Natural Disasters and FDI: Evidence from India

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Abstract

This paper examines the effects of natural disasters on foreign direct investment, considering the case of India. I construct a monthly panel dataset for 16 regions within India and analyze the impact of five disasters between October 2005 and December 2019. Using both a fixed effects model and an event study framework, I find significant evidence of decreased investment in affected regions following a disaster. Additionally, I find evidence of increased investment in unaffected regions, indicating that multinational firms shift operations from affected to unaffected areas. The magnitude of the lost FDI in affected regions is larger than the rise in unaffected regions, and while the affected region effects are immediate, there is a 3-4 month lag between the disaster date and firm movement into unaffected regions. Finally, I find evidence that the effects on FDI flow are persistent, even after a region has otherwise recovered, indicating that the "risk factor" of investing in a region increases after a disaster.

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1 Introduction

As climate change alters weather patterns and increases the number and severity of natural disasters, it becomes paramount to identify the economic impacts of such events.[1] While much work has focused on the macroeconomic consequences of natural disasters, less is known about their effects on multinational firm location. Given the role of foreign direct investment in boosting employment, spreading technological innovation, and increasing human capital, shifts in multinational firm location could be a significant channel through which natural disasters impact the economy (Goud, 2011). In developing countries, where natural disasters enact greater damage and FDI represents a larger share of firm investment, the response of multinationals to disasters is of even greater importance (Noy, 2009).

India provides an ideal environment for studying these effects. Over the past 20 years, both FDI and natural disasters have played a central role in the country's development. On the one hand, India has become an increasingly attractive location for multinational firms; its high growth rate, substantial market size, and low wages make it an appealing choice for firms looking to access the Indian market and produce at low cost. At the same time, India has consistently been one of the most disaster-prone countries in the world. According to the World Bank disaster index, India is in the top ten in terms of disaster risk, and a report conducted by the United Nations finds that natural disasters are a significant concern for firms looking to locate in India (World Bank, 2014; Dilley et al., 2005).

The goal of this paper is to connect these two trends, identifying the causal effect of natural disasters on foreign direct investment. Using data from 16 regions within India, I consider the impact of five disasters between 2005 and 2019, employing both a fixed effects model and an event study framework. I make three key contributions. First, I find evidence that FDI falls in affected regions and rises in unaffected regions following a disaster, indicating that multinational firms shift operations away from affected regions and into unaffected regions. These results emphasize the fact that country-level analyses are not sufficient for understanding the full consequences of a natural disaster, given the presence of within-country investment shifts. Additionally, I show that while the fall in FDI in affected regions is immediate, there is a 3-4 month lag between disaster date and firm movement into unaffected regions. Finally, I find evidence that the effects of a disaster on FDI

[1] See (Hallegatte, 2014) and (Coronese et al., 2019) for the impacts of climate change on natural disasters.

flow are persistent, even after a region has otherwise recovered, indicating that firms update their risk assessment of affected regions.

The rest of the paper is organized as follows. Section 2 discusses the literature on the economic impact of natural disasters. Section 3 presents a theoretical framework for the location decisions of multinational firms under conditions of disaster risk. Section 4 discusses the economic and natural disaster data. Section 5 explores the estimation strategy, considering both a fixed-effects model and an event study framework. Section 6 presents the results and section 7 provides discussion. Finally, section 8 considers key limitations of the study and section 9 concludes.

2 Economic Impact of Natural Disasters

There has been significant work on the macroeconomic impact of natural disasters, and the short-run effects are well established. Most papers find a sizeable decrease in GDP, compared to previous trend, for up to five years after a disaster (Raddatz, 2009; Boustan et al., 2017; Benson and Clay, 2003; Noy, 2009). The magnitude of the effect varies, but appears significantly larger in developing countries, where weaker infrastructure and lower spending capacity magnify the post-disaster dip (Noy, 2009). Even within countries, the negative effects of a disaster are not evenly distributed. Poor and rural areas are hit especially hard, and this result is robust across countries (Dube et al., 2018).

The long-run macroeconomic implications of natural disasters are less clear. Skidmore and Toya (2002) find that the number of natural disasters is correlated with higher rates of human capital accumulation, increases in total factor productivity, and economic growth, due to substitution away from physical capital towards human capital in disaster-prone areas. Other papers reach the opposite conclusion, finding negative long-run growth effects (Berlemann and Wenzel, 2015; Rasmussen, 2004; Benson and Clay, 2003). Raddatz (2009), meanwhile, finds no significant long term effect after a 10-year window. In an attempt to synthesize these competing views, Cuaresma et al. (2008) argue that the creative destruction hypothesis may hold for developed countries, which have the resources to invest in new capital, but that developing countries will see a negative impact in the long run.

The channels responsible for these long-term effects remain understudied. Most of the work in this area focuses on the restructuring of supply chains post-disaster and the impact on international trade. There is significant evidence of disruption in global supply chains following a disaster, with falling exports from the affected regions and altered trade patterns between unaffected countries (Park et al., 2013; Lockamy III, 2014; Silva and Cernat, 2012; Gassebner et al., 2010). Other factors, such as migration patterns and exchange rate effects have received some attention as well (Berlemann and Wenzel, 2015; Drabo and Mbaye, 2015; Parker, 2018).

Less work considers the relationship between natural disasters and FDI specifically. Most studies of natural disasters and FDI use country-level data and examine the correlation between the number of natural disasters in a country and its inward FDI, controlling for other factors. Escaleras and Register (2011), for example, using country-level data from 94 countries over a 120-year period, find natural disasters to be negatively and statistically significantly associated with a country's FDI. Similarly, Kukulka (2014), looking specifically at southeast Asia, finds a negative correlation between FDI inflow, as a percent of GDP, and the occurrence of natural disasters. Other papers, such as Anuchitworawong and Thampanishvong (2015) and Wang (2011), look only at one country, comparing pre-shock and post-shock trends in country-wide FDI, and finding negative effects on FDI in the short-run.

While these works take us some of the way in understanding the impact of natural disasters on FDI, they leave significant gaps in our understanding. Most importantly, the majority of this literature depends on using the cross-sectional correlation between number of natural disasters and FDI to identify causality. Due to unmeasured cross-country variation, this specification raises significant concerns of omitted variable bias. To combat this problem, I instead utilize panel data, allowing me to control for time invariant factors at the regional level. Additionally, previous works ignore the effects of a disaster on regional investment shifts; a significant contribution of this paper is then to quantify these regional trends for the first time. Finally, the persistence of disaster shocks on FDI remains understudied. Using monthly data running from 2005-2019, I am able to show evidence of medium-run impacts.

3 Theory of Multinational Firm Location

3.1 Motives for FDI

Under the Dunning and Buckley (1977) "eclectic" framework, there are three main motives for FDI: ownership advantage, internalization, and location. Ownership advantages refer to activities such as cross-border mergers, which are motivated by acquiring intellectual property or other organizational capital. Internalization, meanwhile, refers to bringing parts of the production process in-house, taking advantage of returns to scale. While ownership advantage and internalization do well at explaining why FDI happens at all, they do not provide any systematic predictions about *where* firms will locate, the main consideration when evaluating the effects of natural disasters. For this reason, I focus on location-based motives for FDI.

A common framework for analyzing these location choices is to divide FDI into two categories, vertical and horizontal. Vertical FDI takes place when a multinational fragments the production process internationally, locating each step of production in the region where it can be produced at the lowest cost. Horizontal FDI occurs when a multinational undertakes the same production activities in multiple regions in order to bi-pass trade barriers, such as tariffs and transportation costs, and serve the foreign market. Vertical and horizontal motives then emphasize different factors when choosing between locations; under the vertical motive, considerations like foreign wages, land costs, and home tariffs are important, while under the horizontal motive, factors like foreign market size, foreign GDP, and foreign tariffs are more critical. Empirical studies of FDI determinants emphasize that some combination of vertical and horizontal considerations drives multinational location decisions, particularly in developing countries, and I therefore construct a model of multinational location choice general enough to capture both motives (Patibandla, 2001; Hanson et al., 2005).[2]

3.2 Probability of a Natural Disaster

There is significant evidence that the occurrence of a natural disaster in a certain region is predictive of future disasters in that region (Amei et al., 2012; Dilley et al., 2005). To be clear, this is not to

[2]Vertical motives make less sense in explaining FDI between developed countries, where wage rates and other production costs are similar. Instead, "border jumping" motivations consistent with horizontal FDI and ownership considerations are emphasized, as well as scale concerns such as those discussed in Krugman (1991).

say that there is a causal relationship between past and future disasters; rather, under conditions of imperfect information, a disaster provides useful information about the likelihood of a future event. For this reason, I make the key assumption that firms update their beliefs about the probability of disaster in a region after it has experienced a shock. More formally, if D_t is the event of a natural disaster in period t, I assume that when making location decisions firms take into account the fact that

$$P(D_{t+i}|D_t) > P(D_{t+i}) \text{ for } i = 1, 2, \ldots \tag{1}$$

Evidence from industry supports this assumption. In particular, the behavior of reinsurance companies shines a light on the impact of disasters on corporate risk calculations. Dahlen and Peter (2012) and Thorne (1984), for example, find significance increases in reinsurance rates for regions which have experienced a natural disaster. Although the risk calculations of other firms are less transparent, it is reasonable that they would similarly update their forecasts. In the model presented below, this relationship between past and future disasters is the key mechanism through which the occurrence of a natural disaster influences changes in multinational location decisions. Importantly, this logic does not hold for "cyclical" disasters, such as floods that happen every wet season. The natural disasters considered in this paper, however, do not fit this pattern (discussed further in section 4.2).

3.3 Model

3.3.1 Environment

I construct a simple model of multinational location choice in which a multinational chooses between three regions to locate production. The multinational can produce domestically, where it earns certain profit, or locate in one of two foreign regions, where it incurs risk of a natural disaster. Critically, the probability of a natural disaster can differ between the foreign regions, and in the event of a disaster in the production region, the firm makes zero profits. I define the operating profits for each region as follows:

Domestic Production:

$$\Pi_d = P * Q - c_d * Q \tag{2}$$

Foreign Production Region 1:

$$E(\Pi_1) = (1 - r_1)(P * Q - c_1 * Q - t * Q) \tag{3}$$

Foreign Production Region 2:

$$E(\Pi_2) = (1 - r_2)(P * Q - c_2 * Q - t * Q) \tag{4}$$

where c_i is the marginal cost in region i, t is the per-unit trade cost (identical across foreign regions), and $r_i \in [0, 1]$ is the probability of a natural disaster in region i.[3] Assuming inverse linear demand of the form $Q = a - P$, the maximum profits for each region can be written as a function of marginal costs, trade costs, disaster risk, and the demand shifter a:

Domestic Production:

$$\Pi_d^{max} = \frac{1}{4}(a - c_d)^2 \tag{5}$$

Foreign Production Region 1:

$$E(\Pi_1)^{max} = (1 - r_1)\left(\frac{1}{4}(a - c_1 - t)^2\right) \tag{6}$$

Foreign Production Region 2:

$$E(\Pi_2)^{max} = (1 - r_2)\left(\frac{1}{4}(a - c_2 - t)^2\right) \tag{7}$$

3.3.2 Natural Disaster Shock

Equations (5)-(7) can be represented graphically by plotting expected profit against the probability of a disaster, where movements along the curves represent changes in risk and shifts indicate changes in c, t, or a. In the analysis that follows, I assume that production costs are cheapest in foreign region 1 and most expensive in the home market. Additionally, I assume that $r_1 = r_2$ and that foreign region 1 is initially the profit maximizing location.

I then introduce a disaster shock in foreign region 1, shown in Figure 1. Following section 3.2,

[3] Because the regions considered in this paper are all in India, I assume transportation costs and tariff rates are the same across regions.

I make the critical assumption that the shock increases the future disaster risk in foreign region 1, leading to $r_1' > r_1$ and a fall in the expected profits associated with region 1 (in Figure 1, this is represented by a movement from point A to point B). Given that the disaster risk in foreign region 2 is not altered by the shock in foreign region 1, foreign region 2 becomes relatively less risky. Because point C has a higher expected profit than point B in, the profit maximizing region shifts from foreign region 1 to foreign region 2 following the disaster, and overall expected profits fall.

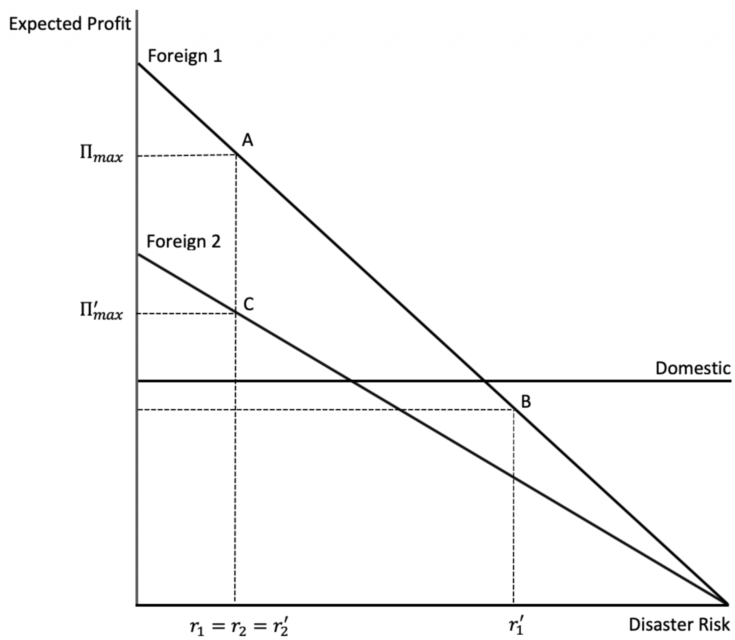

Figure 1: Disaster shock which shifts production from foreign region 1 to foreign region 2

Figure 1 shows only one possible outcome of a disaster shock in the initially profit maximizing region; the shock could induce a shift to domestic production, as well as lead to no change in the profit maximizing location. These cases are considered in Appendix B.

4 Data

4.1 Economic Data

To study the effects of the five disasters, I construct a monthly panel for 16 Indian regions running between October 2005 and December 2019. These regions are based on the Reserve Bank of India's regional branches, which collect monthly FDI inflow statistics for their respective districts. The states included in each region are shown in Table 3 and a map showing the distribution of investment across Indian regions is shown in Figure 6. These numbers only reflect equity capital inflows and therefore do not include reinvested earnings or inter-company debt transactions. I combine these data with controls for regional domestic product and population. The domestic product statistics come from India's Central Statistical Organisation and the population data are projections from the 2001 and 2011 Indian censuses.[4] A summary of these data by region are provided in Table 4.

Due to the right-skewed distribution of the foreign direct investment data, I include the inverse hyperbolic sine of FDI as well as absolute FDI monthly inflow in my regressions.[5] While this transformation is able to partially normalize the distribution, there is still a peak at zero for the inverse hyperbolic sine distribution, given the presence of many observations with no investment inflow. The absolute and transformed distributions are shown in Figure 2 and Figure 3.

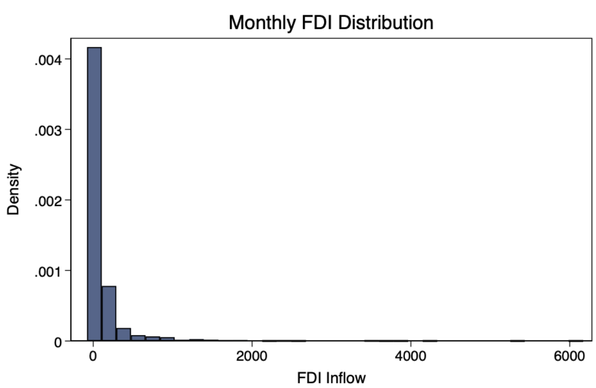

Figure 2: Absolute FDI distribution

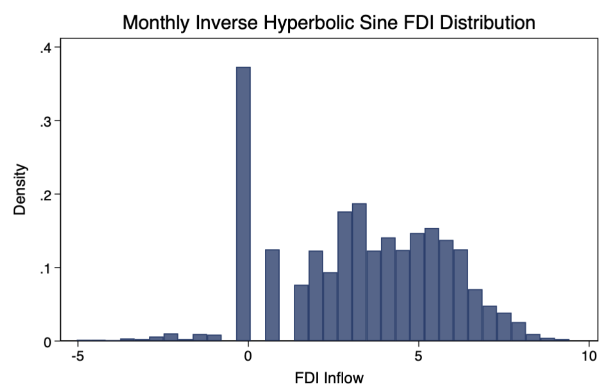

Figure 3: Inverse hyperbolic sine FDI distribution

4.2 Natural Disaster Data

The information regarding the five natural disasters comes from the EM-DAT database, which catalogs detailed statistics on natural disasters around the world. Specifically, the database provides

[4]Because the census is conducted once every 10 years, the population figures for the other years are based on census projections. For 2005-2010, I use the projections from the 2001 census, and from 2012-2019 I use projections from the 2011 census.

[5]The inverse hyperbolic sine is a variant of the log transformation, defined as $\log(y+\sqrt{y^2+1})$. This transformation is defined where y = 0, ensuring that no observations are dropped from regressions.

precise geographic data for the affected areas, as well as start and end dates for the disasters. Table 1 shows the date and affected regions for each disaster, and maps showing the affected areas for each disaster are shown in Figure 7–Figure 11. The EM-DAT database does not provide damage estimates at the regional level, so I treat all regions in the affected areas as if they were impacted equally.

An important feature of these five disasters is that they are not instances of cyclical disasters, such as yearly flooding or heat waves. For this reason, I assume that firms have not already "priced-in" the disaster effects. Additionally, these disasters are the five most significant such events over the period of analysis, and are orders of magnitude more severe than any of the smaller disasters that hit India during this time.

Disaster Name	Date	Affected Regions	Disaster Number
Bihar Flood	August 2008	Kolkata, Patna	1
Eastern Indian Storm	April 2010	Bhubaneshwar, Guwhati, Kolkata, and Patna	2
Uttarakhand Flash Floods	June 2013	Chandigarh, Delhi, and Kanpur	3
South Indian Floods	November 2015	Hyderabad, Chennai	4
Kerala Floods	August 2018	Kochi	5

Table 1: Disaster dates, affected regions, and "disaster number" (used to reference each disaster in tables and figures)

5 Estimation Strategy

To identify the causal effect of the five successive disasters, I take two complementary approaches. First, I estimate a "multiple dummies on" fixed effects model, allowing me to take advantage of the data's panel structure and estimate separate effects for each disaster. Additionally, I utilize an event study framework similar to that of Sandler and Sandler (2014), where I group observations according to their temporal distance from a disaster and estimate separate effects for each period.

5.1 Fixed Effects

The fixed effects specification takes the form:

$$F_{it} = \sum_{k=1}^{5} \gamma_k D_{tk} * A_{ik} + \sum_{k=1}^{5} \delta_k D_{tk} + \beta X_{it} + \omega_t + \alpha_i + \epsilon_{it} \tag{8}$$

where F_{it} is the FDI inflow into region i in month t, D_{tk} is a dummy for whether the k^{th} disaster occurred before or during period t, A_{ik} is a dummy for whether region i was in the affected area of disaster k, X_{it} are controls, ω_t is a continuous time variable, α_i are region fixed effects, and ϵ_{it} is the error term. To identify the effects of a disaster on affected and unaffected regions, the coefficients of interest are γ_k and δ_k for $k = 1, \ldots, 5$.

This model has several advantages. First, the region fixed effects are able to control for time-invariant regional characteristics, such as geography and culture, that would otherwise bias the estimates. Additionally, the model permits multiple dummies to be on at once, allowing it to capture additive effects across disasters. Finally, because all the regions are in India, the time variable allows the model to capture nation-wide policy changes, such as tariff rates, tax incentives, or political risks that affect all regions equally.

There are a few limitations of this specification, however. Even though the model is to control for time-invariant regional characteristics and nation-wide shocks, it is not able to capture unmeasured factors that change across time and impact regions differently. For example, the implementation of region-specific tax incentive for multinational investment could bias the estimates of disaster effects. A particular concern is that unmeasured regional responses to past disasters could bias the model's estimates in future periods. This specification also introduces the possibility of reverse causality between the control variables and FDI.

5.2 Event Study

To address some of the issues presented by the fixed effects model, I also adopt an event studies framework, where I group observations by periods to disaster and estimate the effect of being j periods before or after a disaster as follows:

$$F_{it} = \sum_{j=\underline{j}}^{\bar{j}} \gamma_j \mathbf{1}\{J_{it} = j\} + \beta X_{it} + \alpha_i + \epsilon_{it} \tag{9}$$

The coefficients of interest are γ_j for $j = \underline{j}, \cdots, \bar{j}$ and $[\underline{j}, \bar{j}]$ is the estimation window. Effectively, this model creates an alternate world where only one disaster occurs and groups all observations according to their temporal distance from the disaster. Because the five disasters are reasonably spread out across time, it allows for non-overlapping event windows.

A key feature of the event study model is that it allows measurement of non-constant disaster effects. This allows identification of lags between the disaster date and firm movement and enables measurement of persistence disaster effects across time. Additionally, by estimating the coefficients on natural disaster occurrence in the periods leading up to the disaster date, this framework is able to control for time-variant regional shocks that can bias the fixed-effects regression. In the event study model, only unmeasured regional shocks that were unrelated to the disaster and occurred in the same month would bias the estimate. Finally, by clustering events by time to disaster, the model is able to control for reverse causality between the control variables and FDI.

6 Results

6.1 Fixed Effects

To estimate the effect of the five natural disasters, I first utilize a fixed effects specification. The main results are presented in Table 5, where I predict absolute monthly FDI inflow with controls for GDP and population and include region fixed effects. The occurrence of each of the five disasters is associated with a large and statistically significant fall in FDI in the affected regions. Additionally, disasters 1, 3, and 5 led to a statistically significant rise in FDI in unaffected regions. In each case, the magnitude of the decrease in the affected regions is substantially larger than the increase in unaffected areas. A summary of these results are shown in Table 2.

Disaster Number	Affected Regions		Unaffected Regions	
	Impact on Monthly FDI Inflow (millions USD)	Significant at 90% Level?	Impact on Monthly FDI Inflow (millions USD)	Significant at 90% Level?
1	-138.94	YES	58.09	YES
2	-7.96	YES	1.76	NO
3	-252.152	YES	62.63	YES
4	-375.582	YES	8.77	NO
5	-105.908	YES	54.50	YES

Table 2: Summary of disaster effects in affected and unaffected regions

To check for robustness, I implement two alternate fixed effects specifications, shown in Table 6. Employing robust standard errors clustered by region, I run regressions for both absolute FDI and inverse hyperbolic sine of FDI. Across each of these specifications, the coefficients of interest have identical signs as the main specification. However, while the results are qualitatively identical, there are key differences in terms of significance. In particular, many of the coefficients for the unaffected region effects lose significance under one or both alternate specifications.

Column (1) of Table 6 shows the results for absolute FDI. Under this specification, both effects for disaster 2 are insignificant, and disaster 1 is the only event with significant effects for unaffected regions. In column (2), which presents the results for inverse hyperbolic sine of FDI, the interaction term for disaster 2 regains significance, but disaster 5 is the only event with significant effects for unaffected regions. These results suggest that while the affected region effects remain robust across alternate specifications, the unaffected region effects are weaker. However, given that the signs of the coefficients are identical across specifications and disasters, I interpret these fluctuations in significance level as primarily reflecting the limited sample size, rather than calling into question the main result.

6.2 Event Study

Next, I conduct an event study analysis, which allows me to explore the timing of effects and control for several possibilities of bias in the fixed effects estimates. I divide the data into five non-overlapping event windows, corresponding to the five disasters, and group each observation by months before or after the disaster in its event window. I then regress inverse hyperbolic sine of FDI on the time to event variables, controlling for GDP, population, and region fixed effects. The time to event coefficients for affected and unaffected regions are shown in Figure 4 and Figure 5, with 95% confidence intervals.

This specification provides several insights. First, the results corroborate the findings of the fixed effects model; FDI falls in the affected regions following a disaster and rises in the unaffected regions, and the magnitude of the effects is larger in affected regions. Additionally, a key feature of the event study is that it enables identification of pre-event trends that could bias the measurement of disaster effects. For both the affected and unaffected regions, there is no evidence of a pre-trend, as the time to event coefficients are not significantly different than zero leading up to the disaster. This provides strong evidence that these estimates are capturing the causal effect of the natural disaster. The event study specification also allows measurement of effect timing. In the affected regions, there is an immediate fall in FDI following a disaster, while in unaffected regions there is a 3-4 month lag between the disaster date and the rise in investment. Finally, the effects in both

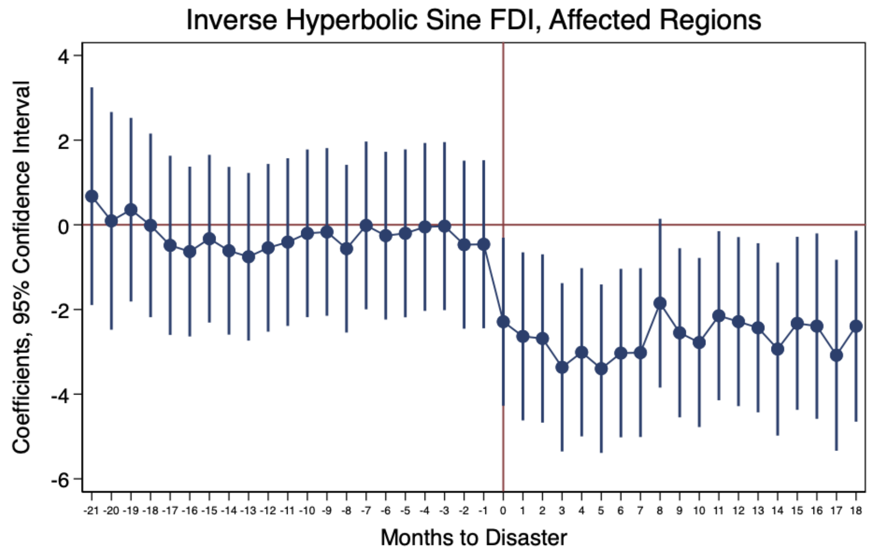

Figure 4: Time to disaster coefficients for affected regions with 95% confidence intervals

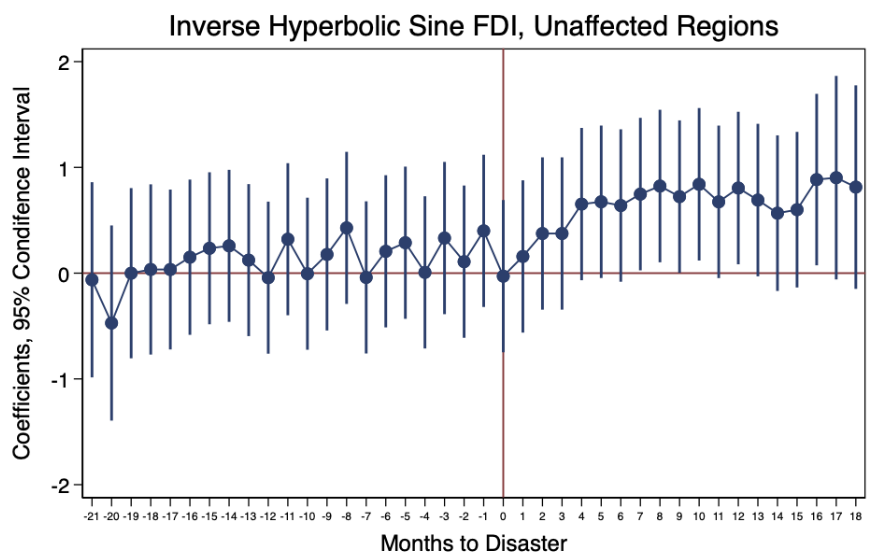

Figure 5: Time to disaster coefficients for unaffected regions with 95% confidence intervals

affected and unaffected regions appear persistent out to 18 months post-disaster.

For robustness, I also group observations by quarters to disaster rather than months and find similar results. These estimates are shown in Figure 12 and Figure 13. Due to the larger number of observations in each group, this specification has smaller standard errors and thus increases the significance of the coefficients for the quarters following the disaster. Additionally, it more clearly illustrates the lag between the disaster date and firm movement into unaffected regions.

7 Discussion

These results provide evidence for the hypothesis that the "risk factor" of investing in a region increases following a disaster, given the presence of persistent effects. Consequently, these findings provide a window into the decision making of multinational firms under conditions of risk. In particular, they indicate that relative disaster risk between regions is a significant consideration in location decisions, since firms shift a portion of investment flows from affected to unaffected regions. Additionally, the salience of this disaster risk does not appear to dissipate for at least 18 months.

The timing of disaster effects is also of particular note. While FDI flows into the affected regions fall immediately after a disaster, it takes 3-4 months before investment begins to rise in unaffected areas. This result is intuitive; while decisions to halt investment can be made quickly, it takes time to find a suitable alternative location for investment.

Finally, the magnitude of the effects emphasizes the economic significance of these findings. In both the fixed effects regression and the event study, the disaster effects in the affected regions are larger than those in the unaffected regions, but even in the unaffected regions, the effect sizes are on the order of ten million dollars per month. The larger affected region effects are likely a result of the fact that the adverse impacts are concentrated in a few regions, while the benefits are distributed more diffusely. This fact would also explain the weaker significance levels for the unaffected region effects found in both the fixed effects and event study models.

8 Limitations

This paper has two significant limitations. First, given that the study focuses solely on India, there are serious challenges to its external validity. The main results hinge on the ability of multinational firms to shift direct investment from affected regions to unaffected regions following a disaster; if India is atypical in the degree of "substitutability" between its regions, these results would not translate to other contexts. In particular, countries with more heterogeneity across regions would seem less likely to experience the effects found in this paper. There is also the possibility that the types of industries which locate in India can more easily shift production to a new location. A key area of future research will be exploring these effects in other countries and contexts.

The second limitation is the possibility that unmeasured regional disaster responses are biasing the estimates. The event study framework rules out the presence of time variant factors that do not occur in the same month as the disaster, but it is unable to control for unmeasured events that occur simultaneously. For this reason, it is possible that differential policy responses to a disaster could challenge the validity of the findings. For heterogeneity in regional disaster response to bias the results, two facts would have to hold; affected and unaffected regions would need to enact different sets of policies following a disaster, and these policies would need to have differential impacts on FDI inflow. More specifically, it would need to be the case that unaffected regions collectively adopt some FDI incentivizing policy during the month of each disaster that affected regions do not. While this situation seems unlikely, it is possible that unaffected regions account for the fact that multinationals will be relocating following a disaster and adopt policies to attract investment.

9 Conclusion

This paper finds significant impacts of natural disasters on FDI. Given the magnitude of these effects and their persistence over time, shifts in multinational firm location could be a significant and understudied mechanism through which natural disasters impact the economy, both in the short and medium run. Additionally, these results emphasize the fact that country-level analyses are not sufficient for understanding the relationship between natural disasters and FDI, given the presence of large within-country investment shifts from affected to unaffected regions. In particular, the use of country-level data will cause researchers to severely underestimate the effects of natural disasters on FDI in the affected regions.

These findings also have important implications for the future. They highlight the challenge of building broad consensus around disaster mitigating policies, such as climate change prevention, given that some regions directly benefit from these events. Furthermore, they reveal the sensitivity of multinational firms to disaster risk. Ultimately, the results of this paper tell a pessimistic story, predicting underinvestment in disaster prevention at the national level and a long-run exit of multinational firms from the regions most affected by climate change.

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A Tables and Figures

Reserve Bank of India Districts	
District	Included States
Ahmedabad	Gujarat
Bangalore	Kamataka
Bhopal	Madhya Pradesh
Bhubaneshwar	Orissa
Chandigarh	Punjab, Haryana, Himachel Pradesh
Chennai	Tamil Nadu
Delhi	New Delhi
Guwahati	Assam, Manipur, Meghalaya, Mizoram, Nagaland, Tripura
Hydereabad	Andhra Pradesh
Jaipur	Rajasthan
Kanpur	Uttar Pradesh, Uttarakhand
Kochi	Kerala, Lakshadweep
Kolkata	West Bengal, Sikkim
Mumbai	Maharasthra
Panaji	Goa
Patna	Bihar

Table 3: Reserve Bank of India District Definitions

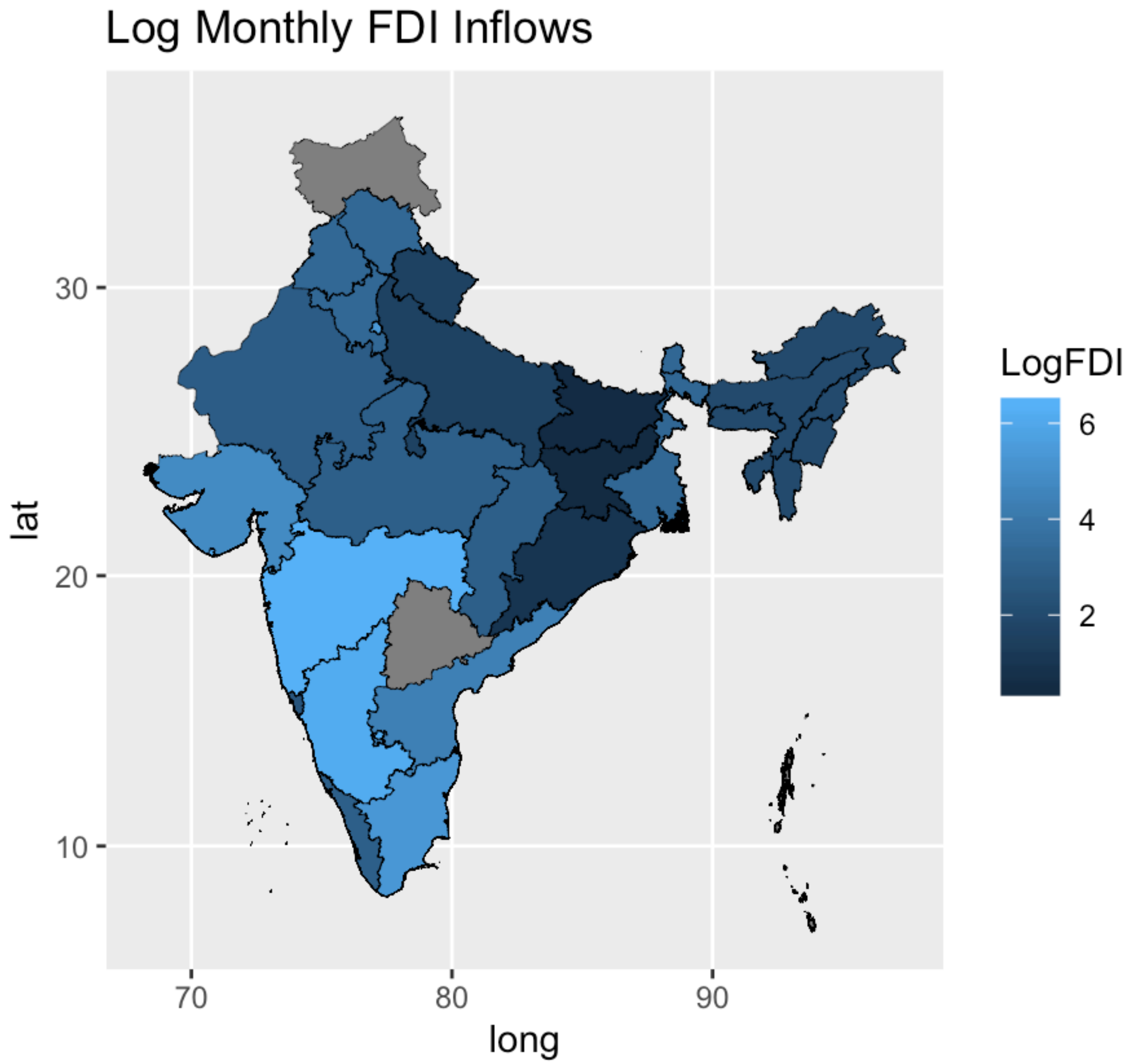

Figure 6: Regional FDI inflow map (grey signifies missing data)

Region	N	Monthly FDI Inflow (Millions, USD)		Regional Domestic Product (Millions, USD)		Population (thousands)	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
Ahmedabad	171	122.398	133.011	759213.67	367460.61	61576.77	4068.32
Bangalore	171	440.766	402.902	718524.62	427446.2	47783.35	20721.21
Bhopal	171	18.947	24.183	408462.19	207878.58	74249.37	5075.03
Bhubaneshwar	171	2.678	7.260	264462.18	115197.63	41853.53	1497.71
Chandigarh	171	29.053	33.926	755872.37	333592.59	61608.46	5512.11
Chennai	171	214.883	273.659	855431.25	422993.37	59210.95	19515.61
Guwhati	171	7.328	15.083	251845.76	119384.97	44815.27	3988.78
Hyderabad	171	81.953	69.803	465241.85	227418.91	55803.93	7955.77
Jaipur	171	16.696	56.651	496423.05	241215.09	69909.81	4796.14
Kanpur	171	5.058	8.404	968871.86	440212.67	214206.23	14053.77
Kochi	171	18.772	30.016	407525.78	198569.15	33895.67	706.44
Kolkata	171	26.836	98.138	638911.98	274520.95	92051.90	3737.99
Mumbai	171	652.023	960.012	1461311.8o	656502.24	92011.63	33412.27
New Delhi	171	207.374	167.047	394786.56	203284.19	17461.68	1421.42
Panaji	171	9.152	11.446	44082.86	18276.87	1482.77	31.35
Patna	171	1.661	5.118	292644.64	138444.01	106151.38	8953.72

Table 4: Regional summary statistics

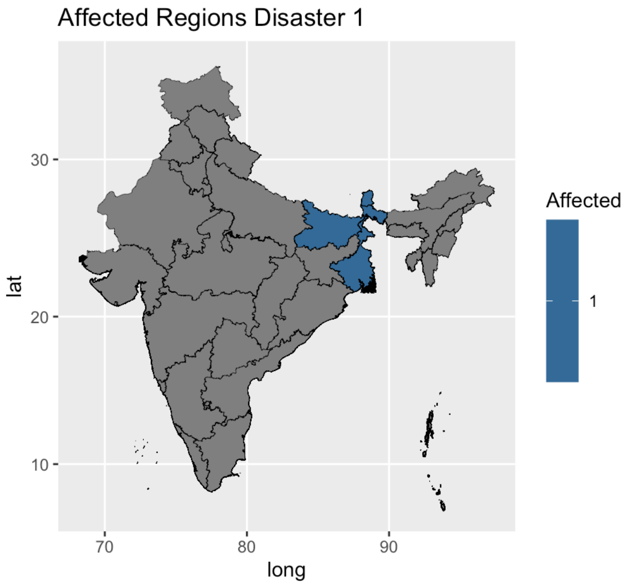

Figure 7: Disaster 1 affected regions

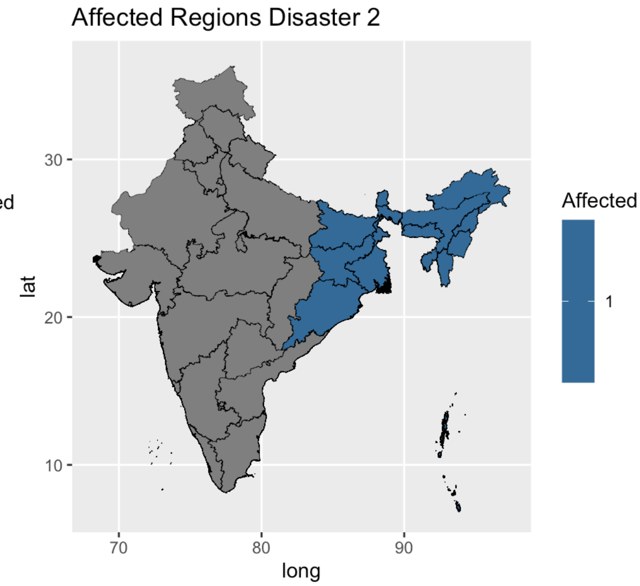

Figure 8: Disaster 2 affected regions

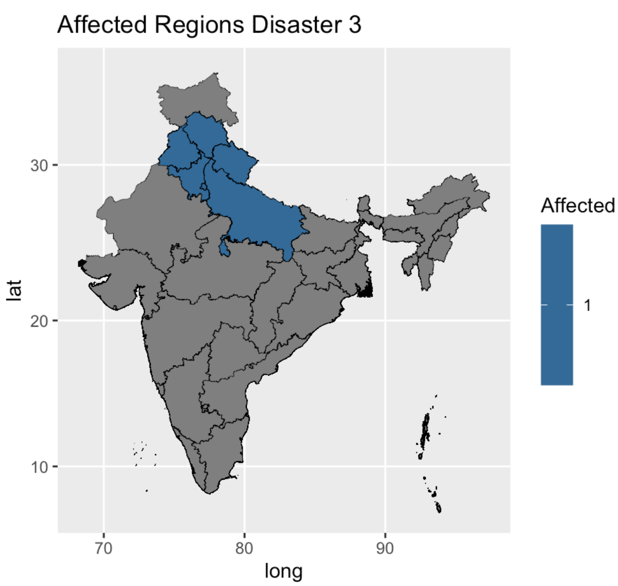

Figure 9: Disaster 3 affected regions

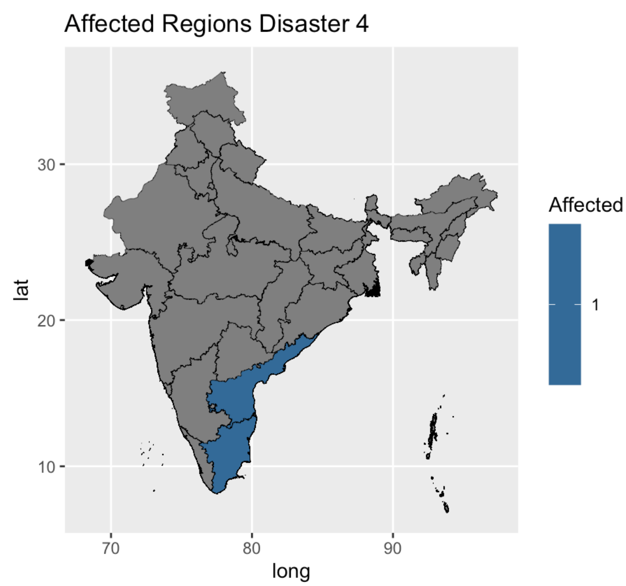

Figure 10: Disaster 4 affected regions

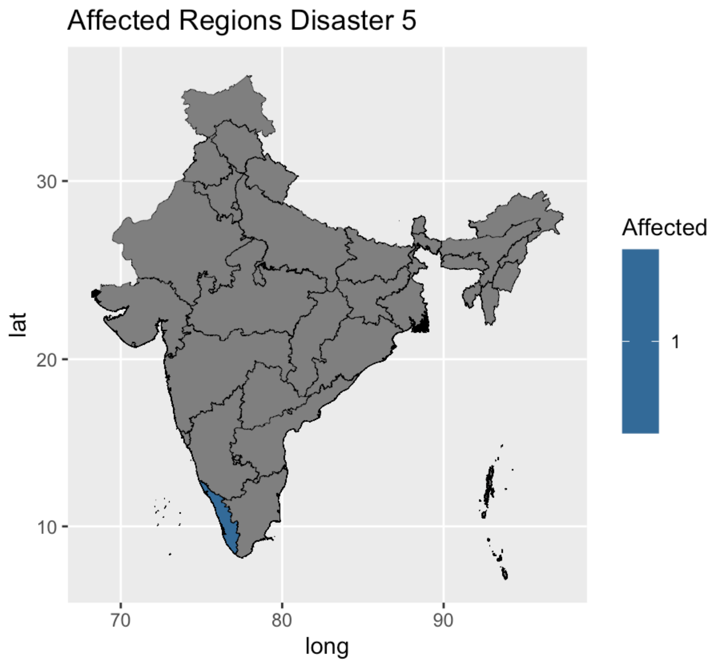

Figure 11: Disaster 5 affected regions

VARIABLE	(1) Monthly FDI Inflow (Millions, USD)
Disaster 1 Occurred = 1	58.091***
	(21.419)
Disaster 1 Occurred * Affected Disaster 1	-197.027***
	(34.569)
Disaster 2 Occurred = 1	1.760
	(22.477)
Disaster 2 Occurred * Affected Disaster 2	-9.723*
	(23.797)
Disaster 3 Occurred = 1	62.632***
	(21.688)
Disaster 3 Occurred * Affected Disaster 3	-260.924***
	(23.209)
Disaster 4 Occurred = 1	8.772
	(21.056)
Disaster 4 Occurred * Affected Disaster 4	-384.354***
	(29.553)
Disaster 5 Occurred = 1	54.503***
	(21.206)
Disaster 5 Occurred * Affected Disaster 5	-160.411***
	(59.784)
Observations	1,792
Regions	16
R-squared	0.381
Between region R-squared	0.615
Controls for GDP, population, and month	YES
Region FE	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Fixed effects results for absolute FDI with controls for GDP, population, and month

VARIABLE	(1) Monthly FDI Inflow (Millions, USD)	(2) Inverse Hyperbolic Sine FDI
Disaster 1 Occurred = 1	58.932**	-0.064
	(23.850)	(0.127)
Disaster 1 Occurred * Affected Disaster 1	-198.262**	-1.605*
	(72.466)	(0.801)
Disaster 2 Occurred = 1	1.092	0.222
	(22.847)	(0.225)
Disaster 2 Occurred * Affected Disaster 2	-9.804	-2.832***
	(73.755)	(0.533)
Disaster 3 Occurred = 1	62.080	0.370
	(40.553)	(0.226)
Disaster 3 Occurred * Affected Disaster 3	-260.971*	-2.943***
	(125.682)	(0.617)
Disaster 4 Occurred = 1	8.114	0.220
	(40.569)	(0.160)
Disaster 4 Occurred * Affected Disaster 4	-382.881**	-2.237***
	(160.285)	(0.336)
Disaster 5 Occurred = 1	54.141	.133***
	(53.971)	(0.131)
Disaster 5 Occurred * Affected Disaster 5	-160.282**	-1.562***
	(84.029)	(0.227)
Observations	2,736	2,736
Regions	16	16
R-squared	0.381	0.294
Between region R-squared	0.615	0.228
Controls for GDP, population, and month	YES	YES
Region FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Fixed effects results for absolute FDI and inverse hyperbolic sine with robust standard errors

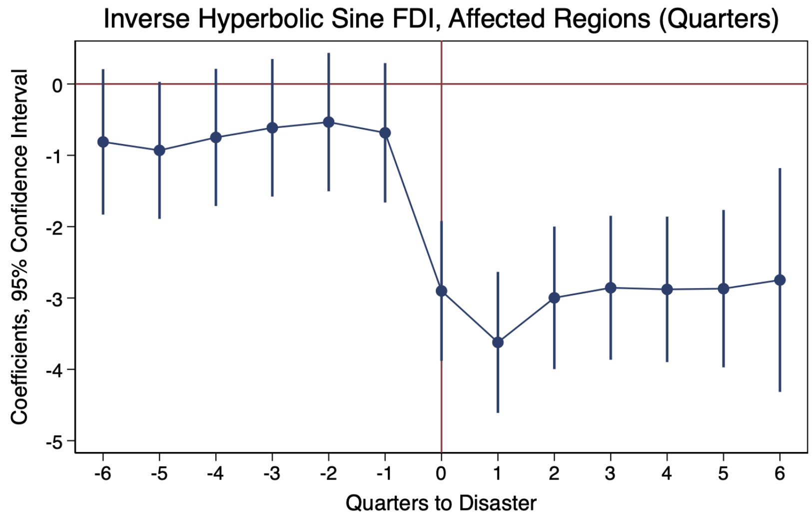

Figure 12: Event study grouped by quarter, affected regions

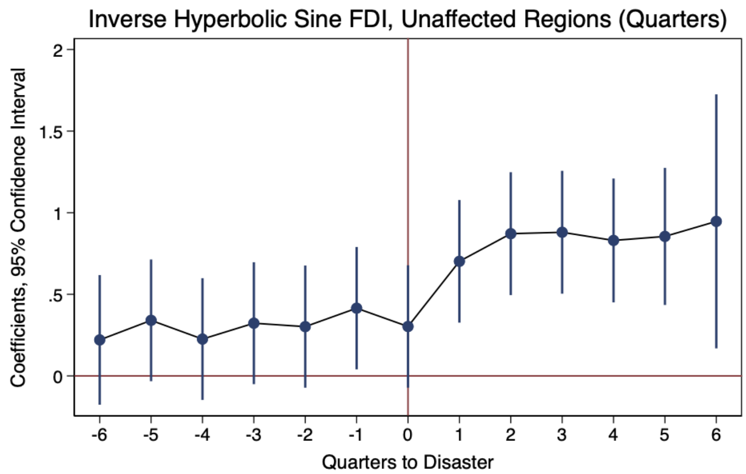

Figure 13: Event study grouped by quarters, unaffected regions

B Further Model Results

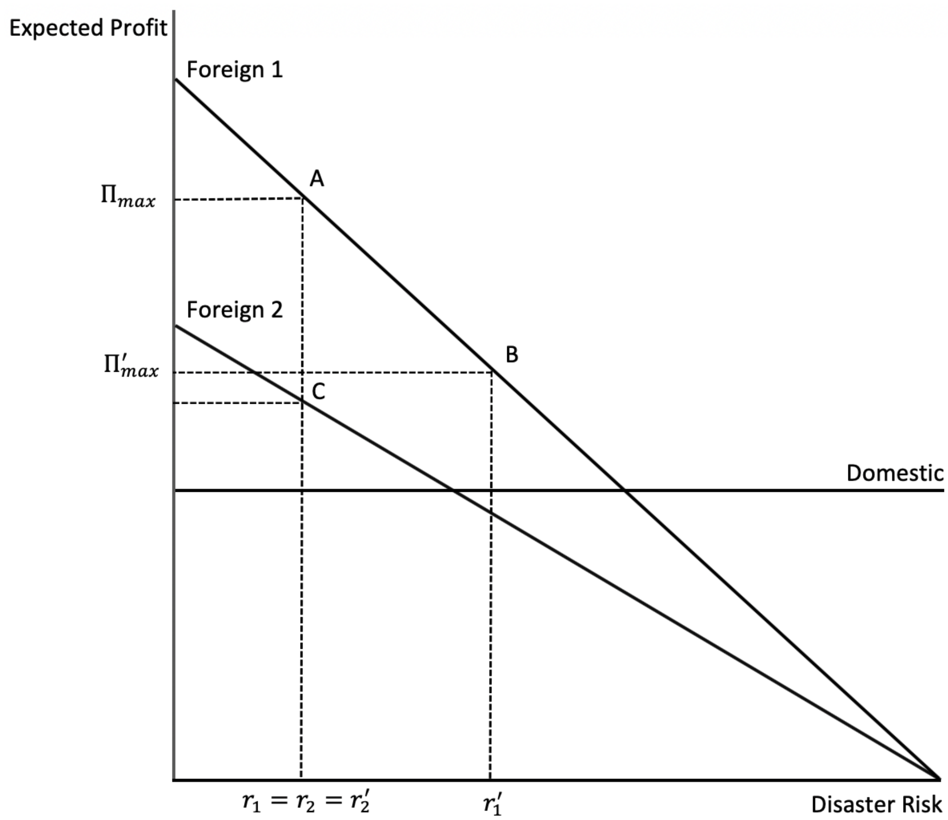

Figure 14: Disaster shock leading to no change in production location

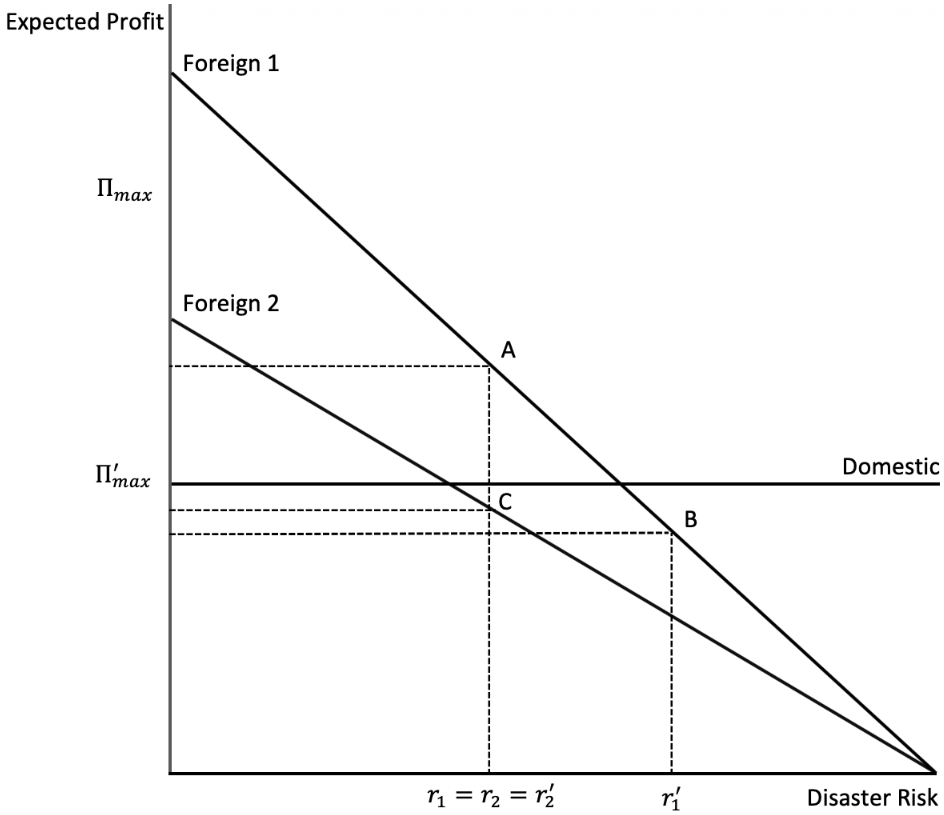

Figure 15: Disaster shock Leading to domestic production