The Impact of Flash Floods on the Spatial Distribution of Businesses and Workers

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Abstract

This paper analyzes how a natural disaster affects the spatial distribution of establishments and workers, using the devastating 2008 Santa Catarina Flash Flood as a natural experiment. We combine synthetic-aperture radar images that show the exact location of flood spots with geocoded employer-employee data to estimate the impact of the disaster. We find that establishments in affected areas have a higher chance of closure but they do not adjust to the shock through business relocation or market entry. Workers dismissed in the wave of disaster face reduced job prospects, with no impact on wages or migration rates for those who do find new employment. These effects persist over the analyzed 5- to 9-year period.

Keywords: Natural Disasters, Business closure, Location of Economic Activity, Brazil.

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1 Introduction

Floods are increasingly recurrent worldwide and are the most common type of natural disaster[1]. Global Warming and higher urbanization in risky areas tend to increase the frequency of and damage by natural disasters (Habitat, 2011). This is a particular concern for developing economies, as they often face more damage from disasters (Kahn, 2005; Kellenberg and Mobarak, 2008) and have limited resources for preparedness and adaptation (Hallegatte, Rentschler and Walsh, 2018). Yet, to implement adequate responses to and prevention of natural disasters, businesses and policymakers require a better understanding of disasters' economic consequences in the first place.

The objective of this paper is to study how a natural disaster affects *both* the spatial distribution of business and workers in the short and medium term. At the establishment level, we analyze the probability of business closure, entry, and relocation. At the worker level, we look at those who had to cope with the consequences of job loss. More specifically, we estimate whether dismissed workers from disaster-induced firm closures show different job prospects, wages, and migration rates. The literature has produced contradictory theoretical and empirical results as disasters can have both short-lived and permanent effects on the location patterns of businesses. On the one hand, disasters can destroy infrastructure and productive capital, prompting firms and individuals to move and causing a permanent alteration of the spatial equilibrium (Barsanetti, 2020; Siodla, 2021; Ager et al., 2020). On the other hand, locational fundamentals may play a dominant role in firms' decision-making, enabling the economy to absorb the shock and recover their initial spatial equilibrium (Brakman, Garretsen and Schramm, 2004; Kocornik-Mina et al., 2020).

To understand the location-related responses of businesses and workers to a temporary negative shock, we exploit the 2008 Santa Catarina Flash Flood[2] as a natural experiment. This flood affected 1.5 million people (equivalent to 24% of the state's population) in 74 cities and it is thus widely recognized as one of Brazil's largest natural disasters. We combine two geocoded micro datasets that allow us to estimate the impact and extension of the 2008 Santa Catarina Flash Flood independent of administrative geographic units. First, the synthetic-aperture radar (SAR) satellite data[3] collected by Marinho et al. (2012) accurately identifies

[1]According to Tellman et al. (2021), the total number of people directly affected by floods is about 255–290 million and increased by 20-24% between 2000 and 2015.

[2]In November 2008, the northern coastal region of the State of Santa Catarina (known as *Vale do Itajaí*) experienced the highest volume of precipitation in history, reaching more than seven times the average volume previously recorded in the area (Severo et al., 2014). As a result of this high volume of rainfall and the geographic characteristics of the region, large and unexpected floods occurred, devastating a large territory and causing economic losses of R$ 4.75 billion (World Bank, 2012).

[3]One of the primary advantages of SAR data, in comparison to traditional satellite images, is their ability to gather precise information about the Earth's surface even in scenarios where areas are obscured by dense

the location and extent of flooded spots. Second, we use matched employer-employee panel data, encompassing the entire formal sector in Brazil. With this combined data, we adopt a data-driven method based on "inner and outer rings" to estimate the potential disaster coverage area (Zhu et al., 2016). Then, we assign establishments into two different groups: the disaster-exposed group, consisting of establishments near the flood spots within a disaster coverage radius estimated at 12.5 km, and the control group, comprising the non-exposed establishments situated between 30 and 50 km from the flooded area. Finally, we adopt a difference-in-differences approach to compare the evolution of outcomes between the treated and control establishments.

Our findings reveal that establishments affected by the 2008 Santa Catarina Flash Flood exhibit a 0.7% higher probability of closure compared to unaffected ones in the immediate aftermath of the shock. This effect persists and increases rapidly in subsequent years, reaching 1.8% four years after the shock. However, we do not observe any significant changes in geographic relocation or market entry as a response to the disaster. These findings suggest that the disaster provoked a lasting change in the spatial distribution of businesses, characterized by higher market exit and equal entry rates. These results remain robust across alternative empirical specifications. We document that the increased probability of closure is primarily driven by micro establishments within the manufacturing, wholesale, and retail industries. Moreover, civil construction establishments in flood-exposed areas have higher entry and relocation rates.

Our identification strategy for the worker-level analysis is based on disaster-induced establishment closures[4]. The matched employer-employee panel enables us to track individuals throughout their careers in Brazil's formal labor market. In this setting, the treatment group consists of workers employed in businesses within the treatment area that completely ceased their operation the year after the flash floods. Our preferred control group comprises similar individuals from the control area, selected through matching techniques. The advantage of this approach is to provide a clear link between the disaster and workers' responses while mitigating non-random selection into displacement.

We find that workers who were dismissed in the aftermath of the 2008 Santa Catarina Flash Flood experience a lower probability of being employed, without subsequent recovery in the following years. This evidence supports the notion that major disasters can have a lasting negative impact on establishments and workers. Additionally, we find that dismissed

cloud cover, which is frequently encountered in hydrological disasters.

[4]Mass layoffs have been used as an identification strategy to study the effects of unemployment on future earning losses (Couch and Placzek, 2010), crime (Britto, Pinotti and Sampaio, 2022), entrepreneurship (da Fonseca, 2022), among others. To avoid biased estimates because "those who experience mass layoffs are systematically selected", recent papers focus on firm closures (Couch and Placzek, 2010). To the best of our knowledge, this is the first approach to exploit disaster-induced establishment closures.

workers who successfully reestablished formal employment do not experience wage losses and do not demonstrate an elevated propensity for out-migration, consistent with the relocation patterns observed among establishments.

Our paper contributes to the growing literature that evaluates the impact of natural disasters on firms in two different ways. Firstly, we investigate how businesses react in terms of location-related outcomes (entry, closure, and relocation) while most previous studies focus on performance indicators. The results in this literature are mixed and contingent upon factors such as the type and magnitude of the disaster, characteristics of the affected economy, and implemented recovery policies. According to the creative destruction hypothesis, disasters offer businesses the chance to replace damaged capital goods with more efficient alternatives, thus presenting an opportunity for improvement. In this sense, disasters can drive capital accumulation and enhance overall performance (Okubo and Strobl, 2021; Leiter, Oberhofer and Raschky, 2009). Yet, most empirical studies show that businesses exposed to major disasters reduce their sales, productivity, and their survival rate (Elliott et al., 2019; Cole et al., 2017; Basker and Miranda, 2018; Pelli et al., 2023). These negative consequences are often more pronounced in less productive firms that are smaller in size, have limited access to credit, and operate in industries with local market orientation (Alves, Lima and Emanuel, 2022; Okubo and Strobl, 2021; Meltzer, Ellen and Li, 2021). Due to these disruptive effects, major disasters can have long-term implications on the spatial distribution of businesses, even without altering the pattern of industrial agglomeration (Siodla, 2021). Moreover, affected businesses also often react to natural disasters by reducing the level of employment and wages (Tanaka, 2015; Alves, Lima and Emanuel, 2022; Indaco, Ortega and Taspınar, 2021). However, the response of individual workers who belong to the affected business is still an unexplored aspect in this literature. In this way, our second contribution is to address this specific gap and provide novel evidence regarding the impacts of major disasters on businesses and their subsequent effects on dismissed workers.

In evaluating how disaster-induced closures affect employees, our paper is also related to the strand of literature that looks at workers' responses to disasters. Previous evidence suggests that major disasters have adverse effects on worker income and employment (Deryugina, Kawano and Levitt, 2018; Groen, Kutzbach and Polivka, 2020; Zissimopoulos and Karoly, 2010; Martínez, Martínez and Romero-Jarén, 2020). However, the local labor market can rapidly adapt to such shocks, leading affected workers to experience earnings growth that surpasses that of unaffected workers after a few years. This positive effect on earnings can be attributed to factors such as reduced labor supply, increased labor demand from rebuilding sectors, and government reconstruction efforts. Furthermore, individuals who experience a disaster often undergo temporary changes in risk perception and attitude, seeking increased protection (Brown et al., 2018; Gallagher, 2014). Such behavioral shifts, coupled with disruptions in the local labor market, can promote spatial redistribution of individuals and workers through out-migration (Shakya, Basnet and Paudel, 2022; Boustan et al., 2020; Kim and Lee, 2023). In our paper, we offer a novel contribution to this literature by specifically investigating the effects on the subgroup of workers who lose their job in the aftermath of the disaster. Dismissed workers are likely to be the most economically vulnerable to adverse shocks. By focusing on this subgroup, our paper can help to design more targeted and effective strategies to support dismissed workers and promote overall labor market resilience.

The remainder of the paper is organized as follows. Section 2 explains the context of the 2008 Santa Catarina Flash Flood. Section 3 presents the data sources, variable definitions, and descriptive evidence. Section 4 defines our research design for the establishment analysis and presents the respective results and robustness checks. Section 5 follows the same order for the worker-level analysis. Further details of additional exercises are available in our online appendix. Section 6 concludes the paper.

2 The 2008 Santa Catarina Flash Flood

In November 2008, the Brazilian state of Santa Catarina experienced one of the most severe natural disasters in its history. As a result of the combination of a high-pressure anticyclone that spread throughout the southern Atlantic coastal zone and the formation of a low-pressure cyclonic vortex, an unprecedented volume of rainfall was observed in the northeast area of the state (Stevaux et al., 2009). The rainfall concentration during the November 2008 weather event[5] exceeded three times the historical monthly average precipitation volume recorded in the region (Severo et al., 2014). Due to the topographic characteristics of the affected area and the high number of hydrographic basins in the Vale do Itajaí, this concentrated and unexpected rainfall generated the formation of flash floods. According to the satellite images collected and treated by Marinho et al. (2012), the 2008 disaster generated more than 1,022 floodings covering a total area of 7,452 hectares.

The 2008 Santa Catarina Flash Flood caused enormous social and economic damage. The disaster affected 1.5 million people (almost 24% of the state's population), leaving 121,000 homeless and 128 dead. The World Bank (2012) estimates that the event caused economic damage of approximately R$ 4.75 billion distributed in the infrastructure, social and productive sectors. This value represents more than five times the total volume of

[5]For instance, in November 2008, the mean monthly rainfall reached remarkable levels, with Joinville experiencing as high as 940 mm, Blumenau with 912.4 mm, and Itajaí with 687.3 mm.

investments made by the state government throughout 2008 and about 2.6% of the state's gross domestic product (GDP). In addition, the natural disaster had a broad geographic scope, causing 60 municipalities to declare a state of emergency and 14 to declare public calamity. Figure 1 shows the spatial distribution of these municipalities and their area. Although the affected region suffers from recurring weather shocks, nothing compares to the 2008 catastrophe: it concentrates 80.3% of the total victims and 60.5% of the economic costs associated with all the floods that hit the state between 1992 and 2012. The 2008 Santa Catarina Flash Flood is among the worst natural disasters in recent Brazilian history (O Globo, 2021).

[Figure 1 about here.]

The economy in the area affected by the 2008 Santa Catarina Flash Flood has a large manufacturing sector (accounting for 34.3% of local employment) and a intermediate urbanization rate (48,61%). In addition, the region is responsible for 60.78% of all GDP generated in the state of Santa Catarina in 2008. Relative to the rest of Brazil, the area is wealthy: it has a GDP per capita of R$ 23.7 thousand, a value 43% higher than the national average. The region is also home to the port of Itajaí, one of the busiest in southern Brazil, which had its activities paralyzed for several weeks due to the 2008 flash flood (World Bank, 2017).

Despite the lack of evidence regarding the impact of the 2008 Santa Catarina Flash Floods on the spatial distribution of economic activity at a micro-level, various studies suggest that the event had negative repercussions on the local economy. For example, Ribeiro et al. (2014) reports that the 2008 flash flood reduced industrial production in the state by 5.13%. Similarly, Lima and Barbosa (2019) show that municipalities directly impacted suffered an average reduction of 7.6% in GDP per capita, decreasing from 2011 onward (except for agriculture).

3 Data, Variables and Summary Statistics

3.1 Data Sources

To estimate the impact of the 2008 Santa Catarina flooding on the spatial distribution of establishments and dismissed workers, we combine two databases: the *Relação Anual de Informações Sociais* (RAIS) and satellite data collected by Marinho et al. (2012) that show the precise location of floods in 2008.

Data on Establishments and Workers: The RAIS is collected annually by the Ministry of Labor and is the official matched employer-employee Brazilian database, covering the entire universe of firms and formal workers. We used data for the period between 2003 and 2012, which allows the construction of an unbalanced panel of establishments and workers with five years prior to and five years after the event. Establishment level entries have a unique and permanent tax identification number (CNPJ) that allows us to track establishments over time. Workers are identified by their personal tax number (CPF), as well. The RAIS also indicates which establishments belong to the same firm. We exploit the following variables: industry classification, opening year, number of employees, address, and zip code. Google Maps API is used to geocode each establishment through the zip code. Thus, we obtain the geographic coordinates for 322,278 establishments located in the area under consideration. Unfortunately, we had to drop 20.5% of the initial number of establishments due to the imprecision of the zip code and the difficulty in carrying out the georeferencing. In addition to establishment-level information, the RAIS database also provides detailed worker-level data, including the total labor earnings, the number of hours worked per week, type of occupation, formal education, age, race, and gender. Although the RAIS is a comprehensive, reliable, and detailed database, its main limitation is that it only covers formal workers. Therefore, the database does not consider the unemployed and individuals in the informal labor market.

Satellite Data of Flood Spots: We use synthetic-aperture radar (SAR) images collected and treated by Marinho et al. (2012) to define the flood spots. These orbital SAR images were obtained from four different satellites between September 2008 and January 2009, making it possible to map the areas flooded directly by the 2008 Santa Catarina Flash Flood. To identify the exact flood spots, the study of Marinho et al. (2012) proceeds with orthorectification, filtration to reduce speckle noise, and conversion of the SAR images to the backscatter coefficient. As shown by Marinho et al. (2012), this methodology for collecting and processing disaster information with SAR images is useful when it is not possible to obtain the traditional satellite images (with optical remote sensors) due to the cover and sprawl of clouds in the area, as was the case of the 2008 event. Through this approach, it was possible to identify and geocode 1,022 individual flood spots in the area affected by the disaster, with extensions ranging from 0.001 km^2 to 18.02 km^2.

With the combination of these geocoded data, it is possible to separate establishments exposed to the 2008 Santa Catarina Flash Floods (assigned as treated units, which are close to the flood spots) from establishments not exposed to the event (assigned as control units, which are further away from the flood spots). Section 4.2 will detail the approach used to define the treatment and control area.

3.2 Variables

Establishments-Level Variables: We will consider three outcome variables to evaluate the disaster's consequences on the spatial distribution of businesses and check whether the shock generates temporary or persistent effects. Our first outcome variable is a closure indicator, which takes the value 0 for active establishments and 1 in the year the establishment closes[6]. We also investigate the effect of the disaster on business entry, which is an indicator variable that assumes 1 in the year the establishment was first registered. Finally, the geographic relocation variable takes the value 1 if the establishment moves from one municipality to another[7] in year t and assumes 0 otherwise. In some alternative specifications, we will include the following control variables at the establishment level: number of employees (a proxy for firm size), age of establishment, number of branches, a dummy for the sector of activity (agriculture, construction, manufacturing, and wholesale/retail) and a dummy for having foreign trade relations (importing or exporting businesses)[8].

Worker-Level Variables: To evaluate the disaster's consequences on workers, we calculate three different outcome variables. The first is an indicator variable that takes value 1 when the worker has formally registered employment in the RAIS. Second, we look at migration to a different municipality in Brazil. A complication here is that we cannot observe migration patterns for workers that leave the formal labor market. To reduce potential bias from sample attrition, we follow Dix-Carneiro and Kovak (2019) and define our migration variable as the months spent away from the original area in each calendar year relative to the number of months with formal employment. The sample composition for this outcome variable is different from the previous one because it is conditional on the worker having formal employment in either the treatment or control area. The third outcome variable is the log

[6] A closure is defined as either one of the following two situations in the RAIS data, following previous studies from Brazil such as Alves, Lima and Emanuel (2022) and Ehrl (2021). In some cases, one observes the exact closure date which means that the firm officially registered a temporal or permanent end of its activities. In other cases, an establishment simply ceases its operation and dismisses all workers, but without de-activating the tax identification number. In this way the establishment leaves the door open when it decides to resume its activities and it avoids to pay certain fees that are involved in a business closure. The latter case is not formally registered but we define a closure also when an establishment disappears from the mandatory record of employment data to the RAIS.

[7] An alternative will be to check if establishments relocate through changes in their ZIP code (*Código de Endereçamento Postal* in Brazil). However, as the ZIP code can change as a result of factors exogenous to the firms' decision (such as changes in urban zoning, creation of neighborhoods, or new avenues), we believe that relocation outside the municipality captures a stronger and more adaptive behavior of firms in regarding the shock. However, in Appendix Table A.4, we present a robustness test using the ZIP code as a reference.

[8] The Brazilian Ministry of Economy collects data on the firms that integrate foreign trade (importers and exporters). Then, we merge this information with the RAIS database through the tax identifier of each establishment.

of workers' monthly average wages to see whether the disaster leads to poorer job prospects, loss of employed human capital, or different equilibrium wage in general (Zissimopoulos and Karoly, 2010). To assign workers to either the treatment or the control area, particularly in the years after the disaster, we need to disregard workers who assume employment that is located in neither of both areas. This restriction applies to the outcome variables employment and average wage.

3.3 Descriptive Evidence

To obtain descriptive evidence about the consequences of the 2008 Santa Catarina Flash Floods on the aggregate spatial distribution of economic activity, it is useful to compare the trajectory of the outcomes of the treated area and the control area before and after the disaster. In this way, Figure 2 presents the evolution in the closure rate[9], entry rate, relocation rate, log of the number of employees per establishment, and log of costs in payrolls per establishment between the period 2003 to 2012, separated by the aggregation of establishments in the treatment area (blue line) and control area (red line).

[Figure 2 about here.]

Firstly, we note that during the pre-disaster period, the affected area had a more favorable business environment. Specifically, the affected area exhibited higher rates of entry and relocation, and a lower rate of business closure compared to the control area. In terms of the labor market conditions, the control area has a slightly higher number of employees per establishment and a nearly equal average payroll. However, what matters for our identification strategy is the trajectory, and not the levels, of outcomes in the pre-disaster period. Figure 2 indicates that this trajectory is similar for the entire set of variables, suggesting that our identification assumption is not violated and that different areas appear to experience similar shocks. After an initial examination, it appears that the 2008 Santa Catarina Flash Flood resulted in an aggregate increase in business closures and a decline in employment. Notably, the rate of business closures rose among affected establishments in the aftermath of the disaster and remained consistently higher. In contrast, the closure rate for the control group of businesses experienced a marked decrease.

Table 1 presents the descriptive statistics (mean and standard deviation) for the same set of outcome variables, as well as the other control variables separated by establishments located in the treatment area and in the control area during the pre-disaster year (2007) and post-disaster year (2008). The findings in Table 1 are consistent with those in Figure

[9] Defined as the ratio of the number of businesses that closed (or relocated or entered) and the total number of businesses in the specific year.

2: before the event, there were no significant differences in outcomes between affected and unaffected businesses, and immediately after the disaster, we note an increase in the closure rate (in 4.62%) and a reduction in employment (in -0.95%) for affected establishments. These aggregated results suggest that the region affected by the 2008 Santa Catarina Flash Flood presents a worsening of economic conditions with a permanent change in the initial spatial equilibrium. As will be shown in sections 5 and 6, this descriptive result is supported by our quasi-experimental approach.

[Table 1 about here.]

4 Flash Floods and the Spatial Distribution of Establishments

4.1 Empirical Strategy

To estimate the effect of the 2008 Santa Catarina Flash Flood on the spatial distribution of businesses, we compare outcomes (probability of closure, entry, and relocation) between establishments located near (treated area) and far from the flood spots (control area) before and after the catastrophic event. Thus, we take advantage of the exogeneity of the disaster in the geographic and time dimension and adopt a difference-in-differences approach in which the treatment group is defined by the set of establishments initially located close to the disaster-affected area (the flood spots). Additionally, since evaluating whether the impacts of the disaster are temporary or persistent is a relevant aspect of our research question, we will estimate an empirical specification that allows us to capture the variability of the effects of the disaster over time. More specifically, we estimate the following equation:

$$Y_{it} = \sum_{\tau=1}^{T} \beta_\tau \times \mathbf{1}[t = \tau] \times FlashFlood_i + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Where Y_{it} is an outcome for establishment i and year t, the indicator $\mathbf{1}[t = \tau]$ is equal to one if the observation falls in year τ that follows the 2008 Santa Catarina Flash Flood, and $FlashFlood_i$ is a treatment variable that assumes one for the establishments located near to floods spots (affected area). The establishment fixed effects (denoted by μ_i) are useful to control for time-invariant non-observable characteristics of establishments that might be correlated with the outcome variable (such as industry classification, initial location, proximity to transport facilities, and local jurisdiction attributes). The year-fixed effects (denoted by λ_t) control for common shocks that affect the establishments in each specific year (such as macroeconomic fluctuations, national or state-level tax changes, regional shocks, etc.). The variable ε_{it} is the error term. Our key parameter of interest in equation (1) is each β_τ, which measures the year-specific impact of flash floods on the outcome variable of affected establishments. To account for geographical and serial correlation in the residuals of our regressions, we make inference using the two-way clustered-robust standard errors developed by Cameron, Gelbach and Miller (2011) at the establishment and year level.

To obtain internal validity of our difference-in-differences estimator is necessary to meet the parallel trends assumption. This assumption implies that in the hypothetical absence of the 2008 Santa Catarina Flash Floods, the outcomes of the exposed establishments would have the same trajectory as those not affected by the shock. In this way, the timing of the flash floods would be uncorrelated with the error term conditioned to the controls. To investigate whether the parallel trends assumption is plausible in our research context, we also estimate the following event study specification:

$$Y_{it} = \sum_{\eta=-q}^{-1} \gamma_\eta \times \mathbf{1}[t=\eta] \times FlashFlood_i + \sum_{\eta=0}^{T} \delta_\eta \times \mathbf{1}[t=\eta] \times FlashFlood_i + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Where q refers to the number of leads or anticipatory effects and T is the number of lags or post-treatment years. The disaster occurs at $\eta = 0$ and we use the year immediately prior to the shock (2007) as a reference in the estimations. The coefficients associated with leads, denoted by γ_η, can be used to check the validity of our identification assumption. If the leads are not statistically significant, we would have evidence that there was no divergence in the outcomes of the establishments exposed and those not exposed before the flash floods occurred. This would suggest the validity of the parallel trends assumption. The coefficients associated with lags (denoted by δ_η) measure the year-specific effects of the disaster in the years that follow it, having the same interpretation as the coefficients of interest in equation (1).

4.2 Defining Treated and Control Establishments

We adopt an "inner and outer ring" approach to assign the establishments in control and treated areas. This strategy is appropriate in geocoded microdata settings, where the evaluated event or shock has an entirely uncertain reach, see for example Gibbons and Machin (2005), Zhu et al. (2016), Asquith, Mast and Reed (2021), or Salvucci and Santos (2020). In our case study, we assume that establishments immediately close to flood spots are the most severely affected by the disaster because they tend to experience the largest and most direct damage (such as the destruction of buildings and fixed assets or disruption of transport accessibility). Therefore, businesses located within the inner radius of the disaster coverage area will be classified as treated units in the treated area. On the other hand, establishments that are geographically distant from the flood spots may form a potential control group in the outer ring of the disaster coverage area (defined as the control area).

There is a clear *trade-off* in choosing the geographical boundaries of the control ring area. Firstly, choosing outer rings that are geographically very distant from the flood spots may include establishments subject to a different economic environment compared to the context of the treated units, generating a potential violation of the parallel trends assumption. The other way round, outer rings very close to those directly affected may form a control group that also suffered from the consequences of the natural disaster, either directly or indirectly (through spillovers). In this case, there would be a potential violation of the stable unit treatment value assumption (SUTVA). This assumption establishes that the outcome of a specific observation unit is unrelated to the treatment status of other units. If the SUTVA is violated, the coefficients of interest in equations (1) and (2) will be lower bound estimates (Delgado and Florax, 2015; Berg, Reisinger and Streitz, 2020).

The "inner and outer ring" approach recognizes the possibility of a SUTVA violation since it excludes the units located in the middle of the treatment and control area from the analysis. However, there is no guarantee that the establishments assigned in the control ring area did not suffer some direct or residual impact from the flash floods. Even with this approach, it is not possible to provide a clear delimitation of the geographic limits that establish the radius of the treatment and the control ring area. The choice of disaster coverage area is commonly made in an empirical way that recognizes the peculiarities of natural disasters. The best solutions seem to follow the approach of Zhu et al. (2016) and estimate equation (1) looking for the effects of the 2008 Santa Catarina Flash Floods considering different distance bands in relation to the flood spots.

Specifically, we start by setting the outer ring for the control area between 30 and 50 km from the flood spots and estimate equation (1) for our primary outcome (business closure), considering alternative treatment bands. Thus, we use the following treatment bands at contiguous intervals of 2.5 km distance from each flood spot: 0-2.5 km, 2.5-5 km, 5-7.5 km, 7.5-10 km, 10-12.5 km, 12.5-15 km, and 15-17.5 km. Through this methodology, it is possible to define the maximum geographic extent of the economic impacts of the 2008 Santa Catarina Flash Floods. The cut-off distance that delimits the extension of the treatment group is defined as the largest distance from the flash floods under which the economic consequences of the disaster for the establishments are still statistically significant. Table 2 reports the results of this exercise.

[Table 2 about here.]

Table 2 clearly shows that after the disaster, the establishments near flood spots were more likely to close when compared to more distant establishments. As expected, the effects are higher for businesses located in the immediate vicinity of the flood spots (columns 1 and 2) and begin to decay as of the 5-7.5 km band (column 3). Additionally, in column (4), we note that establishments located in the band between 12.5 km and 15 km away from the flood spots no longer experience the negative effects of the disaster. Based on this exercise, we can set the cut-off for the extension of the inner radius (treated area) to 12.5 km and, at the same time, have some confidence that the establishments located in the control ring (distance between 30-50 km from the flood spots) are not directly or indirectly affected by flash floods. This implies that spatial spillovers and the violation of SUTVA is not relevant concern in our setting. Therefore, in our main specifications, we will assign the establishments within a radius of up to 12.5 km to the flood spots as treated units and establishments in the 30 to 50 km outer ring as control units. We perform a set of robustness tests modifying the baseline control ring (set arbitrarily at 30-50km intervals) and the treatment radius.

Figure 3 shows the details of the disaster coverage area using the obtained definitions. It displays the geographical distribution of establishments (gray dots) from the RAIS database, the flood spots (blue areas) collected by Marinho et al. (2012), and the extension of the inner treatment area and the outer control ring. The workers and establishments in the remaining locations in the state of Santa Catarina are not included in the analysis.

[Figure 3 about here.]

4.3 Main Results

Table 3 reports the results of the linear probability model in equation (1) using three alternative outcome variables: an indicator for establishment closure, relocation, and entry. For each outcome, we show a specification considering the establishment and the year fixed effect and another where we add a linear census tract-specific trend. The specific trend captures non-observed variables that evolve linearly at the census tract level and can affect business location patterns. As discussed in subsection 4.2, the baseline treatment units are establishments up to 12.5 km from each flood spot. The control units are establishments located in a control ring between 30 km and 50 km to flood areas.

[Table 3 about here.]

Firstly, we note that establishments affected by the 2008 Santa Catarina Flash Floods have a 0.7% higher probability of closing in the aftermath of the disaster when compared to unexposed establishments. In addition, the likelihood of closure of the affected businesses increased rapidly following the shock, reaching 1.8% in 2012[10]. Column (3) indicates that

[10] The magnitude of the effects of the 2008 Santa Catarina disaster on the probability of closure is

affected establishments have a slightly higher probability of relocation than non-affected ones. Still, this effect is small (0.1%), short-term lived, and is not robust to the addition of census tract linear trend. Thus, the units exposed to floods do not systematically adjust to the shock through locational changes. Columns (5) and (6) show that the area directly affected by the shock experienced a reduction in business entry. The effect was only strong and statistically significant in the fourth year after the disaster. In sum, the set of evidence in Table 3 indicates that the businesses affected by the flash flood primarily responded to the shock by shutting down their activities. As this effect is not short-lived, the deterioration of the affected economy seems to have reduced the business prospects of some firms.

In light of the different theories that explain the spatial distribution of economic activity, the evidence in Table 3 partially supports the prediction of the increasing returns approach and the New Economic Geography that large and temporary shocks can permanently shift the locational patterns to a new equilibrium (Davis and Weinstein, 2002). This mechanism occurs because the increasing returns model allows for multiple spatial agglomeration equilibria (Brakman, Garretsen and Van Marrewijk, 2019). Although we observe that establishments do not relocate, the spatial equilibrium is still different because the number of active businesses becomes lower. In appendix A (Table A.3), we perform a robustness exercise extending the post-treatment period to 2016 (the last year with geolocated data) and confirm the lasting effects. So, even nine years after the event, establishments in the affected areas are more vulnerable compared to the nearby region.

Our identification assumption is that the outcomes for the treated and control establishments would have followed parallel trends if the disaster had not happened. A possible violation of this assumption in our setting stems from the fact that establishments with lower (expected) performance can select the areas of higher flood risk to locate. We expect areas subject to more significant natural hazards (near mountain slopes or watersheds) to be less valuable (Bosker et al. (2019)), attracting underperforming businesses. In this specific case, the estimates in Table 3 could be capturing a difference in the trends of the probability of closure and entry that existed even before the natural disaster occurred (due to selection bias), violating the parallel trends assumption. Thus, we also estimate event study specifications (equation (2)) to evaluate the validity of our identification assumption and search for pre-trends.

significantly lower than that found in previous studies that adopted similar approaches. For example, Meltzer, Ellen and Li (2021) evaluated the impact of Hurricane Sandy in New York and showed that establishments exposed to the event increased their chance of closing by 6.29%. In addition, Cole et al. (2017) show that plants affected by the 1995 Kobe earthquake have a 16% greater chance of closure than unaffected ones. Unfortunately, it is not possible to know whether these divergences are due to methodological differences, the magnitude and geographic scope of the natural disaster, or the affected businesses' behavior.

[Figure 4 about here.]

Based on Figure 4, we observe that in the years before the 2008 Santa Catarina Flash Floods, there were no statistically significant differences between the probability of closure, relocation, and entry between affected and unaffected establishments. This result reinforces the descriptive evidence in Figure 2 and points to the validity of the parallel trends assumption. Only in the disaster year did the exposed establishments begin to experience a greater probability of closing. This evidence reduces our concern that the estimates presented in Table 3 are driven by a selection bias associated with the previous business locational choice. Finally, we note that the dynamics of the post-treatment effects in Figure 4 are the same as those presented in Table 3: the affected businesses permanently increase their probability of closing but only marginally reduce the likelihood of entry in the years following the flash floods.

4.4 Heterogeneous Responses

We also evaluate the heterogeneity of our main results concerning different industries and business sizes by estimating equation (1) in different sub-samples. Specifically, we divided our sample of establishments into distinct industries, including civil construction, transport, manufacturing, wholesale and retail, and services, which collectively account for 85% of our sample. The results of this exercise are presented in Table 4. Additionally, we examined potential variations in our findings based on business sizes using the classification provided by the IBGE (2019). We separated the establishments in our sample into three groups: micro-businesses (up to 9 employees), small businesses (10 to 49 employees), and medium and large businesses (50 or more employees). The corresponding results are reported in Table 5.

[Table 4 about here.]

[Table 5 about here.]

The evidence presented in Tables 4 and 5 reveals certain nuances that are hidden within the main results. Notably, the wholesale and retail establishments exhibit the highest probability of closure, as observed in Panel A of Table 4. This finding aligns with prior research indicating that businesses with a greater local market orientation are more vulnerable to the impacts of natural disasters (Meltzer, Ellen and Li, 2021; Alves, Lima and Emanuel, 2022; Okubo and Strobl, 2021). On the other hand, civil construction establishments are less likely to close, as evidenced in Panel A of Table 4, and are more inclined to enter the affected area, with the effect being short-lived (Panel A and C of Table 4). This outcome is consistent with the notion of post-disaster reconstruction efforts that typically ensue after catastrophic events. Furthermore, the results presented in Table 5 highlight that the closure effect is primarily driven by micro businesses (Panel A of 5), which is in line with previous literature and can be attributed to their lower productivity and limited access to credit.

4.5 Robustness Checks

In Appendix A, we assess whether our main results are robust to the following changes to the main specification: alternative length of our baseline control ring, alternative treatment radius, the use of treatment variable based on the distance between establishments and flood spots, the inclusion of initial establishment-level controls, an extension of the post-treatment period and, finally, alternative ways of defining the spatial scope of the relocation outcome. Overall, the results in section 5.1 are robust, making us confident that the 2008 disaster caused a lasting increase in the probability of exit of exposed establishments.

5 Disaster induced-closures and Dismissed Workers

5.1 Empirical Strategy

Establishing a causal link between flash floods and the spatial distribution of workers is more challenging than at the establishment level. Even among disaster-affected firms, some employees may experience none of the consequences. Distressed firms typically mitigate the consequences by systematically reducing the number of low-productivity workers, reducing wages and working hours for employees in the operational area, while simultaneously striving to retain the most productive and qualified staff. Furthermore, workers have different adjustment options and opportunities. In the course of time, it becomes increasingly difficult to tell whether a worker moves to a different municipality or job because of the disaster or due to other reasons. Considering that one of the most remarkable effects of the 2008 Santa Catarina Flash Floods was the persistent increase in business closures in the affected region (see subsection 4.3), we will define treated workers as those dismissed by an establishment located in the disaster area that entirely ceased its operations in 2009[11]. Exploiting the unemployment shock triggered by business closures

[11] We select only 2009 because it is the first year after the flash floods and thus the most directly related period. Yet, our data is imprecise about the exact closing date so we would not be able to distinguish whether in 2008 firms closed before or after the event. Focusing on all displaced workers would increase the treatment group, but estimations may suffer from non-random selection into displacement.

were used to identify causal effects in other contexts such as crime (Britto, Pinotti and Sampaio, 2022), business creation (da Fonseca, 2022), and future earnings losses (Couch and Placzek, 2010). Finally, the focus of (disaster-induced) dismissed workers is interesting from a policy perspective because they are the ones that may truly require emergency and adaptation assistance.

More specifically, we estimate the effect of disaster-induced closures on dismissed workers using the following difference-in-differences specification:

$$Y_{jt} = \sum_{\pi=1}^{T} \omega_\pi \times \mathbf{1}[t = \pi] \times Dismissed_j^D + \gamma_j + \delta_t + \epsilon_{jt} \tag{3}$$

where Y_{jt} is the outcome variable (employment indicator, log wage or migration indicator) for worker j in year t, the indicator $\mathbf{1}[t = \pi]$ is equal to one if the observation falls in year π after the establishment closure ($\pi = 2009, 2010, 2011, 2012$), and $Dismissed_j^D$ is the treatment variable that assumes one for a worker j who was laid off by an establishment that closed in 2009 and was located in the treatment area (based on the criteria described in subsection 4.2). Lastly, γ_j is the worker fixed effect, δ_t is the year fixed effect, and ϵ_{jt} is the error term. The parameters ω_π of equation (3) measure the time-varying effects of the disaster-induced closures on dismissed workers and are our coefficients of interest.

Based on this definition of treated units, we obtain a total sample of 5,598 dismissed workers who were in the area affected by the flash floods. If we define the control group as the entire set of workers who were not dismissed and were in the outer control ring (30-50 km from the flood spots) as we did in the analysis at the establishment level, we would have a disproportionally large control group. Moreover, comparing the observed characteristics of this potential control group to the treated group (columns (1) and (2) of Table B.1 in the appendix), we noticed that there is a strong heterogeneity between them, which may violate the validity of the parallel trends assumption. To minimize the imbalance between the treatment and the control group, we applied a propensity score matching using the nearest neighbor algorithm without replacement (similar to Deryugina, Kawano and Levitt (2018) and Groen, Kutzbach and Polivka (2020)), and we limit the control group to workers who remained employed between 2007 and 2008. To perform the pre-processing sample selection via matching, we utilized the following variables: wage, age, education level categories, weekly working hours, gender, establishment size, and industry sector categories. Columns (4) and (5) of Table B.1 in the Appendix show that the matching procedure leads to a control group with very similar characteristics compared to the treatment group since the difference in the means of both groups for all variables becomes almost zero. We relax these restrictions and use the entire control group as a robustness check.

5.2 Main Results

The baseline results for the employment indicator, log of average wages, and migration indicator are presented in Table 6. In analogy to the establishment level results, regressions in columns (1) to (3) include worker and year-fixed effects, and a linear census tract-specific trend is added in columns (4) to (6). Our preferred estimations are based on the sample of workers where the control group is highly comparable to the treated worker's thanks to balancing the observable variables through propensity score matching. Recall that the number of observations varies across outcome variables because, by data availability and the nature of the variables, wages and employment location (which is used to build the migration indicator) are only observed when an individual has formal employment.

We observe that workers who were dismissed due to a disaster-induced business closure have a significantly lower probability of being formally employed. This probability is as much as 16% lower in 2010 and is still down 10% in the 5^{th} year after the event[12]. Wages of affected workers seem to decrease slightly in the first year but are then about 2-3% percent higher in the following years as compared to workers in the control group. Finally, employees from establishments that were closed in areas hit by the flash floods show no relevant change in migration rates. A significant coefficient of 0.006 is only observed in the second year after the disaster. This 0.6% increase in the probability of migration to another municipality in Brazil is economically irrelevant compared to the magnitude of the disaster.

[Table 6 about here.]

The event study specification in Figure 5 shows parallel trends for the employment and migration indicators. Regarding wages the differences between the treatment and control groups are little, but we observe lower wages with statistical significance in one of the pre-disaster years. The required assumptions for the differences-in-differences model thus seem to hold among the worker sample.

[Figure 5 about here.]

The observations in Table 6 and Figure 5 suggest that workers who lost their job have a hard time getting back into the formal labor market. Apparently, few workers manage to find new employment in a different municipality, in line with the insignificant effect of the disaster on establishment relocation. In other words, the Santa Catarina Flash Floods did not cause massive internal out-migration, either by firms or workers.

[12]Note that the point estimates in 2009 may be biased towards zero because our reference date in the RAIS data is 31. December and for some firms the closing date may exactly be this last day of the year, although operations ceased earlier. Therefore, some workers may still be listed as employees at the end of 2009 despite already being unemployed.

Overall, modest migration flows within Brazil are consistent with high migration frictions (Bernard et al., 2017) and low financial leeway to finance moving costs due to high-interest rates and low savings rates. Only 3 percent of the individuals moved to a different state on aggregate over a five-year period according to the latest Census data from 2010 (Hering and Paillacar, 2016). It thus seems that the dismissed either remain unemployed, settle for an informal job, or become necessity entrepreneurs. The equilibrium wage rate remains relatively unaffected by these transitions. Again, these observations are consistent with the Brazilian labor market being known for its elevated formal labor regulations with lack of enforcement (Almeida and Poole, 2017), employee turnover (Adamczyk, Ehrl and Monasteiro, 2022), transition rates from formal jobs to informality and unemployment (Menezes-Filho and Muendler, 2011), as well as high firm entry and exit rates (Ehrl, 2021).

It is important to recall that due to the focus on dismissed workers, the estimations in Table 6 do not allow us to make much inference about the aggregate labor demand and supply in local labor markets. Yet, a lower employment probability is in line with the frequently observed falling labor after a disaster (Boustan et al., 2020). Regarding migration, previous evidence from disasters such as Hurricane Katrina points to high and permanent responses (Groen, Kutzbach and Polivka, 2020; Boustan et al., 2020). Brazilians did not enjoy a governmental relocation program as in the US, and they may be more credit constraints, which seems key in migration and relocation decisions (Basker and Miranda, 2018). Other studies also indicate that the outside options self-employment, informality, or a living on the cash transfer program *Bolsa Família* may induce dismissed workers to remain in their municipality, even though they do not find formal employment (Zissimopoulos and Karoly, 2010; de Almeida, Ehrl and Moreira, 2021).

5.3 Robustness Checks

Appendix C provides robustness checks regarding the baseline worker-level estimations, in analogy to our establishment analysis in Appendix A. We provide evidence with different control boundaries (Figure C.1), alternative treatment radii (Figure C.2), the unmatched worker sample (Table C.1), and an extension of the post-treatment period (Table C.2). These additional results are much alike the ones in the main text. Only regarding migration, we do observe that results are sensitive to the treatment and control boundaries in the sense that workers very close to the floods (0-2.5km) show positive migration rates.

6 Final Remarks

Natural disasters, including floods, become more and more frequent as Global Warming proceeds. The impacts of these events pose a major challenge for businesses, workers, and policymakers all over the world. This paper contributes to understanding the consequences of flash floods in particular and natural disasters more generally in a developing country.

This paper showed that flash floods cause significant disruptions in the affected areas but the geographic extension of the economic damage is limited to a radius of a few kilometers. We found that the spatial distribution of establishments in affected areas is modified through higher exit rates but not through the relocation of existing establishments. The distribution of workers is relatively stable, too. Disaster-induced dismissed workers do not tend to migrate despite suffering a lower employment probability. Both the effects of the flash floods on workers and businesses are remarkably persistent over time. This research suggests that certain individuals in the regions affected by the historically severe 2008 Santa Catarina Flash Floods are permanently worse-off because they are driven out of the formal labor market. Our observations are consistent with the notion that the spatial distribution of firms and individuals shifts to a new equilibrium leaving failed entrepreneurs and negatively affected workers behind.

The observed pattern of low mobility suggests that disaster-affected workers and businesses are credit constrained. Policymakers may thus consider offering assistance that is tied to relocations. In this way, one would avoid supporting the survival of firms that put their employees and their own operations at greater risk than necessary. In order words, our findings suggest that public policies should facilitate the shift to a more efficient spatial equilibrium without leaving the victims on their own. Further research about the role of emergency assistance and credit supply in migration decisions is required, particularly from developing countries where individuals are more credit constrained than elsewhere.

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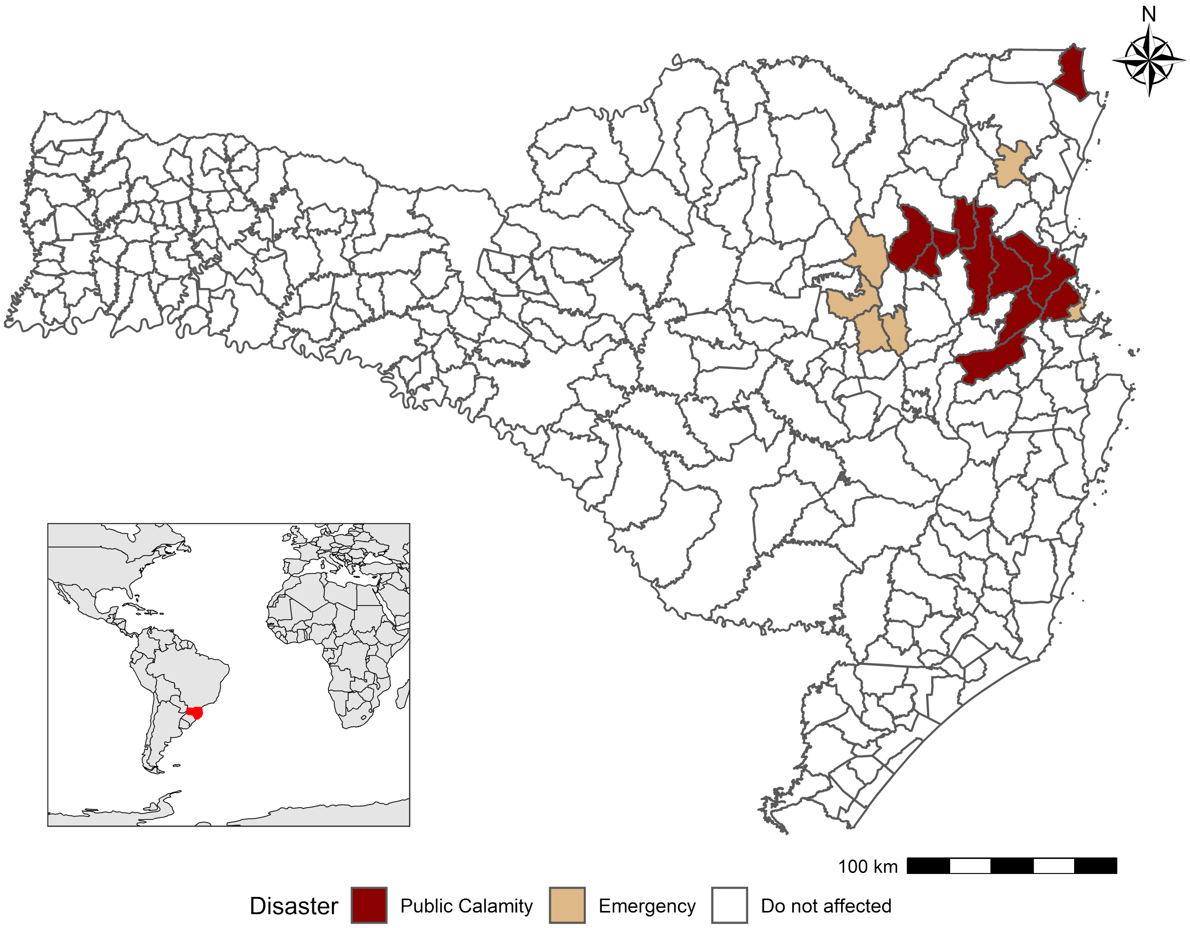
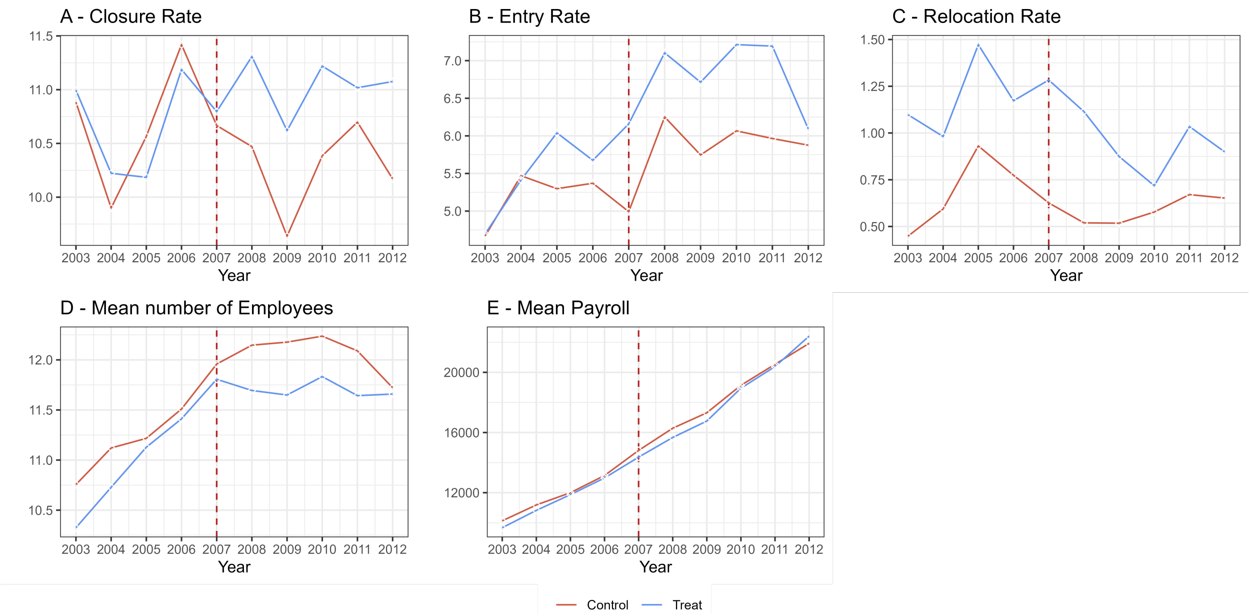
Figure 1: Geographical Distribution of Affected Municipalities



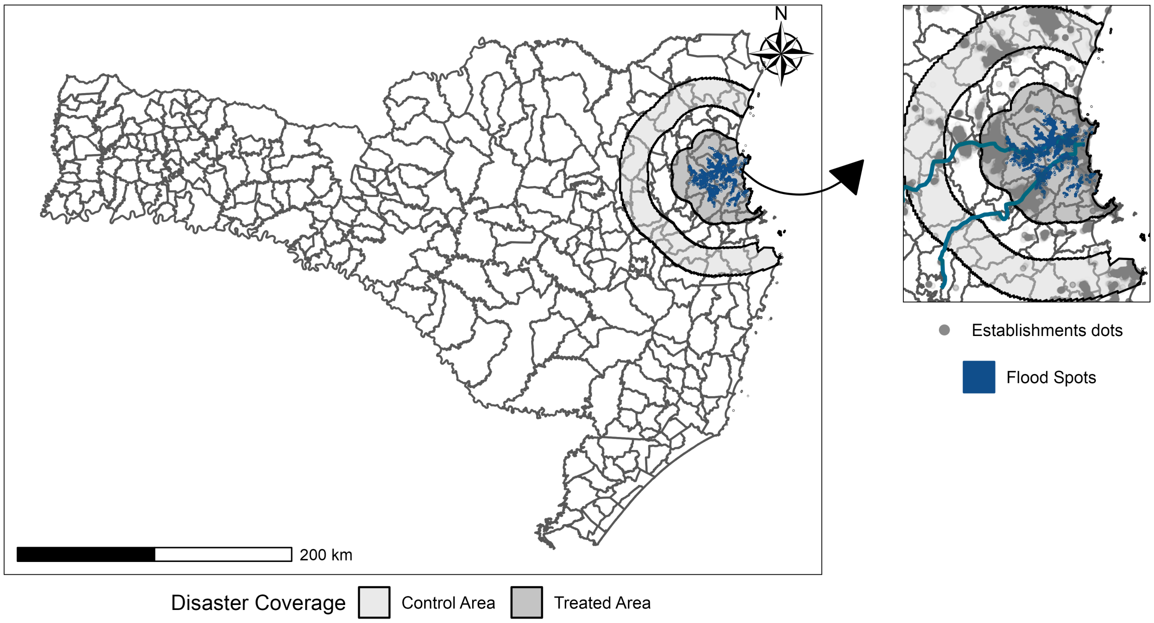
Note: This figure shows the spatial distribution of municipalities that declared a state of emergency or public calamity due to the 2008 Santa Catarina flash floods.

Figure 2: Evolution of Aggregate Outcomes (2003-2012)



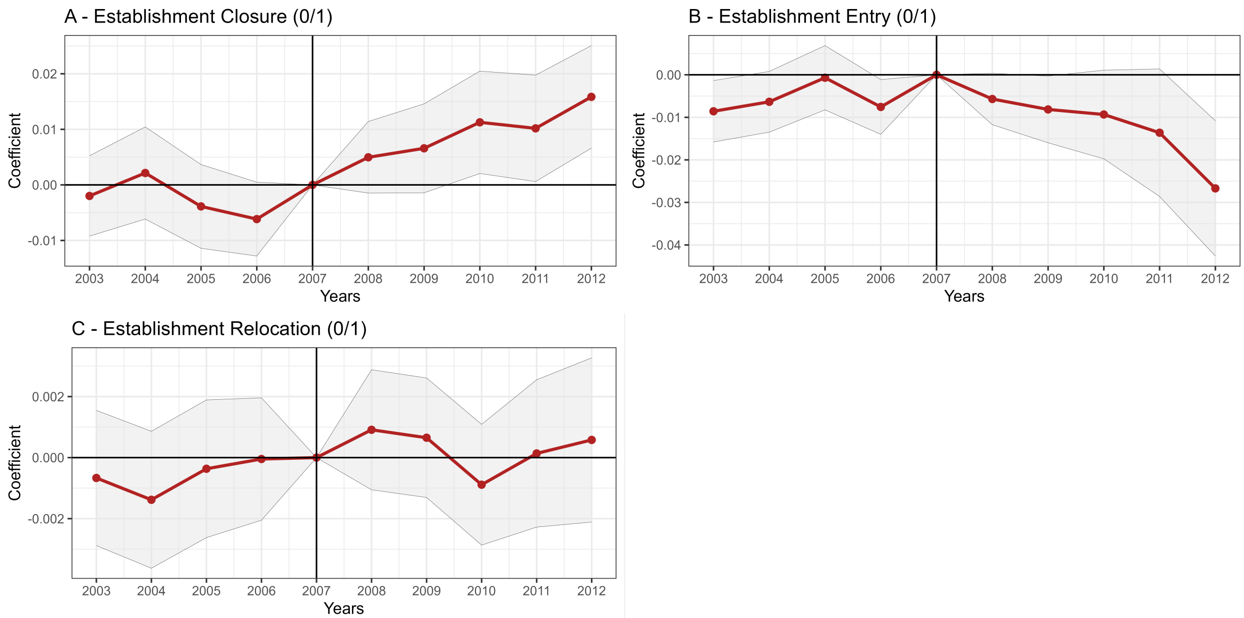
Note: This figure shows the evolution of the closing rate, entry rate, relocation rate, log of average employment, and aggregated payrolls between 2003 and 2012 in our study area, separated into the group of treated (blue line) and control establishments (red line).

Figure 3: The Disaster Coverage Area of the 2008 Santa Catarina Flash Floods.



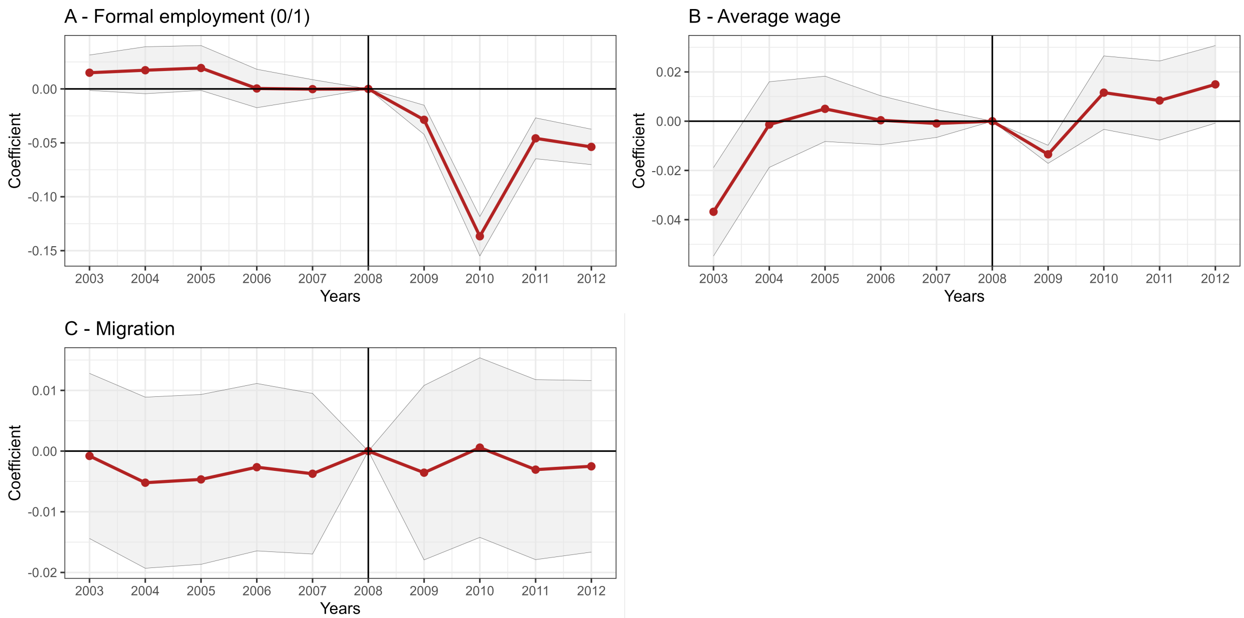
Note: This figure shows the treated and control area in our baseline specification according to the results from table 2. Each establishment is represented by a gray point, and the flood spots are defined by the dark blue areas being close to the main rivers. The figure also shows the inner radius (area within 12.5 km of the flood points) in dark gray color and the outer ring (between 30 km and 50 km from the flood points) marked in light gray color.

Figure 4: Event Study: Effect of the Flash Floods on the Spatial Distribution of Establishments



Notes: This figure plots the lead and lag estimates from the event-study difference-in-differences equation (2) with a 95% confidence interval for the three establishment-level outcome variables, as indicated in the graph title. The treatment radius ranges from up to 12.5km to flood spots. The control ring is between 30-50 km from the flood spots. The standard errors are clustered at the establishment and year level. All estimations include the establishment and time-fixed effects and a specific census-tract trend.

Figure 5: Event Study: Effect of Disaster-induced Closures on Dismissed Workers



Notes: This figure plots estimates from the event-study difference-in-differences with a 95% confidence interval for the three worker-level outcome variables. The sample is composed of workers that were dismissed by an establishment closed in 2009 and located within the treatment radius of up to 12.5km from the flood spots. Workers in the control group are selected from establishments within the control ring is between 30-50 km from the flood spots. Then the sample is balanced using propensity score matching on worker characteristics. The standard errors are clustered at the establishment and year level. All estimations include the workers and time fixed effects and a specific census-tract trend.

Table 1: Summary Statistics

	Pre-Disaster (2007)				Post-Disaster (2008)			
	Treated Units		Control Units		Treated Units		Control Units	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Outcome Variables - Establishments								
Establishment Closure	0.108	0.310	0.107	0.309	0.113	0.316	0.104	0.306
Establishment Relocation	0.006	0.080	0.004	0.061	0.006	0.080	0.004	0.059
Establishment Entry	0.062	0.241	0.050	0.218	0.071	0.257	0.062	0.242
Labor Market								
Number of Employees	11.803	55.042	11.981	57.962	11.690	52.446	12.171	59.430
Payroll Value (thousand, in R$)	14.353	109.205	14.846	95.204	15.658	109.465	16.327	100.781
Industry Sector								
Agriculture	0.003	0.053	0.002	0.049	0.002	0.048	0.002	0.045
Retail and Wholesale	0.399	0.490	0.389	0.488	0.394	0.489	0.384	0.486
Construction	0.025	0.157	0.026	0.159	0.030	0.171	0.030	0.172
Manufacturing	0.226	0.419	0.197	0.398	0.226	0.418	0.195	0.396
Observations	75,823		49,725		96,144		60,877	

Note: The table displays the mean and standard deviation (S.D.) in the pre-disaster and post-disaster years for establishments separated by treated and control assignment.

Table 2: Definition of Treatment Radius: Effects of Flooding using Different Treatment Bands

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment group	0-2.5 km	2.5-5 km	5-7.5 km	7.5-10 km	10-12.5 km	12.5-15 km	15-17.5 km
Control group	30-50 km	30-50 km	30-50 km km	30-50 km	30-50 km	30-50 km	30-50 km
Flash Flood 2008	0.010**	0.008**	-0.003	0.024***	-0.024***	-0.009	0.005
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.011)	(0.008)
Flash Flood 2009	0.014**	0.012**	-0.003	0.009	0.010	-0.021	0.001
	(0.005)	(0.005)	(0.004)	(0.006)	(0.009)	(0.012)	(0.007)
Flash Flood 2010	0.019**	0.009*	0.008**	0.022**	0.035**	-0.015	-0.003
	(0.006)	(0.005)	(0.004)	(0.007)	(0.011)	(0.010)	(0.006)
Flash Flood 2011	0.015**	0.013**	0.013**	0.011	0.026*	-0.025**	-0.008
	(0.007)	(0.005)	(0.004)	(0.008)	(0.014)	(0.011)	(0.007)
Flash Flood 2012	0.028***	0.024***	0.002	0.015	0.019	-0.025**	-0.002
	(0.006)	(0.004)	(0.005)	(0.008)	(0.012)	(0.010)	(0.007)
Observations	173,093	172,244	140,230	122,375	117,035	113,564	117,631
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the estimation of equation (1) using business closure as the outcome variable. In column 1, the treatment area is defined as the radius between 0 to 2.5km to the flood spots. In column 2, the treatment area is defined as the ring between 2.5 km and 5 km from the flood spots. Columns 3, 4, 5, 6, and 7 use different treatment group definitions as indicated in the second row. The control ring is fixed and defined as the area located between 30 km to 50 km from the disaster points. Robust standard errors clustered at the establishment and year level are shown in parentheses. *** represents $p < 0.01$,** represents $p < 0.05$,* represents $p < 0.1$.

Table 3: The Effect of the Flash Floods on the Spatial Distribution of Establishments

	(1)	(2)	(3)	(4)	(5)	(6)
	Closure	Closure	Relocation	Relocation	Entry	Entry
Flash Flood 2008	0.007**	0.007**	0.001*	0.001	-0.002	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)
Flash Flood 2009	0.009**	0.008**	0.001	0.000	-0.004	-0.005
	(0.003)	(0.003)	(0.001)	(0.001)	(0.004)	(0.004)
Flash Flood 2010	0.013***	0.013***	-0.000	-0.001*	-0.005	-0.006
	(0.004)	(0.004)	(0.001)	(0.001)	(0.005)	(0.005)
Flash Flood 2011	0.012**	0.012**	0.001	-0.001*	-0.009	-0.011
	(0.004)	(0.004)	(0.001)	(0.001)	(0.007)	(0.007)
Flash Flood 2012	0.018***	0.018***	0.001	-0.001	-0.023**	-0.025**
	(0.004)	(0.004)	(0.001)	(0.001)	(0.007)	(0.008)
Observations	282,569	282,569	282,569	282,569	282,569	282,569
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Census trend	No	Yes	No	Yes	No	Yes

Notes: This table shows estimates from the differences-in-differences (equation (1)) for the following outcomes: an indicator for business closure, relocation, and entry, as indicated in the second row. The treatment radius ranges from up to 12.5km to flood spots. The control ring is between 30-50 km from the flood spots. The two-way clustered-robust standard errors at the establishment and year level are in parenthesis. *** represents $p < 0.01$, ** represents $p < 0.05$, * represents $p < 0.1$.

Table 4: The Effect of the Flash Floods on Establishments by Industry Sector

	(1)	(2)	(3)	(4)	(5)
	Construction	Transportation	Manufacturing	Retail and Wholesale	Services
Panel A. Establishment Closure					
Flash Flood 2008	-0.021	0.009	0.005	0.011**	0.011*
	(0.013)	(0.012)	(0.005)	(0.005)	(0.005)
Flash Flood 2009	-0.034**	0.019	0.019***	0.014*	0.004
	(0.014)	(0.016)	(0.005)	(0.007)	(0.006)
Flash Flood 2010	0.006	-0.022	0.021**	0.016**	0.001
	(0.016)	(0.018)	(0.007)	(0.007)	(0.005)
Flash Flood 2011	-0.010	-0.017	0.015	0.029***	-0.007
	(0.016)	(0.019)	(0.008)	(0.007)	(0.005)
Flash Flood 2012	-0.002	0.023	0.020**	0.024***	0.017**
	(0.018)	(0.019)	(0.008)	(0.006)	(0.005)
Panel B. Establishment Relocation					
Flash Flood 2008	0.018**	-0.001	0.003	-0.000	0.003
	(0.008)	(0.005)	(0.002)	(0.001)	(0.002)
Flash Flood 2009	0.003	-0.001	0.000	0.003**	-0.001
	(0.009)	(0.005)	(0.002)	(0.001)	(0.002)
Flash Flood 2010	0.006	0.005	-0.002	-0.000	0.001
	(0.008)	(0.005)	(0.002)	(0.001)	(0.002)
Flash Flood 2011	0.007	0.011*	-0.004*	0.001	0.003
	(0.008)	(0.005)	(0.002)	(0.001)	(0.002)
Flash Flood 2012	0.007	-0.010	-0.001	0.003*	-0.002
	(0.008)	(0.006)	(0.002)	(0.001)	(0.002)
Panel C. Establishment Entry					
Flash Flood 2008	0.041*	0.017	-0.008	0.003	-0.001
	(0.018)	(0.011)	(0.006)	(0.007)	(0.005)
Flash Flood 2009	0.003	0.012	-0.003	-0.009	0.003
	(0.019)	(0.012)	(0.006)	(0.007)	(0.006)
Flash Flood 2010	0.062***	-0.014	-0.016**	-0.004	-0.005
	(0.018)	(0.012)	(0.006)	(0.007)	(0.008)
Flash Flood 2011	0.023	0.001	-0.009	-0.010	-0.012
	(0.020)	(0.013)	(0.007)	(0.011)	(0.009)
Flash Flood 2012	0.032	-0.010	-0.015*	-0.032**	-0.025**
	(0.023)	(0.014)	(0.007)	(0.012)	(0.009)
Observations	9,266	9,697	55,075	109,165	56,923
Establishment FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents estimates obtained through the differences-in-differences equation (1) for different sub-samples categorized by industry sector. The two-way clustered-robust standard errors at the establishment and year level are in parenthesis. *** represents $p < 0.01$, ** represents $p < 0.05$, * represents $p < 0.1$.

Table 5: The Effect of the Flash Floods on Establishments by Business Size

	(1)	(2)	(3)
	Micro Business	Small Business	Medium Business
Panel A. Establishment Closure			
Flash Flood 2008	0.010**	0.004	-0.013
	(0.003)	(0.003)	(0.008)
Flash Flood 2009	0.011**	0.004	0.003
	(0.004)	(0.003)	(0.006)
Flash Flood 2010	0.015**	0.012***	0.001
	(0.005)	(0.004)	(0.009)
Flash Flood 2011	0.013**	0.014***	0.009
	(0.005)	(0.004)	(0.010)
Flash Flood 2012	0.025***	0.005	-0.003
	(0.005)	(0.004)	(0.011)
Panel B. Establishment Relocation			
Flash Flood 2008	0.001	0.001	-0.004
	(0.001)	(0.002)	(0.006)
Flash Flood 2009	0.001	-0.001	0.001
	(0.001)	(0.002)	(0.006)
Flash Flood 2010	-0.001	-0.001	-0.002
	(0.001)	(0.002)	(0.005)
Flash Flood 2011	0.001	-0.002	0.003
	(0.001)	(0.001)	(0.006)
Flash Flood 2012	0.001	-0.000	0.002
	(0.001)	(0.002)	(0.006)
Panel C. Establishment Entry			
Flash Flood 2008	-0.001	-0.003	0.002
	(0.005)	(0.004)	(0.008)
Flash Flood 2009	-0.006	0.003	0.008
	(0.005)	(0.005)	(0.007)
Flash Flood 2010	-0.008	0.002	0.004
	(0.006)	(0.005)	(0.007)
Flash Flood 2011	-0.014	0.000	0.005
	(0.008)	(0.005)	(0.010)
Flash Flood 2012	-0.029***	-0.002	-0.011
	(0.009)	(0.005)	(0.010)
Observations	220,625	53,072	8,872
Establishment FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table presents estimates obtained through the differences-in-differences equation (1) for different sub-samples categorized by business size. The two-way clustered-robust standard errors at the establishment and year level are in parenthesis. *** represents $p < 0.01$, ** represents $p < 0.05$, * represents $p < 0.1$.

Table 6: The Effect of Disaster-induced Closures on the Dismissed Workers.

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment	Employment	log Wage	log Wage	Migration	Migration
Flash Flood 2009 x Closure	-0.045***	-0.032***	-0.010**	-0.009**	0.002	0.001
	(0.007)	(0.006)	(0.003)	(0.004)	(0.002)	(0.001)
Flash Flood 2010 x Closure	-0.153***	-0.161***	0.015*	0.021**	0.006**	0.006**
	(0.009)	(0.012)	(0.008)	(0.008)	(0.002)	(0.002)
Flash Flood 2011 x Closure	-0.062***	-0.086***	0.012	0.020*	0.003	0.003
	(0.010)	(0.013)	(0.009)	(0.009)	(0.003)	(0.003)
Flash Flood 2012 x Closure	-0.070***	-0.097***	0.018**	0.030***	0.003	0.002
	(0.008)	(0.010)	(0.008)	(0.008)	(0.002)	(0.002)
Observations	107,290	107,090	76,261	76,127	72,579	72,445
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Census trend	No	Yes	No	Yes	No	Yes

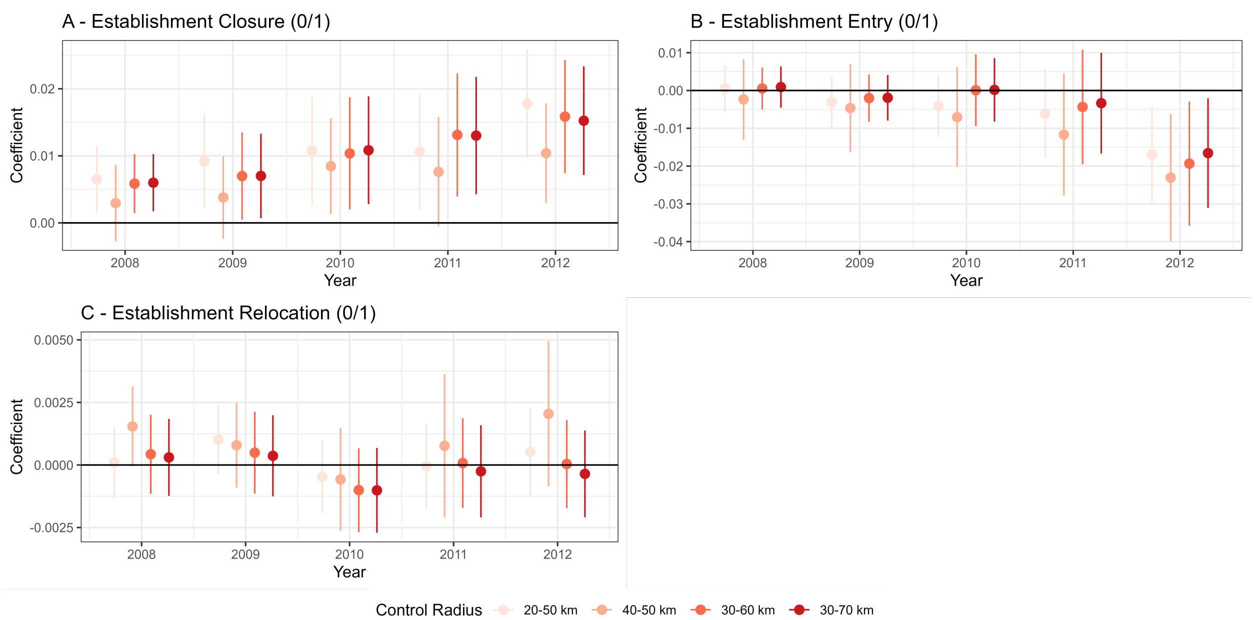
Notes: This table shows estimates from the differences-in-differences equation (3) for the outcomes: employment, log average wage and migration, as indicated in the second row. The sample is composed of workers that were dismissed by an establishment closed in 2009 and located within the treatment radius of up to 12.5km from the flood spots. Workers in the control group are selected from establishments within the control ring is between 30-50 km from the flood spots. Then the sample is balanced using propensity score matching on worker characteristics. The two-way clustered-robust standard errors at the establishment and year level are in parenthesis. *** represents p < 0.01, ** represents p < 0.05, * represents p < 0.1.

Online Appendix

A Robustness Checks for the Establishment-level Analysis

Alternative Control Rings. In our main specifications, we adopt an "inner and out ring" approach and assign the establishments in the ring as control units located at a distance of 30 to 50 km from the flood spots. To evaluate whether our results are robust to this specific control ring, we also estimate alternative specifications for equation (1) using the following alternative control rings: 20-50km, 40-50km, 30-60km, and 30-70km. Figure A.1 reports the results.

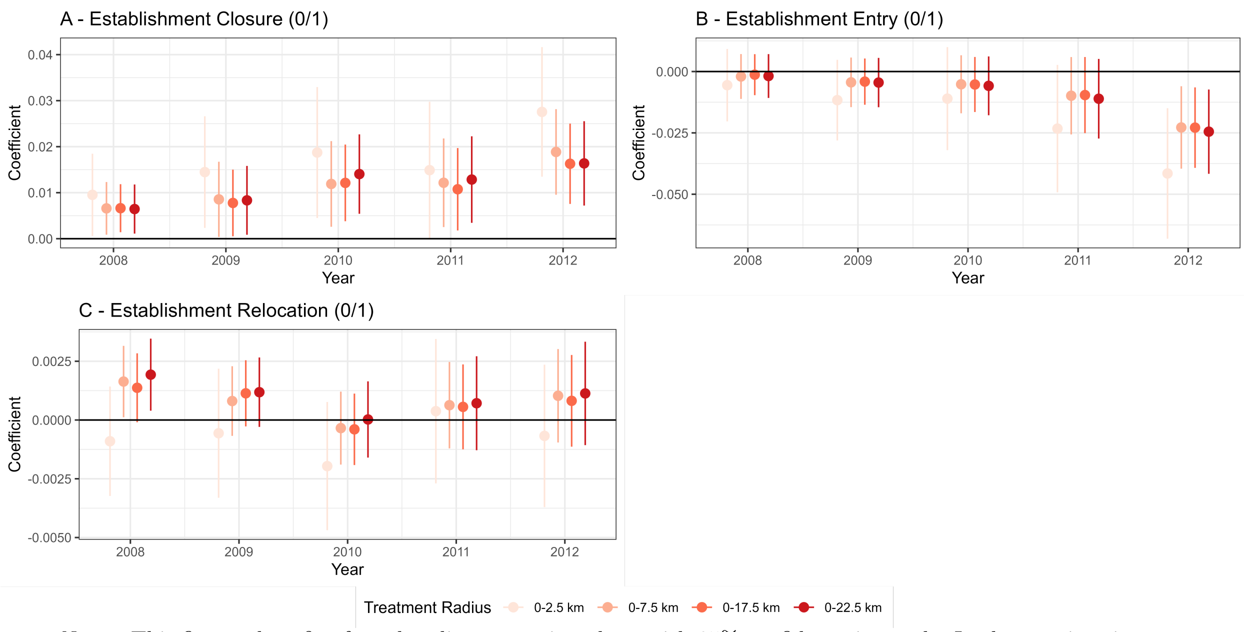
Figure A.1: Alternative Control Rings in Establishment Level Estimates.



Notes. This figure plots β_τ of our baseline regression along with 95% confidence intervals. In these estimations, we change the control ring size to 20-50 km, 40-50 km, 30-60 km, and 30-70km. The standard errors are clustered at the establishment year level. All estimates include the establishment and year-fixed effects.

Alternative Treatment Radius. To define the treated establishments, we search for the effects of the 2008 Santa Catarina Flash Floods using the approach of Zhu et al. (2016), which considers different treatment bands. In this way, we obtain the cut-off of 12.5 km as the distance from the flood spots where the establishments still experience the economic consequences of the disaster concerning the probability of closure. Therefore, we define this distance as the limit of the treatment radius. To check whether this specific radius drives our results, we also estimate alternative specifications for equation (1) using the following maximum distances from the flood spots to define the treated establishments: 2.5 km, 7.5 km, 17.5 km, and 22.5 km. Figure A.2 shows the results.

Figure A.2: Alternative Treatment Radius in Establishment Level Estimates.



Notes. This figure plots β_τ of our baseline regression along with 95% confidence intervals. In these estimations, we change the treatment radius extension to 2.5 km, 7.5 km, 17.5 km, and 22.5 km from the flood spots. The standard errors are clustered at the establishment and year level. All estimates include the establishment and year fixed effects.

Variable of Interest Based on the Distance to Flood Spots. In our main specification, we adopt a treatment indicator that separates the establishments close (treatment group) and distant (control group) from the flood spots through the "inner and out ring" approach. We also evaluated whether our main results are robust when considering the minimum distance (in kilometers) from the establishment to each specific flood spot as a variable of interest. Table A.1 presents the results of this robustness exercise. The treatment variable is the log of the distance from the flooded areas. It is possible to notice that, qualitatively, the pattern of the results is like those presented in Table 3: the smaller the business distance to the flooded area, the greater probability of closing/relocation and the lower likelihood of entry.

Table A.1: Establishment Estimates Using the Distance to Flood Spot as a Variable of Interest.

	(1)	(2)	(3)
	Closure	Relocation	Entry
Log Distance Flood 2008	-0.00205***	-0.00031*	0.00132*
	(0.00057)	(0.00015)	(0.00065)
Log Distance Flood 2009	-0.00135	-0.00022	0.00167*
	(0.00077)	(0.00015)	(0.00075)
Log Distance Flood 2010	-0.00315***	-0.00004	0.00170*
	(0.00083)	(0.00015)	(0.00085)
Log Distance Flood 2011	-0.00546***	-0.00030*	0.00221*
	(0.00085)	(0.00016)	(0.00113)
Log Distance Flood 2012	-0.00468***	-0.00038*	0.00451***
	(0.00082)	(0.00017)	(0.00124)
Observations	853,809	853,809	853,809
Establishment FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table shows estimates of equation (1) using the following outcomes: an indicator for business closure, relocation, and entry. The variable of interest is the log of the distance between the flooded spots and each individual establishment. We report the two-way clustered-robust standard errors at the establishment and year level at parenthesis. *** represents $p < 0.01$,** represents $p < 0.05$,* represents $p < 0.1$.

Including Establishment Level Controls. In Table A.2, we present the results of alternative specifications considering the inclusion of the following control variables measured at the establishment level: number of employees, number of firm branches, time of opening the business, international trade indicator, and the average level of education of the workforce. To avoid a bad control issue, this set of control variables is measured in the year before the disaster (2007) and interacted with a linear time trend.

Table A.2: Establishment Level Estimates Including Control Variables.

	(1)	(2)	(3)
	Closure	Relocation	Entry
Flash Flood 2008	0.007**	0.001*	-0.002
	(0.002)	(0.001)	(0.004)
Flash Flood 2009	0.008**	0.001	-0.004
	(0.003)	(0.001)	(0.004)
Flash Flood 2010	0.012**	-0.000	-0.004
	(0.004)	(0.001)	(0.005)
Flash Flood 2011	0.010**	0.001	-0.008
	(0.004)	(0.001)	(0.007)
Flash Flood 2012	0.017***	0.001	-0.021**
	(0.004)	(0.001)	(0.007)
Observations	282,569	282,569	282,569
Establishment FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: This table shows estimates of equation (1) using the following outcomes: an indicator for business closure, relocation, and entry. The treatment radius ranges from up to 12.5km to flood spots. The control ring is between 30-50 km from the flood spots. We report the two-way clustered-robust standard errors at establishment and year level at parenthesis. *** represents $p < 0.01$,** represents $p < 0.05$,* represents $p < 0.1$.

Extending the Post-Treatment Period. In Table A.3, we present the results of our main specification expanding the number of post-treatment periods until 2016 to check whether the effects of the disaster are temporary or lasting. We stopped at 2016 because it is the last year with available geolocated establishment data. The results in Table A.3 need to be evaluated carefully because the credibility of our identification assumption is lower with a longer time frame since there is more possibility of other economic shocks affecting the treatment or control area.

Table A.3: Establishment Level Estimates Increasing the Post-Treatment Period.

	(1)	(2)	(3)
	Closure	Relocation	Entry
Flash Flood 2008	0.007***	0.002***	-0.001
	(0.002)	(0.001)	(0.003)
Flash Flood 2009	0.008**	0.001**	-0.002
	(0.003)	(0.001)	(0.004)
Flash Flood 2010	0.012***	-0.000	-0.002
	(0.004)	(0.001)	(0.004)
Flash Flood 2011	0.011**	0.000	-0.002
	(0.004)	(0.001)	(0.004)
Flash Flood 2012	0.018***	0.000	-0.014***
	(0.005)	(0.001)	(0.005)
Flash Flood 2013	0.011**	0.001	-0.011**
	(0.004)	(0.001)	(0.005)
Flash Flood 2014	0.011**	0.001	-0.015***
	(0.004)	(0.001)	(0.004)
Flash Flood 2015	0.015***	0.001	-0.015***
	(0.004)	(0.001)	(0.004)
Flash Flood 2016	0.014***	0.004***	-0.017***
	(0.004)	(0.001)	(0.004)
Observations	427,041	427,041	427,041
Establishment FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table shows estimates of equation (1) using the following outcomes: an indicator for business closure, relocation, and entry. The treatment radius ranges from up to 12.5km to flood spots. The control ring is between 30-50 km from the flood spots. We report the two-way clustered-robust standard errors at establishment and year level at parenthesis. *** represents $p < 0.01$,** represents $p < 0.05$,* represents $p < 0.1$.

Alternative Definition of Relocation. In our main estimates, we considered the municipality's territory as the spatial unit of reference to investigate the effects of the 2008 Santa Catarina Flash Flood on the relocation behavior of affected establishments. Table A.4 shows estimates with alternative definitions of the geographical scope of relocation: the ZIP code (column (1)) and the census tract (column (2)).

Table A.4: Establishment Level Estimates Using Alternative Definitions of Relocation.

	(1)	(2)
	Relocation based on ZIP code	Relocation based on Census Tract
Flash Flood 2008	-0.000	0.007*
	(0.009)	(0.002)
Flash Flood 2009	-0.001	0.004
	(0.009)	(0.003)
Flash Flood 2010	0.001	0.005
	(0.009)	(0.003)
Flash Flood 2011	-0.000	0.006
	(0.009)	(0.003)
Flash Flood 2012	0.016	0.012***
	(0.009)	(0.003)
Observations	282,569	282,569
Establishment FE	Yes	Yes
Year FE	Yes	Yes

Notes: This table shows estimates of equation (1) using alternative definitions of relocation. The treatment radius ranges from up to 12.5km to flood spots. The control ring is between 30-50 km from the flood spots. We report the two-way clustered-robust standard errors at establishment and year level at parenthesis. *** represents $p < 0.01$,** represents $p < 0.05$,* represents $p < 0.1$.

B Comparison Between the Group of Treated and Control Workers Before and After Matching.

Table B.1: Comparison of Variables Before and After Data Balancing.

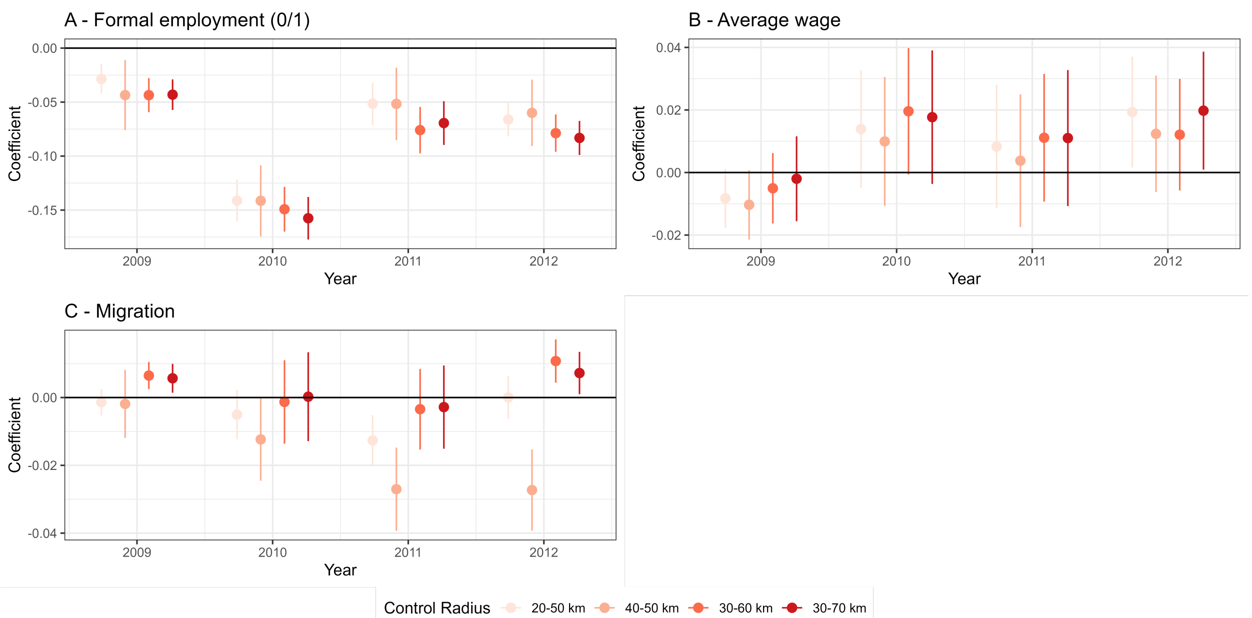
	Unmatched data			Matched data		
	(1)	(2)	(3)	(4)	(5)	(6)
	Treated	Control	ATT	Treated	Control	ATT
General Characteristics						
Establishment Size	3.42	4.97	-1.55***	3.42	3.43	-0.01
Average Working Hours	31.03	46.13	-15.1***	30.48	31.03	-0.55
Average Wage	1034	1291	-257***	1034	1046	-12
Age	33.95	32.68	-0.73***	33.95	32.06	-0.11
Gender Dummy (Male)	0.55	0.56	-0.01	0.55	0.55	0.00
Worker's Education						
Incomplete Primary Education	0.06	0.06	0.00	0.06	0.06	0.00
Complete Primary Education	0.29	0.28	0.01*	0.29	0.29	0.00
Complete high school	0.49	0.49	0.00	0.49	0.49	0.00
Higher education	0.16	0.17	-0.01**	0.16	0.16	0.00
Employment Sector						
Agriculture	0.00	0.00	0.00	0.00	0.00	0.00
Construction	0.03	0.03	0.00	0.03	0.03	0.00
Manufacturing	0.36	0.39	-0.03***	0.36	0.36	0.00
Retail and Wholesale	0.29	0.21	0.08***	0.29	0.29	0.00
Others Sectors	0.32	0.37	-0.05***	0.32	0.32	0.00

Notes: The table displays the mean and standard deviation (S.D.) for individual worker separated by treated and control assignment. Data are for pre-closure years 2009.

C Robustness Checks for the Worker-Level Analysis

Alternative control rings. In our main specifications, we adopt an "inner and out ring" approach and select workers in the control group from establishments located at a distance of 30 to 50 km from the flood spots. To evaluate whether our results are robust to this specific control ring, we also estimate alternative specifications for equation 3 using the following alternative control rings: 20-50km, 40-50km, 30-60km, and 30-70km. Figure C.1 reports the results.

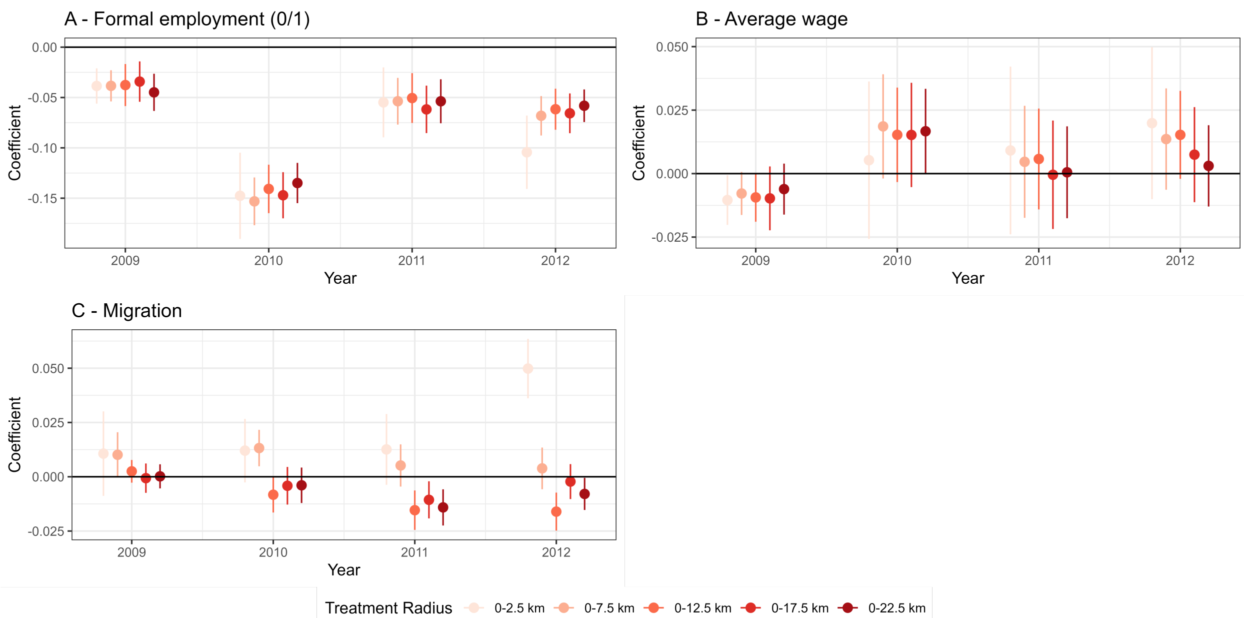
Figure C.1: Alternative Control Rings in Worker Level Estimations.



Notes: This figure plots ω_τ of equation (3) along with 95% confidence intervals. The sample is composed of workers that were dismissed by an establishment closed in 2009 and located within the treatment radius of up to 12.5km from the flood spots. Workers in the control group are selected from establishments within the control ring either set at 20-250 km, 40-50 km, 30-60 km, or 30-70 km from the flood spots. Then the sample is balanced using propensity score matching on worker characteristics. The standard errors are clustered at the establishment and year level. All estimations include worker and time-fixed effects.

Alternative Treatment Radius. To define the treated establishments, we search for the effects of the 2008 Santa Catarina Flash Floods using the approach of Zhu et al. (2016), which considers different treatment bands. In this way, we obtain the cut-off of 12.5 km as the distance from the flood spots where the establishments still experience the economic consequences of the disaster concerning the probability of closure. Therefore, we define this distance as the limit of the treatment radius. To check whether this specific radius drives our results, we also estimate alternative specifications for equation 3 using the following maximum distances from the flood spots to define the treated workers from closed establishments: 2.5 km, 7.5 km, 17.5 km, and 22.5 km. Figure C.2 shows the results.

Figure C.2: Alternative Treatment Radius in Worker Level Estimations



Notes. This figure plots ω_τ of equation (3) along with 95% confidence intervals. The sample is composed of workers that were dismissed by an establishment closed in 2009 and located within the treatment radius of up to 12.5km from the flood spots. Workers in the control group are selected from establishments within the control ring either set at 20-250 km, 40-50 km, 30-60 km, or 30-70 km from the flood spots. Then the sample is balanced using propensity score matching on worker characteristics. The standard errors are clustered at the establishment and year levels. All estimations include worker and time-fixed effects.

Alternative Control Groups in Worker Level Estimates. In our baseline worker-level analysis, we intended to minimize the imbalance between a relatively small treatment group of 5,598 workers and a much larger control group by applying propensity score matching (PSM). Moreover, we limited the control group to workers who remained employed between 2007 and 2008. The estimations in Table C.1 relax both restrictions. Columns (1) to (3) report the results for the three outcome variables as indicated in the third row for a sample of workers where we did not apply the PSM. Columns (1) to (3) report the results for the three outcome variables and apply the PSM but do not condition workers in the control group to be employed in the years 2007 and 2008.

Table C.1: Effect of Closures on Dismissed Workers: Alternative Control Groups

	(1)	(2)	(3)	(4)	(5)	(6)
	Unmatched sample			Matched no restriction sample		
	Employment	log Wage	Migration	Employment	log Wage	Migration
Flash Flood 2009 x Closure	0.007	-0.009**	0.060**	-0.038***	-0.000	0.003
	(0.015)	(0.004)	(0.019)	(0.006)	(0.005)	(0.002)
Flash Flood 2010 x Closure	-0.082***	0.019**	0.111***	-0.125***	0.022**	0.008**
	(0.017)	(0.007)	(0.016)	(0.007)	(0.008)	(0.003)
Flash Flood 2011 x Closure	-0.000	0.026***	0.122***	-0.052***	0.016	0.001
	(0.017)	(0.007)	(0.014)	(0.008)	(0.009)	(0.003)
Flash Flood 2012 x Closure	-0.004	0.034***	0.146***	-0.063***	0.021**	0.003
	(0.016)	(0.007)	(0.012)	(0.006)	(0.008)	(0.003)
Observations	1,032,550	793,790	747,108	153,912	96,953	92,161
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Census trend	No	No	No	No	No	No

Notes: This table shows estimates from the differences-in-differences (equation (3)) for the outcomes: employment, log average wages and migration, as indicated in the second row. The sample is composed of workers that were dismissed by an establishment closed in 2009 and located within the treatment radius of up to 12.5km from the flood spots. Workers in the control group are selected from establishments within the control ring is between 30-50 km from the flood spots. Then the sample is either used unmatched or matched without the restriction on employment in 2007 and 2008 as explained above the table and indicated in the second row. The two-way clustered-robust standard errors at the establishment and year level are in parenthesis. *** represents $p < 0.01$, ** represents $p < 0.05$, * represents $p < 0.1$.

Extending the Post-Treatment Period. In Table C.2, we present the results of our main specification expanding the number of post-treatment periods until 2016 to check whether the effects of the disaster are temporary or lasting. We stopped at 2016 because it is the last year with available geolocated establishment data. The results in Table C.2 need to be evaluated carefully because the credibility of our identification assumption is lower with a longer time frame since there is more possibility of other economic shocks affecting the treatment or control area.

Table C.2: Worker Level Estimates Increasing Post-Treatment Period

	(1)	(2)	(3)
	Employment	log Wage	Migration
Flash Flood 2009 x Closure	-0.043***	-0.012***	0.004
	(0.006)	(0.002)	(0.002)
Flash Flood 2010 x Closure	-0.152***	0.015*	0.006
	(0.009)	(0.008)	(0.006)
Flash Flood 2011 x Closure	-0.061***	0.012	0.009
	(0.009)	(0.009)	(0.006)
Flash Flood 2012 x Closure	-0.069***	0.018*	0.005
	(0.011)	(0.008)	(0.006)
Flash Flood 2013 x Closure	-0.041***	0.029***	0.006
	(0.010)	(0.009)	(0.007)
Flash Flood 2014 x Closure	-0.038***	0.035***	0.003
	(0.009)	(0.009)	(0.007)
Flash Flood 2015 x Closure	-0.024**	0.045***	0.009
	(0.009)	(0.010)	(0.007)
Flash Flood 2016 x Closure	-0.023**	0.053***	0.009
	(0.009)	(0.009)	(0.007)
Observations	148,141	100,196	94,961
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table shows estimates from the differences-in-differences (equation (3)) for the outcomes: employment, log hourly wage and migration, as indicated in the second row. The sample is composed of workers that were dismissed by an establishment closed in 2009 and located within the treatment radius of up to 12.5km from the flood spots. Workers in the control group are selected from establishments within the control ring is between 30-50 km from the flood spots. Then the sample is balanced using propensity score matching on worker characteristics. The two-way clustered-robust standard errors at the establishment and year level are in parenthesis. *** represents $p < 0.01$, ** represents $p < 0.05$, * represents $p < 0.1$.