10.1016/j.jue.2020.103257.

Brouwer, Aleid E., Ilaria Mariotti, and Jos N. Van Ommeren. "The Firm Relocation Decision: An Empirical Investigation." *The Annals of Regional Science* 38, no. 2 (June 1, 2004): 335–47. https://doi.org/10.1007/s00168-004-0198-5.

Castro-Vincenzi, Juanma, Gaurav Khanna, Nicolas Morales, and Nitya Pandalai-Nayar. "Weathering the Storm: Supply Chains and Climate Risk." *SSRN Electronic Journal*, 2024. https://doi.org/10.2139/ssrn.4754763.

Cevik, Serhan, and Fedor Miryugin. "Rogue Waves: Climate Change and Firm Performance." *Comparative Economic Studies* 65, no. 1 (March 2023): 29–59. https://doi.org/10.1057/s41294-022-00189-0.

Chaurey, Ritam. "Location-Based Tax Incentives: Evidence from India." *Journal of Public Economics* 156 (December 2017): 101–20. https://doi.org/10.1016/j.jpubeco.2016.08.013.

Chu, Xiaojun, and Jing Xu. "The Impact of Climate Disasters on the Cost of Equity Capital: Evidence from China." *Weather, Climate, and Society* 14, no. 4 (October 2022): 1273–85. https://doi.org/10.1175/WCAS-D-22-0002.1.

Correa, Ricardo, Ai He, Christoph Herpfer, and Ugur Lel. "The Rising Tide Lifts Some Interest Rates: Climate Change, Natural Disasters, and Loan Pricing." *International Finance Discussion Paper*, no. 1345 (June 2022): 1–56. https://doi.org/10.17016/ifdp.2022.1345.

CWC. "Study Report: Kerala Floods of 2018." Central Water Commission, Government of India, 2018.

De Mel, Suresh, David McKenzie, and Christopher Woodruff. "Enterprise Recovery Following Natural Disasters." *The Economic Journal* 122, no. 559 (March 1, 2012): 64–91. https://doi.org/10.1111/j.1468-0297.2011.02475.x.

Dilley, Maxx, Robert S. Chen, Uwe Deichmann, Arthur L. Lerner-Lam, and Margaret Arnold. *Natural Disaster Hotspots: A Global Risk Analysis*. The World Bank, 2005. https://doi.org/10.1596/0-8213-5930-4.

Ellis-Petersen, Hannah. "India Landslides: Death Toll Passes 100 with Dozens Feared Missing." *The Guardian*, n.d. https://www.theguardian.com/world/article/2024/jul/30/india-landslides-kerala-death-toll-latest-updates-wayanad.

Escaleras, M., and C. A. Register. "Natural Disasters and Foreign Direct Investment." *Land Economics* 87, no. 2 (May 1, 2011): 346–63. https://doi.org/10.3368/le.87.2.346.

Friedt, Felix L., and Aidan Toner-Rodgers. "Natural Disasters, Intra-National FDI Spillovers, and Economic Divergence: Evidence from India." *Journal of Development Economics* 157 (June 2022): 102872. https://doi.org/10.1016/j.jdeveco.2022.102872.

Gramlich, Dieter, Thomas John Walker, Aoran Zhang, and Philip Zhao. "How Do Companies Respond to Natural Disasters? Evidence from Corporate Innovation." *SSRN Electronic Journal*, 2020. https://doi.org/10.2139/ssrn.3963928.

Gröger, André, and Yanos Zylberberg. "Internal Labor Migration as a Shock Coping Strategy: Evidence from a Typhoon." *American Economic Journal: Applied Economics* 8, no. 2 (April 1, 2016): 123–53. https://doi.org/10.1257/app.20140362.

Grover, Arti, and Matthew E. Kahn. *Firm Adaptation to Climate Risk in the Developing World*. Washington, DC: World Bank, 2024. https://doi.org/10.1596/1813-9450-10797.

Gu, Grace Weishi, and Galina Hale. "Climate Risks and FDI." *Journal of International Economics* 146 (December 2023): 103731. https://doi.org/10.1016/j.jinteco.2023.103731.

Hossain, Farzana. "Creative Destruction or Just Destruction? Effects of Floods on Manufacturing Establishments in India." *SSRN Electronic Journal*, 2020. https://doi.org/10.2139/ssrn.3704612.

Hu, Xi, Raghav Pant, Jim W. Hall, Swenja Surminski, and Jiashun Huang. "Multi-Scale Assessment of the Economic Impacts of Flooding: Evidence from Firm to Macro-Level Analysis in the Chinese Manufacturing Sector." *Sustainability* 11, no. 7 (April 1, 2019): 1933. https://doi.org/10.3390/su11071933.

Indaco, Agustín, Francesc Ortega, and And Süleyman Taşpınar. “Hurricanes, Flood Risk and the Economic Adaptation of Businesses.” *Journal of Economic Geography* 21, no. 4 (October 8, 2021): 557–91. https://doi.org/10.1093/jeg/lbaa020.

Inoue, Hiroyasu, and Yasuyuki Todo. “Firm-Level Propagation of Shocks through Supply-Chain Networks.” *Nature Sustainability* 2, no. 9 (August 12, 2019): 841–47. https://doi.org/10.1038/s41893-019-0351-x.

IPCC, 2014: “Annex II: Glossary“. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Christopher B. Field and Vicente R. Barros, 1757-1772. New York: Cambridge University Press.

IPCC, 2023: “Climate Change 2023: Synthesis Report”. *Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, H. Lee and J. Romero (Eds.)]. IPCC, Geneva, Switzerland. Intergovernmental Panel on Climate Change (IPCC), July 25, 2023. https://doi.org/10.59327/IPCC/AR6-9789291691647.

Kling, Gerhard, Ulrich Volz, Victor Murinde, and Sibel Ayas. “The Impact of Climate Vulnerability on Firms’ Cost of Capital and Access to Finance.” *World Development* 137 (January 2021): 105131. https://doi.org/10.1016/j.worlddev.2020.105131.

Kocornik-Mina, Adriana, Thomas K. J. McDermott, Guy Michaels, and Ferdinand Rauch. “Flooded Cities.” *American Economic Journal: Applied Economics* 12, no. 2 (April 1, 2020): 35–66. https://doi.org/10.1257/app.20170066.

Li, Frank Weikai, Yupeng Lin, Zuben Jin, and Zilong Zhang. “Do Firms Adapt to Climate Change? Evidence from Establishment-Level Data.” *SSRN Electronic Journal*, 2020. https://doi.org/10.2139/ssrn.3573260.

Li, Xia. “Physical Climate Risk and Firms’ Adaptation Strategy.” *SSRN Electronic Journal*, 2024. https://doi.org/10.2139/ssrn.4143981.

Linnenluecke, Martina K., Andrew Griffiths, and Monika I. Winn. "Firm and Industry Adaptation to Climate Change: A Review of Climate Adaptation Studies in the Business and Management Field." *WIREs Climate Change* 4, no. 5 (September 2013): 397–416. https://doi.org/10.1002/wcc.214.

Linnenluecke, Martina K., Alexander Stathakis, and Andrew Griffiths. "Firm Relocation as Adaptive Response to Climate Change and Weather Extremes." *Global Environmental Change* 21, no. 1 (February 2011): 123–33. https://doi.org/10.1016/j.gloenvcha.2010.09.010.

McCann, P. *Urban and Regional Economics*. Oxford University Press. Oxford, 2001.

Moore, Frances C. "Learning, Adaptation and Weather in a Changing Climate." *Climate Change Economics* 08, no. 04 (November 2017): 1750010. https://doi.org/10.1142/S2010007817500105.

Neise, Thomas, Franziska Sohns, Moritz Breul, and Javier Revilla Diez. "The Effect of Natural Disasters on FDI Attraction: A Sector-Based Analysis over Time and Space." *Natural Hazards* 110, no. 2 (January 2022): 999–1023. https://doi.org/10.1007/s11069-021-04976-3.

Pankratz, Nora, Rob Bauer, and Jeroen Derwall. "Climate Change, Firm Performance, and Investor Surprises." *Management Science* 69, no. 12 (December 2023): 7352–98. https://doi.org/10.1287/mnsc.2023.4685.

Pankratz, Nora M.C., and Christoph M. Schiller. "Climate Change and Adaptation in Global Supply-Chain Networks." *Finance and Economics Discussion Series* 2022, no. 056 (August 2022). https://doi.org/10.17016/FEDS.2022.056.

Pelli, Martino, Jeanne Tschopp, Natalia Bezmaternykh, and Kodjovi M. Eklou. "In the Eye of the Storm: Firms and Capital Destruction in India." *Journal of Urban Economics* 134 (March 2023): 103529. https://doi.org/10.1016/j.jue.2022.103529.

Rábano, A., and J. Rosas. "The Transmission of Climate Shocks: The Case of Floods in India." Barcelona: *Universidad Pompeu Fabra*, 2023.

Rentschler, J., E. Kim, S. Thies, S. Robbe, A. Erman, and S. Hallegatte. "Floods and Their Impacts on Firms: Evidence from Tanzania," Vol. *9774*. *Policy Research Working Paper Series*. The World Bank, 2021.

Rentschler, Jun, Martin Kornejew, Stephane Hallegatte, Johannes Braese, and Marguerite Obolensky. *Underutilized Potential: The Business Costs of Unreliable Infrastructure in Developing Countries*. World Bank, Washington, DC, 2019a. https://doi.org/10.1596/1813-9450-8899.

Rentschler, Jun, Marguerite Obolensky, and Martin Kornejew. *Candle in the Wind? Energy System Resilience to Natural Shocks*. World Bank, Washington, DC, 2019b. https://doi.org/10.1596/1813-9450-8897.

Rentschler, Jun, Melda Salhab, and Bramka Arga Jafino. "Flood Exposure and Poverty in 188 Countries." *Nature Communications* 13, no. 1 (June 28, 2022): 3527. https://doi.org/10.1038/s41467-022-30727-4.

Tellman, B., J. A. Sullivan, C. Kuhn, A. J. Kettner, C. S. Doyle, G. R. Brakenridge, T. A. Erickson, and D. A. Slayback. "Satellite Imaging Reveals Increased Proportion of Population Exposed to Floods." *Nature* 596, no. 7870 (August 5, 2021): 80–86. https://doi.org/10.1038/s41586-021-03695-w.

Van Dijk, Jouke, and Piet H. Pellenbarg. "Firm Relocation Decisions in The Netherlands: An Ordered Logit Approach." *Papers in Regional Science* 79, no. 2 (May 1, 2000): 191–219. https://doi.org/10.1007/s101100050043.

Vu, Tam B., and Ilan Noy. "Natural Disasters and Firms in Vietnam." *Pacific Economic Review* 23, no. 3 (August 2018): 426–52. https://doi.org/10.1111/1468-0106.12184.

Walia, A., and N. Nusrat. "Kerala Floods, 2018." *National Institute of Disaster Management*. Ministry of Home Affairs, Govt. of India, 2020.

World Bank. "The First Resilient Kerala Program Development Policy Operation (P169907): Implementation, Completion and Results Report." Urban, Resilience and Land Global Practice. South Asia Region, 2022.

Yasuyuki, S., N. Hiroyuki, and S. Kunio. "Natural Disasters, Land Price, and Location of Firms: Evidence from Thailand," Vol. 14029. *Research Institute of Economy, Trade and Industry (RIETI)*, 2014.

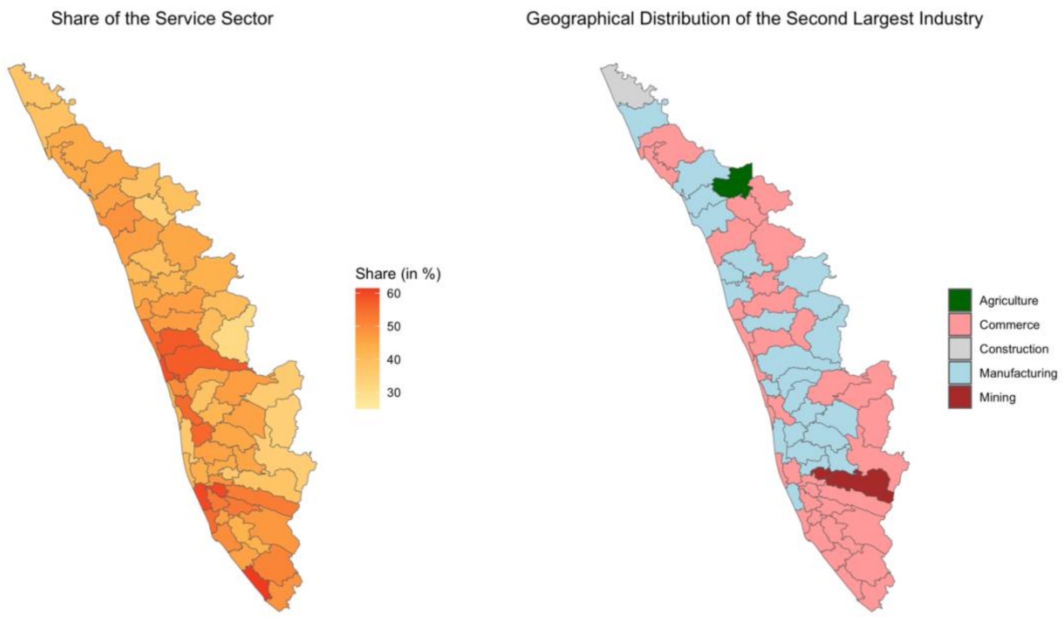
Zhou, Fujin, and Wouter Botzen. "Firm Level Evidence of Disaster Impacts on Growth in Vietnam." *Environmental and Resource Economics* 79, no. 2 (June 2021): 277–322. https://doi.org/10.1007/s10640-021-00562-0.

Data Sources

Data	Source
Company Data	Government of India, 2024. Company Master Data, taken from the Open Government Data Platform India. https://www.data.gov.in/catalog/company-master-data#, [accessed on 20th of February, 2024]
Flood Shapefile	Brakenridge, G.R. and Kettner, A. J., 2024, "DFO Flood Event 4663", Dartmouth Flood Observatory, University of Colorado, Boulder, Colorado, USA. https://floodobservatory.colorado.edu/Events/4663/2018India4663.html, [accessed on 2nd of March, 2024]
Administrative Boundaries	Asher, Sam, Tobias Lunt, Ryu Matsuura, and Paul Novosad. 2021. The Shrug 2011 population census polygon geometries of district, subdistrict and villages. https://www.devdatalab.org/shrug_download/, [accessed on 6th of April, 2024]
Flood Risk Geotiff File	UNEP WESR, 2024. Flood Hazard 100 Years (cm) based on the GAR Atlas global flood hazard assessment. https://wesr.unepgrid.ch/?project=MX-XVK-HPH-OGN-HVE-GGN&theme=color_light&language=en, [accessed on 24th of June, 2024]
2011 Census Data	Asher, Sam, Tobias Lunt, Ryu Matsuura, and Paul Novosad. 2021. The Shrug 2011 Population Census Village Directory and Population Census Abstract. https://www.devdatalab.org/shrug_download/, [accessed on 8th of July, 2024]

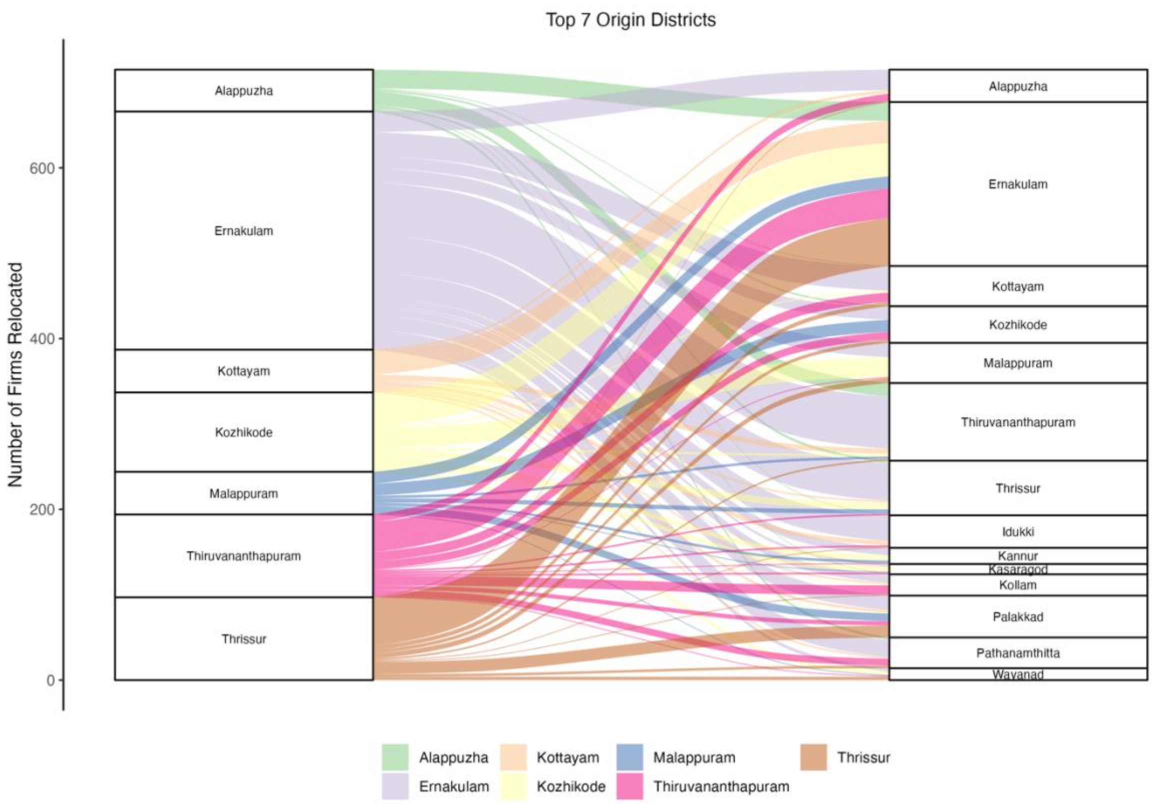
9 Appendix

Figure A1: Geographical Distribution of Industries in Kerala



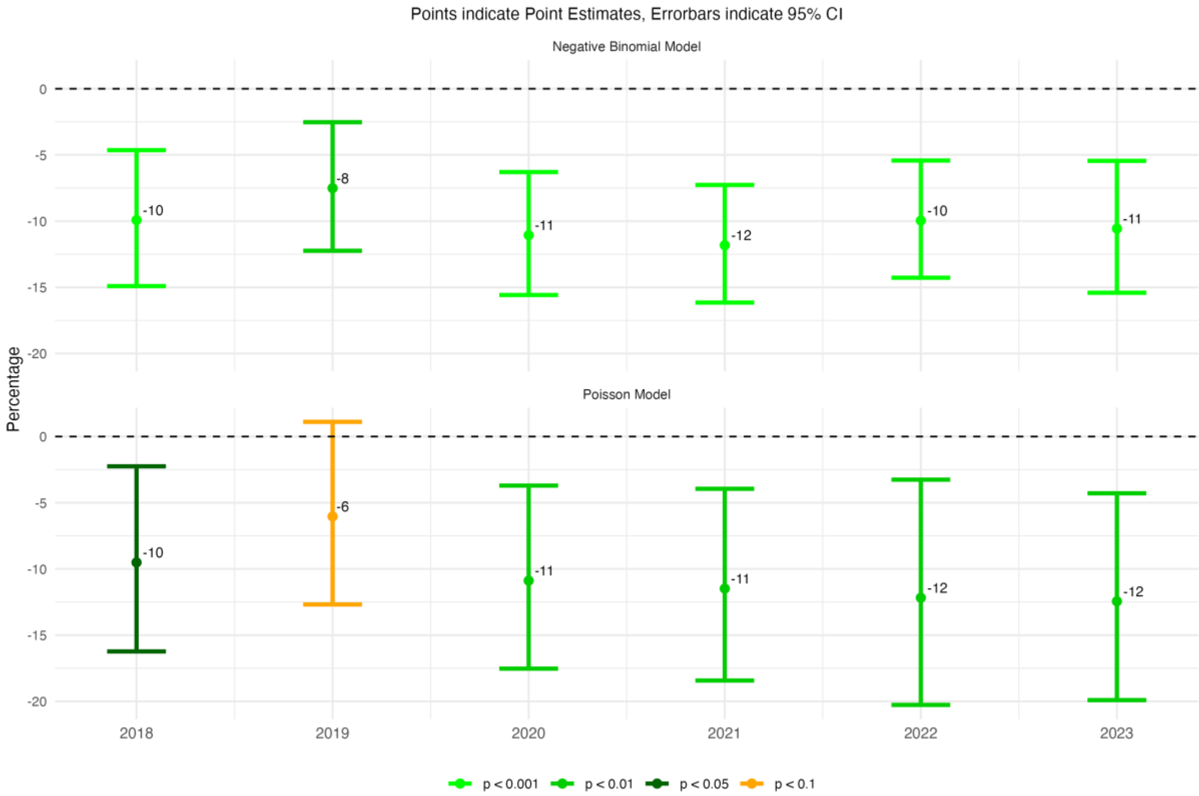
Own elaboration

Figure A2: Firm Relocations between Districts



Own elaboration

Figure A3: Percentage Reduction in the Expected Number of New Firms in Treated Villages Relative to Control Villages for the Mean Treated Village



Note: The coefficients and confidence intervals were transformed using the formula $(1 - e^{x \times 0.056}) \times 100$, as described in the paper. Own elaboration

Table A1: Statistics on Relocating Firms

Variable		Value
Relocation Distance (in km)	Min	1.00
	Median	7.86
	Mean	32.84
	Max	470.88
Share of Firms Relocated ≥ 1km		0.115
Share of Firms Relocated ≥ 2km		0.100
Share of Firms Relocated ≥ 5km		0.073
Share of Firms Relocated ≥ 10km		0.050
Share of Firms Relocated ≥ 20km		0.036

Own elaboration

Table A2: Treatment and Control Group Composition for the Firm Entry Model

Variable	Control	Treatment
Area (in km^2)	23.13	32.54
Population	23,291.29	33,755.59
Share of Population Employed	0.35	0.36
Literacy Rate	0.83	0.85
Number of Firms in 2023	32.58	158.37
Average Annual Firm Entry	0.26	1.23
Average Distance to the District Capital (in km)	34.60	34.64
Share of Villages with Major District Road	0.87	0.83
Number of Villages	790	517

Note: All non-firm related variables based on the 2011 Indian Census; own elaboration

Table A3: Treatment and Control Group Composition for the Firm Relocation Model

Variable	Control	Treatment
Firm Age (in years)	8.75	10.24
Authorized Capital (in INR mil)	9.61	20.29
Paid-up Capital (in INR mil)	6.70	12.91
Share of Firms Relocated	0.10	0.11
Relocation Distance (in km)	31.49	26.27
Share of the Service Sector	0.52	0.50
Share of the Manufacturing Sector	0.15	0.17
Share of the Commerce Sector	0.15	0.16
Share of the Construction Sector	0.07	0.07
Share of the Transport Sector	0.03	0.04
Share of the Agriculture Sector	0.04	0.03
Share of Other Sectors	0.03	0.02
Geocoding Match Score (of 100)	84.09	84.29
Number of Observations	3,936	10,915

Own elaboration

Table A4: Impact of Flooding on Firm Entry

	Dependent variable: Number of New Firms	
	(1)	(2)
Flood 2018	-3.657****	-1.594**
	(0.741)	(0.731)
Flood 2019	-2.665****	-1.498**
	(0.648)	(0.713)
Flood 2020	-4.828****	-2.997****
	(0.841)	(0.881)
Flood 2021	-5.616****	-3.643****
	(0.911)	(0.876)
Flood 2022	-4.777****	-2.301**
	(1.160)	(1.056)
Flood 2023	-0.411	0.873
	(1.055)	(0.897)
Village FE	Yes	Yes
Year FE	Yes	Yes
District × Year FE	No	Yes
R^2	0.730	0.735
Adjusted R^2	0.718	0.720
Number of Observations	31272	31272

Linear Regression Model. Standard errors in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; $^{****}p < 0.001$

Table A5: Impact of Flooding on Firm Relocation, only Manufacturing Firms

	Dependent variable: Relocation Dummy			
	(1)	(2)	(3)	(4)
Firm within 2km buffer	0.662***	0.724***	0.587**	0.696**
	(0.223)	(0.237)	(0.264)	(0.309)
Firm Age	-0.041****	-0.042****	-0.044****	-0.040****
	(0.007)	(0.008)	(0.009)	(0.010)
Paid-up Capital	0.098***	0.110***	0.101**	0.093**
	(0.032)	(0.034)	(0.039)	(0.045)
Constant	-3.271****	-3.520****	-3.674****	-3.937****
	(0.527)	(0.549)	(0.634)	(0.723)
District FE	Yes	Yes	Yes	Yes
Relocation Threshold	1km	2km	5km	10km
Control Band	5-10km	5-10km	5-10km	5-10km
Observations	2,475	2,475	2,475	2,475

Logistic Regression Model. Standard errors in parentheses.

*p < 0.1; **p < 0.05; ***p < 0.01; **** p < 0.001

Table A6: Impact of Flooding on Firm Relocation

	Dependent variable: Relocation Dummy			
	(1)	(2)	(3)	(4)
Firm within 2km buffer	0.236^{***}	0.261^{****}	0.113	-0.027
	(0.075)	(0.078)	(0.088)	(0.101)
Firm Age	-0.045^{****}	-0.044^{****}	-0.046^{****}	-0.043^{****}
	(0.003)	(0.004)	(0.004)	(0.005)
Paid-up Capital	0.137^{****}	0.137^{****}	0.138^{****}	0.146^{****}
	(0.011)	(0.011)	(0.013)	(0.015)
Constant	-3.697^{****}	-3.807^{****}	-3.808^{****}	-4.063^{***}
	(0.276)	(0.289)	(0.309)	(0.343)
District FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Relocation Threshold	1km	2km	5km	10km
Control Band	≥ 5km	≥ 5km	≥ 5km	≥ 5km
Observations	19,691	19,691	19,691	19,691

Logistic Regression Model. Standard errors in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; $^{****} p < 0.001$

Table A7: Impact of Flooding on Firm Relocation by Sector

	Dependent variable: Relocation Dummy				
	Services	Manufacturing	Commerce	Construction	Agriculture
	(1)	(2)	(3)	(4)	(5)
Firm within 2km buffer	0.151	0.507**	0.063	0.761**	0.795*
	(0.104)	(0.198)	(0.191)	(0.308)	(0.460)
Firm Age	-0.047****	-0.041****	-0.058****	-0.026*	-0.010
	(0.005)	(0.006)	(0.009)	(0.015)	(0.010)
Paid-up Capital	0.114****	0.135****	0.196****	0.178****	0.203****
	(0.017)	(0.027)	(0.024)	(0.035)	(0.062)
Constant	-3.102****	-17.905	-4.458****	-4.707****	-3.746****
	(0.346)	(371.438)	(0.705)	(0.875)	(0.959)
District FE	Yes	Yes	Yes	Yes	Yes
Relocation Threshold	1km	1km	1km	1km	1km
Control Band	≥ 5km	≥ 5km	≥ 5km	≥ 5km	≥ 5km
Observations	9,531	3,332	3,151	1,585	747

Logistic Regression Model. Standard errors in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; $^{****}p < 0.001$

Table A8: Impact of Flooding on Firm Relocation, only Manufacturing Firms

	Dependent variable: Relocation Dummy			
	(1)	(2)	(3)	(4)
Firm within 2km buffer	0.507**	0.522**	0.383*	0.508*
	(0.198)	(0.207)	(0.229)	(0.267)
Firm Age	-0.041****	-0.041****	-0.041****	-0.044****
	(0.006)	(0.006)	(0.007)	(0.009)
Paid-up Capital	0.135****	0.137****	0.134****	0.139****
	(0.027)	(0.028)	(0.031)	(0.035)
Constant	-17.905	-17.936	-17.899	-17.938
	(371.438)	(371.517)	(372.010)	(371.680)
District FE	Yes	Yes	Yes	Yes
Relocation Threshold	1km	2km	5km	10km
Control Band	≥ 5km	≥ 5km	≥ 5km	≥ 5km
Observations	3,332	3,332	3,332	3,332

Logistic Regression Model. Standard errors in parentheses.

*p < 0.1; **p < 0.05; ***p < 0.01; **** p < 0.001

Table A9: Impact of Flooding on Firm Relocation (5km Treatment Band)

	Dependent variable: Relocation Dummy			
	(1)	(2)	(3)	(4)
Firm within 2km buffer	0.117^{*}	0.173^{**}	0.076	0.026
	(0.065)	(0.069)	(0.078)	(0.092)
Firm Age	-0.041^{****}	-0.042^{****}	-0.046^{****}	-0.044^{****}
	(0.003)	(0.003)	(0.004)	(0.004)
Paid-up Capital	0.113^{****}	0.119^{****}	0.107^{****}	0.111^{****}
	(0.009)	(0.010)	(0.011)	(0.014)
Constant	-3.337^{****}	-3.496^{****}	-3.415^{****}	-3.698^{****}
	(0.194)	(0.202)	(0.230)	(0.270)
District FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Relocation Threshold	1km	2km	5km	10km
Control Band	5-10km	5-10km	5-10km	5-10km
Observations	26,373	26,373	26,373	26,373

Logistic Regression Model. Standard errors in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; $^{****}p < 0.001$

Table A10: Impact of Flooding on Firm Relocation (Continuous Treatment)

	Dependent variable: Relocation Dummy			
	(1)	(2)	(3)	(4)
Share of 2km Buffer Flooded	-1.349**	-0.689	-1.002	-1.114
	(0.617)	(0.615)	(0.730)	(0.849)
Firm Age	-0.043****	-0.043****	-0.046****	-0.044****
	(0.003)	(0.003)	(0.003)	(0.004)
Paid-up Capital	0.127****	0.132*****	0.128****	0.135****
	(0.008)	(0.009)	(0.010)	(0.012)
Constant	-3.461****	-3.627***	-3.534****	-3.817****
	(0.249)	(0.261)	(0.279)	(0.312)
District FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Relocation Threshold	1km	2km	5km	10km
Observations	31,248	31,248	31,248	31,248

Logistic Regression Model. Standard errors in parentheses.

*p < 0.1; **p < 0.05; ***p < 0.01; **** p < 0.001

Table A11: Impact of Flooding on Firm Exit

	Dependent variable: Firm Exit Dummy	
	(1)	(2)
Firm within 2km Buffer	-0.067	
	(0.054)	
Share of 2km Buffer Flooded		-0.139
		(0.383)
Firm Age	-0.002	0.001
	(0.002)	(0.001)
Paid-up Capital	-0.295***	-0.283***
	(0.011)	(0.007)
Constant	2.096***	2.034***
	(0.201)	(0.186)
District FE	Yes	Yes
Sector FE	Yes	Yes
Control Band	5-10km	
Observations	14,816	31,248

Logistic Regression Model. Standard errors in parentheses.

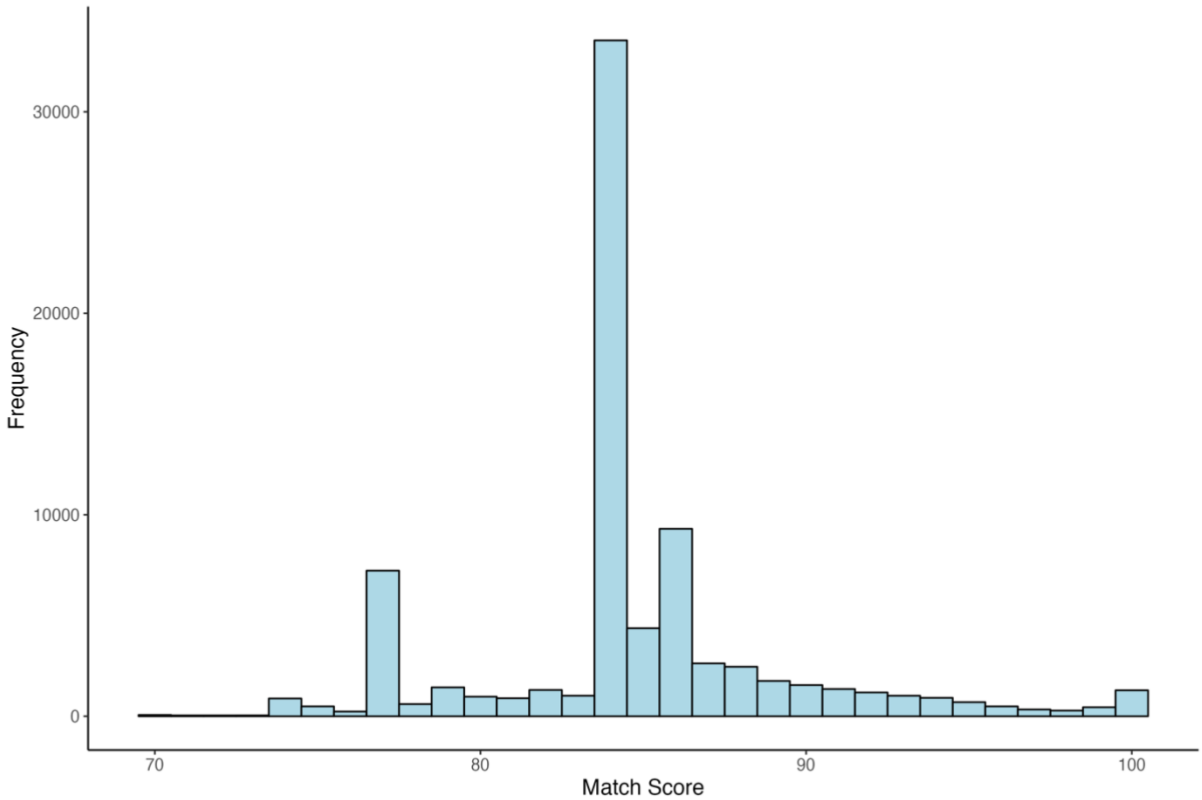
*p < 0.1; **p < 0.05; ***p < 0.01; **** p < 0.001

Further Details on the Dataset Creation

a) Cleaning and geocoding of company data

Before the address strings could be geocoded, several cleaning operations had to be conducted. These included removing incorrectly encoded special characters and unnecessary strings that systematically appeared across all observations, such as the abbreviation "KL" for Kerala. Likewise, it seems that the data entry process followed some specific structure. So, within the address string of the raw data, there were several components (street, village, subdistrict, district, postcode, etc.). However, in the majority of cases, the addresses were incomplete regarding these components. Missing components were often replaced with an "na" string, which was frequently attached directly (without spaces) to the preceding or following address component. Therefore, these "na" strings had to be carefully removed, ensuring that any valid instances of "na" within a word (such as in the district name Ernakulam, for example) were preserved. Finally, in some cases, the postcode appeared twice within the address line and had to be removed.

Figure A4: Distribution of Geocoding Match Scores in the Location Dataset



To maximize geocoding accuracy, the raw datasets were split in chunks of 500 observations and then geocoded in separate batches, following the recommendations by ESRI. Each geocoded address was assigned with a match score (ranging from 0 to 100), indicating the accuracy of the match. Match scores above 80 are generally considered matches with high accuracy. Overall, the accuracy of the geocoding was quite high, with a mean of 84.7 and a median of 84. Figure A4 provides an overview of the match score distribution.

b) *Classification of relocations*

As outlined in the methodology section, due to the limited availability of credits for the ArcGIS Geocoding API, a function was developed to measure the similarity between the 2018 and 2023 addresses. This was done to avoid unnecessary repetition of geocoding for firms that had not changed their addresses over time. Given the notable differences in data entry formats across different rounds of the administrative data, it was essential to create a function that accurately detects when addresses remained unchanged over time. This function first standardizes the addresses by converting all characters to a common encoding, changing letters to lowercase and removing all non-alphanumeric characters from the address string. It then calculates the distance between the two strings using the Levenshtein method, which determines the minimum number of single-character edits needed to change one string into the other.[9] This distance was then converted into a similarity percentage based on the maximum possible distance between the two strings (i.e., the length of the longer string). In case that the postcodes were dissimilar across the two addresses, the similarity percentage was set to zero as a change in postcodes was considered as a certain indication of the firm having relocated. After reviewing the results, it was determined that address strings with a similarity percentage of less than 75% were considered dissimilar and were therefore geocoded again. Firm observations with a similarity percentage of 75% or more were classified as cases where no relocation had occurred. For cases with a similarity percentage below 75%, the Haversine distance between the coordinates of the 2018 and 2023 addresses was calculated to assess whether the two locations were actually different. Upon closer examination, all instances where the 2018 and 2023 addresses were more than 1 km apart were classified as relocations.

[9] Source: https://www.sciencedirect.com/topics/computer-science/levenshtein-distance#:~:text='Levenshtein%20Distance'%20is%20a%20method,transform%20one%20word%20into%20another.

c) *Creation of control variables and exclusion of observations*

The sector variable used to include industry fixed effects in all the firm-level models is derived from the sector information provided in the company data. This variable summarizes the detailed sector information of the raw data into seven broad categories: Agriculture, Commerce, Construction, Manufacturing, Services, Transport, and Others. The variable indicating firm age was created by subtracting the firm registration dates from the approximate date of the flood. Before conducting the analysis, several observations were excluded from the dataset, including firms with insufficient or entirely missing address information, as well as state-owned enterprises. Additionally, for the relocation analysis, only active firms were retained in the dataset, excluding firms with the company status “under strike-off,” “dissolved,” or “under liquidation” in 2018. Importantly, these firms were not removed from the location dataset, as the objective of that dataset was to identify the total number of registrations in a given year, irrespective of whether firms eventually exited or not.

d) *Processing of flood and flood risk shapefiles*

The shapefiles of the Kerala floods and the UNEP WESR hazard map were processed using QGIS. This processing involved simplifying the files, verifying their validity, and reprojecting them to the project's coordinate system (EPSG: 4326 - WGS 84). To create the treatment variable for the firm entry model, the flood layer was intersected with the village layer using the intersection tool. This process yielded all spatial intersections between the two layers, which were then joined with the village layer to calculate the proportion of each village that was flooded. For the relocation dataset, the “inner-and-outer-ring” approach was implemented as follows: Buffer zones around the flood spots, as described in section 4.3, were created using the buffer tool. The 2km-5km spillover buffer was then generated by subtracting the 2km buffer from the 5km flood buffer using the difference tool. Company locations were subsequently spatially matched with these buffers. The alternative (continuous) treatment specification was created by drawing circles of a 2km radius around company locations and then spatially intersecting them with the flood layer. After these spatial intersections, the results were rejoined with the company layer to calculate the percentage of each company’s buffer area that was flooded.