Natural Disasters, FDI and Intra-National Spillovers: Evidence from India*

Aidan Toner-Rodgers†
Macalester College

Felix L Friedt‡
Macalester College

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Abstract

This paper examines the effects of natural disasters on FDI, considering the case of India. Our analysis evidences persistent investment reductions in affected regions following a disaster as well as lasting positive investment spillovers into unaffected Indian regions. We show that these intra-national shifts in multinational firms' investment patterns are non-random and tend to flow into more developed regions with more skilled labor and greater market potential. Combined, our findings suggest that natural disasters may permanently increase the "risk factor" of investing in affected regions, while systematic FDI spillovers may help explain the prominent divergence in India's regional economic growth.

Keywords: Foreign Direct Investment, Multinationals Corporations, Risk, Economic Growth, Divergence
JEL Codes: F, F43, O12, O16, Q54

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†Macalester College, atonerro@macalester.edu.
‡Department of Economics, Macalester College, 1600 Grand Avenue, Saint Paul, MN 55105; ffriedt@macalester.edu.

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 (FDI) 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 and could contribute to regional disparities in economic growth (Noy, 2009).

India provides a compelling environment for studying these effects. Over the past 15 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. Historically, however, this economic growth has been uneven across Indian regions and the resulting spatial disparities in development have become a real concern for Indian policy makers (Ghosh et al., 1998; Sachs et al., 2002; Ghosh, 2012). On the other hand, 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 trends, identifying the causal effect of natural disasters on FDI inflows into directly affected regions and quantifying the resulting intra-national investment spillovers into unaffected areas. Using data from 16 regions within India, we consider the impact of five disasters between January 2006 and December 2019 and derive three key insights. First, we find evidence that FDI falls substantially in the affected regions following a disaster. The average losses total around $130 million per month, representing an 86 percent drop in monthly inflows. Second, we identify large positive spillover effects in unaffected regions, indicating that multinational firms shift investment intra-nationally away

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

from affected areas. Spillovers average around $90 million per month, indicating that for every dollar of investment lost in affected regions, more than 66 cents are reallocated to unaffected regions *within* India. Using an event study design, we show that both the affected and unaffected region effects are persistent out to 18 months post-disaster and argue that these longer-term impacts are consistent with a model of multinational location choice in which firms take into account relative disaster risk when selecting regions for production. Finally, we explore the predictors of where multinationals choose to reinvest following a disaster, identifying variation in the spillover effects across several regional characteristics. We find that market potential, development, and labor skill are key determinants of these spillovers.

Our findings contribute to three related literatures. Most immediately, we add to the evidence on the economic impacts of natural disasters. While there has been significant work on macroeconomic consequences of disasters, both in terms of their short-run effects (Benson and Clay, 2003; Noy, 2009; Raddatz, 2009; Boustan et al., 2020), and their longer-term impacts (Skidmore and Toya, 2002; Rasmussen, 2004; Cuaresma et al., 2008; Raddatz, 2009; Berlemann and Wenzel, 2016), the channels responsible for these results remain understudied. In particular, only a handful of studies have considered the relationship between natural disasters and FDI. Most such works 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, use country-level data from 94 countries over a 120-year period and find natural disasters to be negatively and statistically significantly associated with a country's FDI. Other papers, such as Kukułka (2014) and Anuchitworawong and Thampanishvong (2015), look at only one country or region and find a similarly negative relationship between natural disasters and FDI. Wang (2011) builds upon these findings and estimates the positive contagion effects of political and natural disasters in Japan on the stock of FDI in neighboring Asian countries.

While these works have improved our understanding of the impact of natural disasters on national FDI flows, we are able to expand the current state of knowledge by considering effects at the intra-national level. The magnitude and persistence of our direct and indirect effect estimates show that within-country investment shifts are critical to understanding the full scope of a disaster's impact on FDI. Moreover, our results suggest that studies at the national level will severely underestimate a disaster's impact in directly affected regions.

Second, we add to the literature on the decision making of multinational firms under conditions of risk

(Ahmed et al., 2002). The presence of large investment shifts from affected to unaffected regions indicates that relative disaster risk may be a significant concern for multinational firms - even after a region has begun to recover. Additionally, the persistence of the measured effects indicates that the salience of the disaster effects does not quickly dissipate. Our findings are in contrast to previous work in this area, such as Oh and Oetzel (2011), who find insignificant effects of disasters on multinational location choice at the national level. We argue that the large within-country investment shifts found in our analysis may be masking the disaster effects in studies that use country-level data and could mislead local policy efforts.

Finally, our results contribute to work on agglomeration effects and regional divergence (Fujita and Mori, 1996; Baldwin and Martin, 2004; Quah, 2002; Mariotti et al., 2010; Alfaro and Chen, 2014), providing a channel through which such disparities can emerge and endure. The persistence of our estimates 18 months post-disaster emphasizes an element of path dependence in the location decisions of multinational firms, where multinationals exit a region following a disaster and are reluctant to return even once the region has otherwise recovered. In India, where regional inequality has persisted despite a high rate of overall economic growth and has become a major policy concern (Ghosh et al., 1998; Sachs et al., 2002; Ghosh et al., 2013), our findings point to past disasters as an important contributor to this divergence.

The remainder of our paper is organized as follows. Section 2 provides background on economic growth and FDI inflows in India and discusses in detail the five disasters included in our analysis. In section 3, we present a theoretical framework for the location decisions of multinational firms under conditions of disaster risk and discuss the economic and disaster data used for our analysis in section 4. Our empirical results are presented in Section 5 and detail 5.1) the average treatment effect of each disaster; 5.2) the dissection of these effects into direct FDI disruptions and indirect intra-national spillovers; and 5.3) the non-random heterogeneity in spillover patterns across Indian regions with varying socioeconomic characteristics. We provide a brief discussion of our analysis and its limitations in section 6 and conclude in section 7.

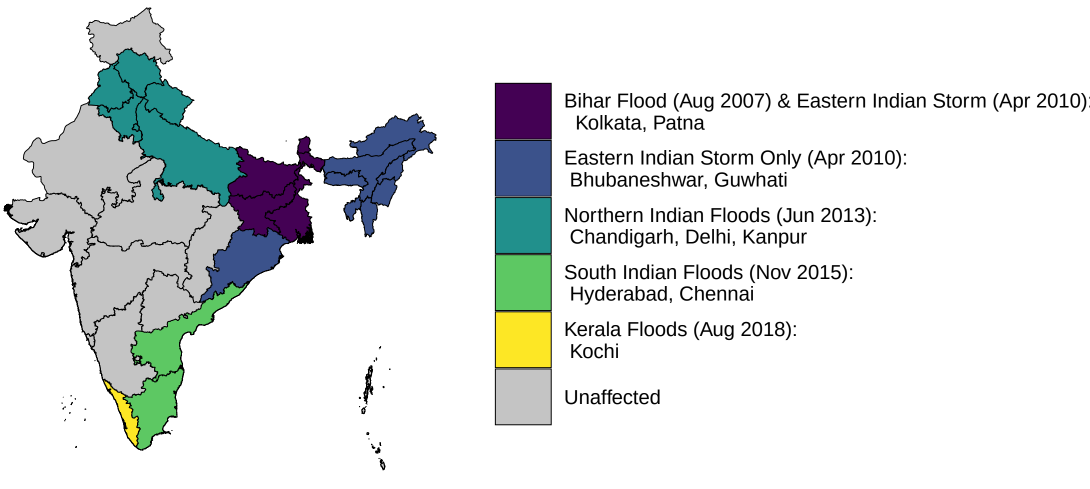
2 Economic Growth, Natural Disasters and FDI Inflows in India

Several studies have investigated India's economic growth over the past few decades (particularly post-reform) and noted the considerable divergence in growth patterns across Indian states (Ghosh et al., 1998; Sachs et al., 2002; Ghosh, 2012). Data published by the Ministry of Statistics and Programme Implementation, for example, indicate that state-level GDP growth rates have ranged from 195% to 472% between 1999 and 2015 and tend to be positively correlated with the initial economic size of a state. Common explanations for these disparities include varying rates of urbanization (Sachs et al., 2002), variations in physical and social infrastructures (Lall, 1999, 2007) and state-level policy reforms (Ghosh, 2012). Differences in FDI inflows are also named as one of the primary determinants of non-convergence (see, for example, Ghosh (2012)).

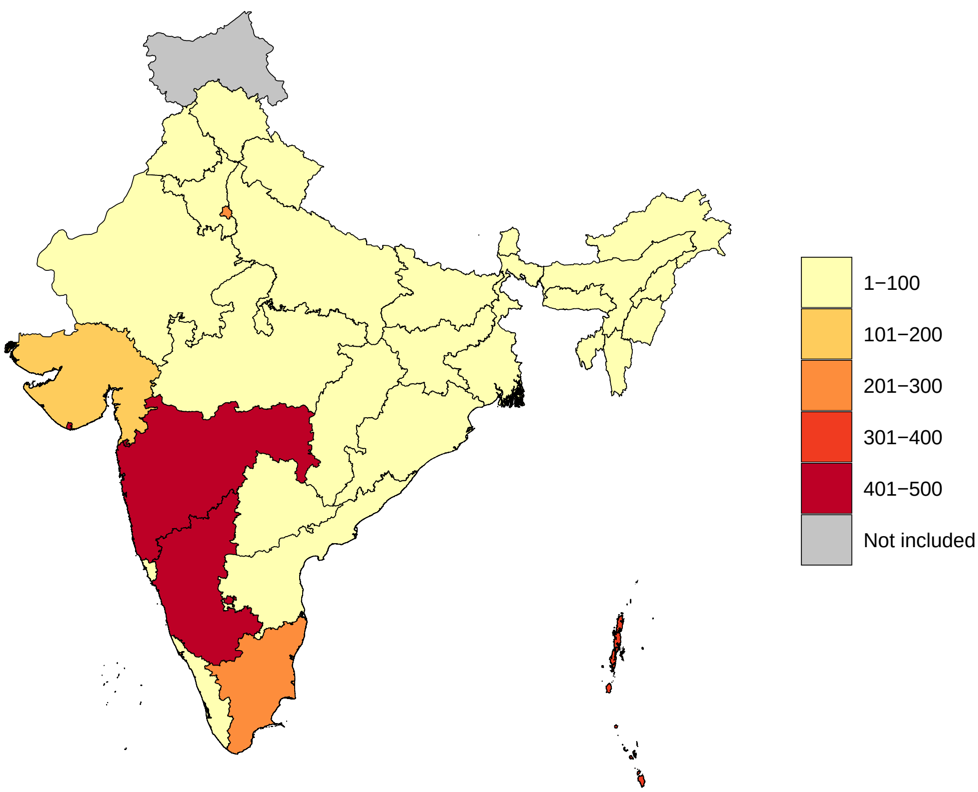
Over the more recent time period (2006-2019), India has not only experienced growing regional inequalities, but has also suffered from five major natural disasters, shown in Figure 1a. The first of these was the August 2007 Bihar Flood, which devastated the Indian states of Bihar and Sikkim and represents the region's worst disaster in over 50 years. The consequences were severe, forcing over 2 million people from their homes, destroying over 300,000 buildings, and flooding more than 840,000 acres of cropland. Furthermore, the rehabilitation efforts were slow; of the 100,000 houses planned to be rebuilt, only 12,500 had been erected by the end of 2013 (Biharprabha News, 2014).

The second disaster to hit India during this period was the Eastern Indian Storm, which struck the regions of Assam, Bihar, Orissa, and West Bengal on April 13, 2010. While storms over the Bay of Bengal are common, the severity of this disaster was unexpected, flattening over 100,000 homes and disrupting the region's power, communication, and transportation systems (Reuters, 2010). The reconstruction efforts were limited, and lack of aid following the disaster even led to protests in several states (Hindustan Times, 2010). The third disaster occurred in June 2013, when India was hit by the Northern Indian Floods. Several days of heavy rainfall caused over 5,700 deaths and destroyed more than 4,000 villages in Chandigarh, Delhi, Uttarakhand, and Uttar Pradesh (CBS News, 2010). The floods represent the region's worst disaster in nearly 100 years and caused lasting damage to the power grid, infrastructure, and agriculture.

The fourth disaster included in our analysis is the November 2015 South Indian storm, which struck the Indian states of Andhra Pradesh and Tamil Nadu. The resulting floods caused over 500 deaths and displaced 1.8 million people, as well as damaging manufacturing capabilities across several industries (Deccan Herald, 2015). Finally, in August of 2018, the Kerala Floods devastated the southern state of Kerala, representing the region's worst disaster since 1924. Along with displacing over a million residents, the floods destroyed an estimated 6,000 miles of roads, seriously damaging the state's transportation infrastructure (The Independent, 2018).



(a) Affected Regions for the Five Disasters



(b) Average FDI Inflows by Region

Figure 1: Affected Regions for the Five Natural Disasters and Regional FDI Inflows (2006-2019)

While there is significant heterogeneity across these five disasters, several shared features make them well suited for analysis. First, none of the disasters are instances of cyclical or seasonal disasters, such as routine flooding every wet season, and we therefore do not expect multinational firms to have already "priced-in" the disaster effects. Second, 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.[2] Finally, the disasters are not concentrated in one region (see Figure 1a) and therefore make our identification strategy more credible.

Over this time period (2006-2019), we are able to not only observe differences in regional economic growth and the occurrence of natural disasters, but also the spatial variation in FDI inflows recorded at the district level. Average investment streams, shown in Figure 1b, indicate that multinationals tend to invest in the south-western part of India over our sample period, particularly in the regions of Bangalore and Mumbai, which were unharmed by the five major disasters. To produce preliminary insights into whether these natural disasters exerted any influence over regional FDI inflows, we plot the FDI data over time and differentiate across five types of regions: those affected by natural disasters (ND) 1 and 2[3], those affected by ND 3, those affected by ND 4, those affected by ND 5, and those not directly affected by any of these calamities.

Figure 2 shows that average monthly FDI inflows are fairly similar across regions prior to any of the disasters and rather small at the beginning of our sample in January 2006. Over time, these regional investments show considerable divergence that seems to be influenced by the occurrence of major natural disasters. The Northern Indian Floods (ND 3), for example, coincide with a drastic reduction of around \$200 million per month in average FDI inflows in the affected regions and an uncharacteristic uptick of around the same amount in investments in those regions unaffected prior to this date. Similarly, the South Indian Floods (ND 4) coincide with a notable loss in average FDI inflows into the affected regions of approximately \$500 million per month and contemporaneous increases in investments in the unaffected regions (and to some extent those regions affected by ND 3). These observed investment patterns provide first

[2] The 2004 Indian Ocean earthquake and tsunami, which is the most severe disaster in India's recent history, occurred before our data begins and is therefore not included in our analysis. In India, it affected the Andaman and Nicobar Islands, which are not included in our panel, and the southern state of Tamil Nadu, which we do include. For the disasters where Tamil Nadu is in the unaffected region, this may lead to downward bias in our spillover effect estimates. Sensitivity analyses show that the inclusion of Tamil Nadu does not drive our results.

[3] The districts Patna and Kolkata were affected by both disasters 1 and 2, while regions Bhubaneshwar, and Guwhati were only affected by the second disaster. For expositional purposes, we combine these four regions and graph the respective average FDI inflows.

evidence of disaster-induced disruptions of FDI inflows and intra-national substitution in multinational investment locations from directly affected to unaffected regions.

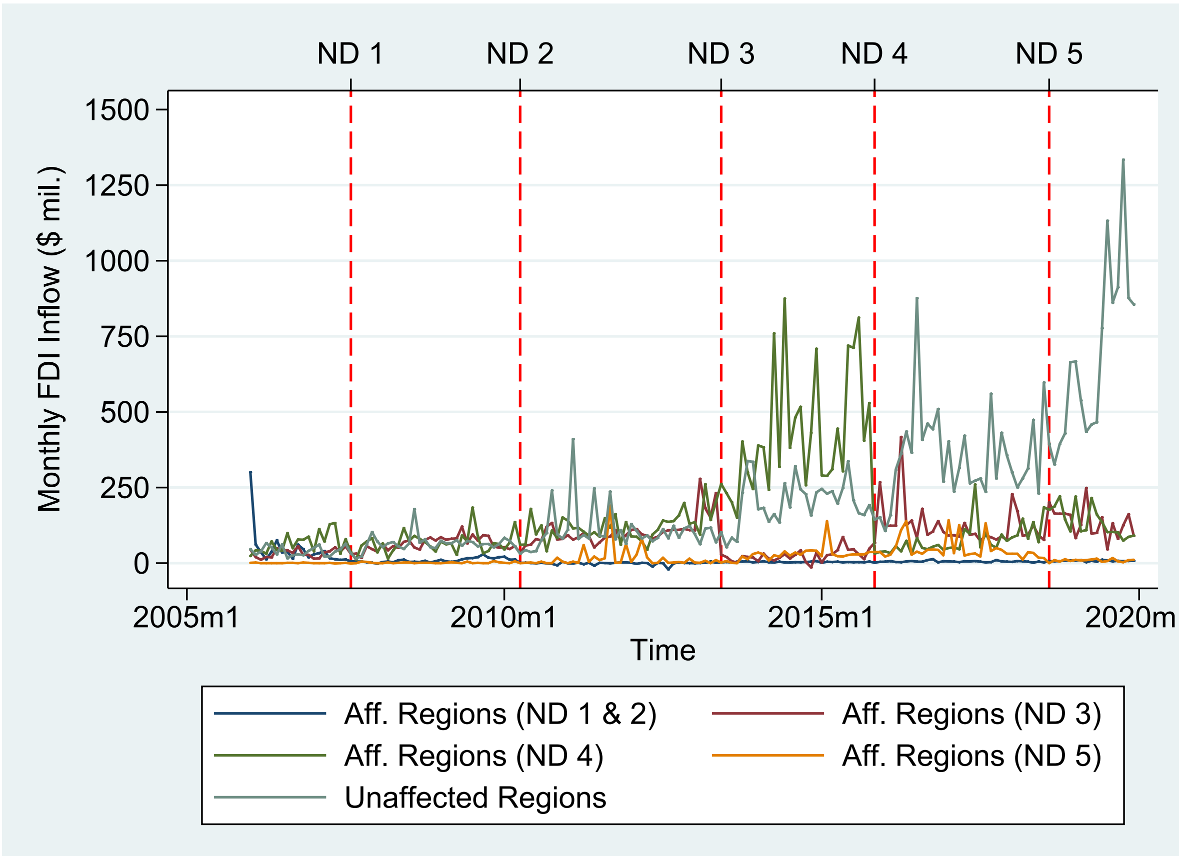


Figure 2: Average FDI Inflows by Disaster-Affected Regions (2006-2019)

3 Theory of Multinational Firm Location

3.1 Motives for FDI

Motivated by the potential influence of natural disasters on these striking investment patterns, we develop a simple theoretical model that helps explain the observed phenomena and guides our empirical analysis. A common framework for analyzing the location choices of multinational firms 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 international locations in order to bi-pass trade barriers, such as tariffs and transportation costs, and serve these foreign markets. 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 and foreign tariffs are more critical. Since we study the FDI disaster effects in India, we build on the vertical FDI framework.[4]

3.2 Probability of a Natural Disaster

To begin, we consider the channels through which a past disaster can influence present and future FDI location choices. 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 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.[5] For this reason, we 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, we 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 significant 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.

[4] Extensions to the horizontal model are straight forward and produce the analogous predictions regarding the regional (within India) FDI adjustments in response to a local natural disaster.

[5] Importantly, this logic does not hold for "cyclical" disasters, such as floods that happen every wet season. As discussed in section 2, we restrict our analysis to disasters which do not fit this pattern.

3.3 Model

To incorporate this feature we extend a simple vertical model of multinational location choice by allowing a multinational to choose between three regions to locate production, some of which are subject to disaster risk. Specifically, the multinational can produce domestically, where it earns certain profit, or locate in one of two foreign regions located in the same country, where it incurs risk of a natural disaster.[6] Critically, the probability of a natural disaster can differ between the foreign regions (even within a single foreign country). For simplicity, we assume that in the event of a disaster in the production region, the firm makes zero profits and that the fixed costs of setting up production are identical across all possible locations. We define the expected operating profits for each region as follows:

Domestic Production:

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

Foreign Production Region 1:

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

Foreign Production Region 2:

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

where c_i is the marginal cost in region i, t is the per-unit trade cost (identical across foreign regions within a foreign country), and $r_i \in [0, 1]$ is the probability of a natural disaster in region i.[7] Assuming inverse linear demand of the form $Q = a - P$, the maximum expected profits for each region can be written as a function of marginal costs, trade costs, disaster risk, and the demand shifter a:

[6] This is an assumption of convenience. It is straightforward to show that the results hold if all three regions are subject to disaster risk. One may reinterpret this assumption as the additional disaster risk foreign locations have over the domestic site.

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

Domestic Production:

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

Foreign Production Region 1:

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

Foreign Production Region 2:

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

From these equations one can derive the multinational's location decision rule, which hinges on costs (c and t), demand (a), and disaster risk (r_1 and r_2). Alternatively, one can graphically represent the key relationship of interest expressed in Equations $(5) - (7)$ by plotting expected profits by location against the probability of a disaster, where movements along the curves represent changes in risk and shifts indicate changes in c, t, or a.

Consider, for example, the initial (pre-disaster) scenario, where foreign disaster risks are equal ($r_1 = r_2$) and production costs are cheapest in foreign region 1 (FR1), more expensive in foreign region 2 (FR2), and most expensive in the home market. Further, suppose that the assumed cost advantage in FR1 and FR2 outweigh the additional transport costs and risk premiums, such that FR1 is the profit maximizing location in this initial scenario and preferred to FR2, which in turn is preferred to the domestic option.

How does this location choice vary if FR1 experiences a natural disaster? As shown in Figure 3 and following section 3.2, the shock increases the perceived risk of future disasters in FR1 ($r_1' > r_1 = r_2$) and leads to a fall in the expected profits. In addition, one may assume that the local devastation of productive capacity due to the disaster has a negative impact on marginal costs that further erodes FR1's competitive advantage and causes a leftward pivot in FR1's expected profit curve.

Conditional on the assumption that the expected profits from the domestic location remain unchanged, several potential location choice adjustments are possible. First, if cost and/or disaster risk rise sufficiently, expected profits from locating in FR1 will fall below those attainable in FR2, such that multinationals will locate in FR2 rather than FR1 (see Figure 3 below). In this case, the disaster will cause FDI inflows to decline in the directly affected region (i.e. FR1) and lead to intra-national FDI spillovers in the otherwise unaffected FR2. Yet, because the expected profits are lower in FR2 than pre-disaster profits in FR1, one should not expect spillovers to perfectly offset the FDI reductions in FR1, resulting in a moderate net loss in FDI inflows in the foreign country.

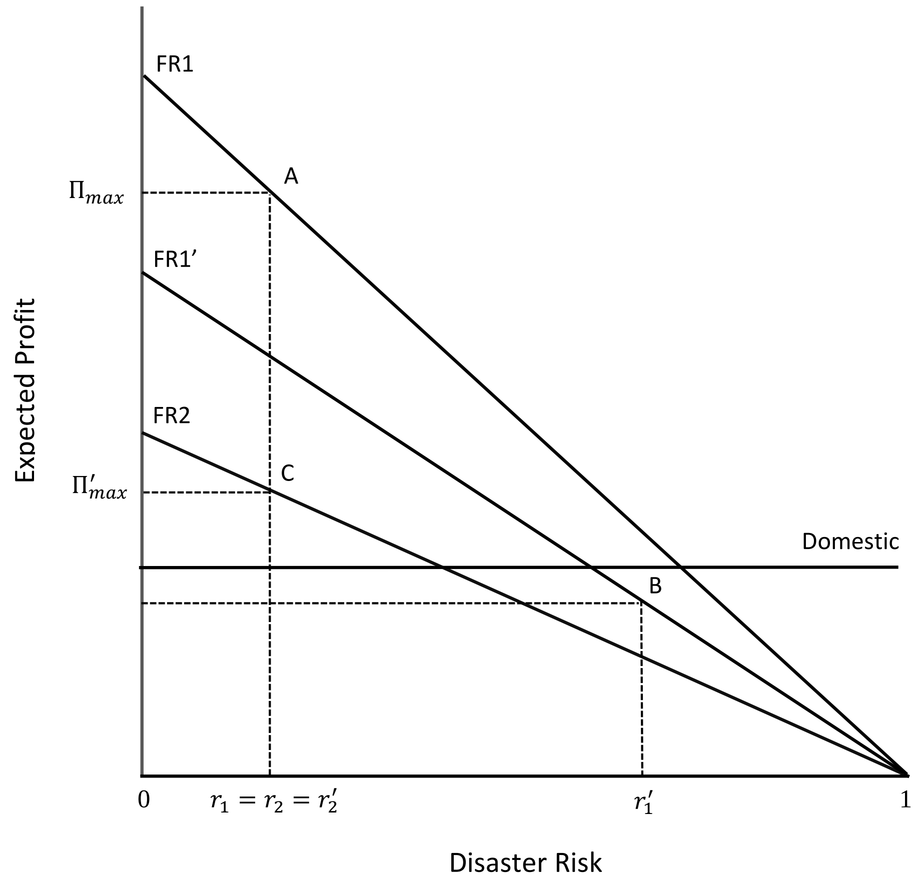


Figure 3: Disaster-Induced Location Switching from FR1 to FR2

Second, if cost and risk increases in FR1 are small, the ranking of preferred location choices may not change and FR1 remains the profit maximizing location (see Figure A1a in the Appendix). Nonetheless, expected profits will decline and one would expect less FDI inflows in FR1 as a result of the disaster. Lastly, it is possible that the disaster not only causes a large perceived risk increase regarding FR1, but also leads to a reassessment of disaster risk in FR2. Depending on the relative size of these risk increases, it possible that the domestic option becomes the preferred location choice and FDI inflows fall for both foreign regions (see Figure A1b).

Combined, this framework provides several testable hypotheses regarding the impact of a disaster on firm investment in the foreign country. First, our model predicts that a disaster will lead to a fall in investment in the affected regions and that size of this FDI reduction depends on the adjustments in perceived disaster risk and marginal cost. Second, our model predicts that the disaster may lead to intra-national spillovers in investment into otherwise unaffected regions. The sign and size of these spillovers depends on the unaffected region's competitive advantage and the multinationals' new risk assessment after the event. Lastly, the model shows that the inclusion of disaster risk can introduce a new mechanism allowing both direct and spillover effects to persist over time.

4 Data

To study the effects of the five disasters and test the theoretical predictions, we construct a monthly panel dataset for 16 Indian regions running from January 2006 to 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.[8] We combine these data with commonly used controls, such as annual statistics on regional domestic product and population (Blonigen and Piger, 2014), which are publicly available from India's Central Statistical Organisation.[9] Additionally, we include cross-sectional data on a variety of regional characteristics in order to identify heterogeneity in spillover effects. These data were collected as part of the 2001 Census and therefore predate any of the disasters in our analysis.

Table 1 reports the regional sample averages for these statistics and confirms some of the patterns previously noted in section 2. Average FDI inflows, for example, tend to be concentrated in a few regions that are largely unaffected by natural disasters, are greater in economic size, are more urbanized and developed, have more skilled labor, and boast access to one of the major seaports in India. Somewhat unexpectedly, these raw descriptive statistics also indicate no clear correlation between FDI inflows and the size of the region's population.

From Table 1, we also note the skewness in the distribution of FDI inflows, where a few regions receive the majority of investments. To adjust for this skewness while also retaining the useful information con-

[8]The states included in each region are listed in Table A1 in the Appendix.

[9]State-level population data are based on projections derived from the 2001 and 2011 Indian censuses. For 2006-2010, we use the projections based on the 2001 census, while projections for 2012-2019 are based on the 2011 census.

Table 1: Regional Sample Averages

	Monthly FDI Inflows ($ mil)	Natural Disaster	GDP ($ mil)	Pop. (millions)	Density ($100/km^2$)	% Urban	Access to Latrine	Major Seaport	Literacy Rate	% College Graduate	% Manu. Employment
Ahmedabad	122.4	0	759.2	61.6	2.6	37.4	23.7	0.0	48.2	3.3	17.7
Bangalore	440.8	0	718.5	47.8	2.8	34.0	22.9	1.0	57.6	4.2	28.6
Bhopal	18.9	0	408.5	74.2	2.8	46.8	13.8	0.0	52.7	3.1	28.4
Bubaneshwar	2.7	2	264.5	41.9	2.4	15.0	9.6	0.0	53.9	3.2	28.5
Chandigarh	29.1	3	755.9	61.6	3.6	24.3	37.8	1.0	59.5	3.9	29.8
Chennai	214.9	4	855.4	59.2	4.8	43.9	21.2	1.0	65.0	3.6	34.2
Guwhati	7.3	2	251.8	44.8	0.8	23.4	25.8	0.0	54.1	2.8	18.0
Hyderabad	82.0	4	465.2	55.8	2.8	27.8	20.8	1.0	52.4	3.7	30.8
Jaipur	16.7	0	496.4	69.9	1.6	23.4	21.9	0.0	49.0	2.6	25.8
Kanpur	5.1	3	968.9	214.2	4.2	23.2	23.5	0.0	46.3	3.1	38.7
Kochi	18.8	5	407.5	33.9	8.2	26.0	65.1	1.0	80.0	4.5	21.1
Kolkata	26.8	1 & 2	638.9	92.1	9.0	28.0	23.5	1.0	58.9	4.0	33.8
Mumbai	652.0	0	1461.3	92.0	3.1	42.4	28.3	1.0	66.0	5.0	31.0
New Delhi	207.4	3	394.8	17.5	92.9	93.0	68.0	0.0	69.8	12.7	26.0
Panaji	9.2	0	44.1	1.5	3.6	49.8	45.8	1.0	73.1	7.3	17.5
Patna	1.7	1 & 2	292.6	106.2	6.1	16.4	13.8	0.0	39.0	2.7	33.1

Notes: Monthly information on regional FDI inflows is collected by the regional branches of Reserve Bank of India and published from January 2006 through December 2019. Annual state-level GDP and population data are aggregated to the regional level. Information on density, urbanization, access to latrine, literacy rate, share of college graduates, and the share of manufacturing employment are based on the 2001 Census.

tained in zero-valued observations, we transform the FDI data using the inverse hyperbolic sine (IHS).[10] Our results tend to be robust, however, regardless of this transformation.

Lastly, 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 precise geographic data for the affected areas, shown in Figure 1a, as well as dates for the disasters, discussed in section 2. The EM-DAT database does not provide damage estimates at the regional level, so we treat all regions in the affected areas as if they were impacted equally. Importantly, there is significant variation in the regions affected by these five disasters and only two of the 16 regions are in the treated area for more than one disaster.

5 Empirical Strategy & Results

To identify the causal effects of the five disasters and shed light on the intra-national spillover patterns, we take three complementary approaches. We begin by estimating a simple difference-in-differences (DD) model that produces the traditional average treatment effects (ATE) for each disaster (see section 5.1). The ATE measures the change in mean FDI inflows between the directly affected regions (treatment group) and the otherwise unharmed regions (control group) and provides a useful baseline estimate of the overall disaster impact. However, unlike a traditional DD, we do not expect our "control group" to be unaffected by the disasters; on the contrary, our theoretical framework predicts positive investment spillovers into unaffected regions. Consequently, the DD estimates capture the sum of the direct and indirect effects.

Given that the DD estimates reflect both the reduction in FDI in affected regions and any investment spillovers into unaffected regions, we use an event study design to disentangle these effects (see section 5.2). By grouping observations by months to disaster and estimating separate time-to-event coefficients for affected and unaffected regions, we are able to dissect the DD estimates into direct effects and spillovers. Moreover, the event study allows us to capture the timing of disaster effects and check for any systematic variations in FDI inflows leading up to the disasters that could violate the parallel trends assumption underlying our DD estimates.[11]

[10] The inverse hyperbolic sine is a form of a log transformation, defined as $\log(y + \sqrt{y^2 + 1})$. Because the transformation is defined where y = 0, it is a common tool when working with skewed data (e.g. Zhang et al., 2000; Kristjánsdóttir, 2005)

[11] The time plot in Figure 2 also allows us to evaluate these parallel trends pre-treatment. Reassuringly, the plot shows that most regions are on similar trajectories prior to the first disaster. Thereafter, regions affected by disasters 1, 2 and 5, divert from the common

Lastly, we explore whether the estimated spillovers effects vary with regional characteristics. Our estimates point to several policy-relevant patterns in multinationals' relocation decisions that reveal how natural disasters can contribute to lasting regional inequalities (see section 5.3).

5.1 Baseline Estimates

We first estimate the ATE for each of the five disasters. To capture these effects, we estimate a fixed effects model of the form:

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

where F_{it} represents FDI inflows into region i in month t, D_{tk} is a dummy for whether the k^{th} disaster occurred before or during period t, and A_{ik} is an indicator for whether region i was in the affected area of disaster k. The interaction between D_{tk} and A_{ik} identifies post-disaster periods in the treatment group, and γ_k captures the coefficients of interest, namely the disaster-specific ATE. The inclusion of region and time fixed effects, α_i and ω_t, controls for time-invariant regional characteristics (i.e. geography) as well as common trends across all regions (i.e. national changes in tariff rates or tax incentives) and therefore suppresses the separate inclusion of D_{tk} and A_{ik}. The matrix X_{it} represents the constant term and the control variables, while ϵ_{it} captures the random error component.

Despite its appeal and common use in the literature, this specification has a few notable shortcomings. Even though the model is able 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 if these incentives are correlated with the location and timing of natural disasters. A particular concern is that regional responses to past disasters could bias our model's estimates in future periods. An advantage of our sample that helps address this concern is the multitude of disasters and their geographic and temporal variation. Consequently, we can separately estimate each disaster's ATE and look for common patterns. Because it is unlikely that region-specific changes are similarly correlated across all five disasters over the 14 year sample period, commonalities in the five treatment effects would lend support to the model's validity.

trend observed for regions affected by disasters 3 and 4 as well as the unaffected regions.

We present our baseline estimates in Table 2. Columns (1) through (5) report estimation results for each disaster separately. The point estimates of interest indicate statistically significant reductions in FDI caused by each of the major calamities. Our preferred specification is presented in column (6) and reports the coefficient estimates we obtain when regressing the IHS of FDI on all five disaster dummies simultaneously. Again, our estimates suggest that the occurrence of each of the five disasters is associated with an economically and statistically significant divergence in investment between affected and unaffected regions.

When we estimate the disaster impacts on total FDI inflows (column (7)) or logged FDI (column (8)) these results remain robust. In fact, all of the disaster effect estimates are statistically significant at the 1 percent level. The magnitude of the changes in FDI between treatment and control group range from -109 to -293 million dollars per month and represent between a 77.8 and 95.4 percent fall in investment relative to unaffected regions. These estimates, however, must be interpreted with care. In the absence of investment spillovers, our results could be interpreted as the direct disaster-induced reduction in FDI inflows in affected regions. In the presence of spillovers, however, they are the sum of two components: the direct reduction in FDI in affected regions and any potential spillovers into unaffected regions. For example, the estimated treatment effect of around -$110 million for Disaster 1 may be comprised of an $80 million dollar reduction of FDI inflows in the directly affected regions of Patna and Kolkata and a $30 million dollar positive spillover effect on unaffected regions. While the estimates presented in Table 2 cannot distinguish between these two components, we attempt to disentangle these effects via an event study design in the next section.

Lastly, we note that across all specifications reported in Table 2 we include one year lagged controls for log GDP and log population and report heteroskedasticity-robust standard errors.[12] Coefficients on our control variables tend to be statistically significant and carry the expected sign, with both regional GDP and population exerting a positive influence on FDI inflows.

[12] Our panel is comprised of 16 regions, which is a difficult complication to deal with when considering a clustered standard error structure. Cameron and Miller (2015) argue that there is no clear definition of what constitutes too *few* clusters, but suggest that thresholds may range from 20 to 50 for balanced clusters. Accordingly, we adjust the reported standard errors for common heteroskedasticity, rather than clustered. Of course, we test the sensitivity of our inference against this assumption and the results are qualitatively similar under either specification and available upon request.

Table 2: Average Treatment Effects

	(1) IHS FDI	(2) IHS FDI	(3) IHS FDI	(4) IHS FDI	(5) IHS FDI	(6) IHS FDI	(7) Total FDI	(8) Natural Log (FDI+1)
Disaster 1 ATE	-3.709					-2.554	-109.3	-2.529
	(0.185)					(0.197)	(30.97)	(0.238)
Disaster 2 ATE		-2.212				-2.499	-130.0	-1.686
		(0.135)				(0.124)	(13.72)	(0.124)
Disaster 3 ATE			-2.254			-3.094	-146.4	-2.102
			(0.133)			(0.129)	(16.43)	(0.105)
Disaster 4 ATE				-1.413		-2.297	-293.1	-1.915
				(0.105)		(0.0993)	(27.93)	(0.0909)
Disaster 5 ATE					-0.642	-1.609	-234.5	-1.503
					(0.245)	(0.223)	(44.24)	(0.164)
Ln(GDP$_{t-1}$)	2.255	1.298	2.241	2.409	2.229	1.722	78.89	0.728
	(0.366)	(0.378)	(0.422)	(0.420)	(0.419)	(0.334)	(104.8)	(0.323)
Ln(Pop$_{t-1}$)	0.633	0.427	0.424	0.715	0.707	-0.142	448.4	0.323
	(0.104)	(0.105)	(0.109)	(0.106)	(0.109)	(0.0966)	(45.78)	(0.0896)
Constant	-31.91	-17.47	-29.71	-35.13	-32.79	-16.09	-5654.5	-8.811
	(4.564)	(4.752)	(5.228)	(5.235)	(5.201)	(4.216)	(1121.8)	(4.032)
N	2688	2688	2688	2688	2688	2688	2688	2209
R^2	0.722	0.729	0.729	0.704	0.696	0.811	0.475	0.811
# of Affected Regions	2	4	3	2	1	10	10	10
Regional FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Standard errors, reported in the parenthesis, are heteroskedasticity-robust. The results presented in columns (1)-(5) show the separately estimated disaster ATEs, whereas the results given in columns (6) through (8) are based on jointly estimated disaster impacts. The dependent variable underlying regressions reported in columns (1) and (6) is the inverse hyperbolic sine of FDI, whereas the results given in columns (7) and (8) on raw FDI inflows and logged FDI data, respectively. The sample consists of a total of 16 Indian regions.

5.2 Event Study

The previous DD estimates are large, and likely represent a combination of the reduction in FDI experienced by directly affected regions as well as potential investment spillovers experienced by otherwise unaffected areas. To disentangle these two components, we utilize an event study design and apply it separately to the affected and unaffected regions. This framework has the added benefit of allowing us to evaluate the dynamics of the disaster impacts and test whether these treatment effect estimates are causal or a spurious result of diverging pre-disaster trends.

For the purposes of this analysis, we group observations according to their temporal distance from a disaster and estimate time-to-disaster coefficients for all but one reference period (t^*) representing the month prior to the strike of a disaster. The resulting estimation equation can be written as follows:

$$F_{it} = \sum_{j=\underline{j}}^{\bar{j}} \gamma_{t^*+j} I_{t^*+j} + \beta X_{it} + \alpha_i + \epsilon_{it}, \tag{9}$$

where F_{it} represents the IHS of FDI inflows into region i in month t, α_i controls for time-invariant regional characteristics, and the control variable matrix X_{it} includes an intercept, lagged regional GDP and population as before. The random error component is given by ϵ_{it}.

The key distinction from the previous DD analysis lies in the fact that we are identifying the disaster impact strictly from the temporal variation in regional FDI inflows before and after the natural disasters.[13] That is, we are no longer comparing temporal changes in FDI across affected and unaffected regions, but instead solely focus on pre- and post-disaster movements in investments for each of these groups separately. The fact that we observe five major natural disasters over our sample period strengthens our identification, but also limits the number of pre- and post-treatment months we can consider without overlapping post-treatment periods of previous disasters with pre-treatment periods of future disasters. Accordingly, the event window is given by $[\underline{j}, \bar{j}]$ and includes 18 months pre-disaster ($\underline{j} = 18$) and 18 months post-disaster ($\bar{j} = 18$).

The critical explanatory variables in Equation 9 are given by the set of indicators I_{t^*+j}, which mark the time periods relative to the disaster. The first post treatment period, for example, is identified by (I_{i,t^*+1}) and equals one at different points in time for regions affected by different disasters (i.e. $I_{i,t^*+1} = 1$ for Guwhati in April 2010 and for Kanpur in June 2013). The coefficients of interest are given by γ_{t^*+j} and capture both pre-trends leading up to the disaster as well as the dynamic disaster effects post landfall. Depending on the estimation sample, the coefficients on post-treatment months capture either the direct reductions in FDI experienced in affected regions or the spillovers effects in unaffected regions.

We present the pertinent coefficient estimates of these event studies in Figures 4a and 4b, and translate these results into percentage changes (Figures 4c and 4d) as well as adjustments in total monthly inflows (Figures 4e and 4f). The estimates provide compelling evidence in support of our baseline findings and emphasize that the treatment effects measured in the DD specification represent a combination of FDI inflow reductions in directly affected regions and positive investment spillovers into otherwise unaffected regions.

[13] This prohibits the inclusion of time fixed effects. An alternative to these fixed effects may be the inclusion of a time trend, and our results are robust to this inclusion.

The direct effect estimates (Figures 4a, 4c, and 4e) show a significant and immediate reduction in FDI inflows at the time of the disaster. In relative terms, foreign investment falls by 86.2% on average following the disaster. In absolute terms, our estimates suggest that average FDI inflows fall by approximately $133 million per month across the affected regions. Moreover, the loss in foreign investment appears persistent for at least 18 month post-disaster, suggesting that natural disasters may cause lasting damage to a region's competitiveness in multinational location decisions.

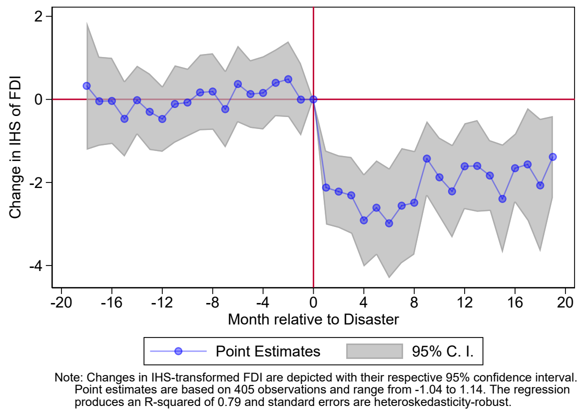
The indirect effect estimates (Figures 4b, 4d, and 4f) demonstrate that an economically and statistically significant portion of lost FDI inflows are reallocated towards unaffected areas in India. Relative to inflows observed during the excluded reference month, these positive spillovers amount to an $89 million dollar increase in monthly foreign investment after the disaster. The dynamics of these estimated spillover effects show that the relocation of investment requires a transition period of around 3-5 months. Thereafter, the disaster leads to remarkably persistent spillover effects and multinationals do not appear to transition back to the affected regions within the first 18 month.

Combined, the event study estimates indicate that multinational firms shift investment from affected to unaffected areas, such that for every dollar of investment lost in affected regions, 67 cents are reallocated to other regions *within* India. Together, these effects widen the gap in FDI inflows between affected and unaffected regions by around $220 million per month. This result is broadly consistent with the DD specification, where our estimates ranged from -$109 to -$293 million dollars across the five disasters.

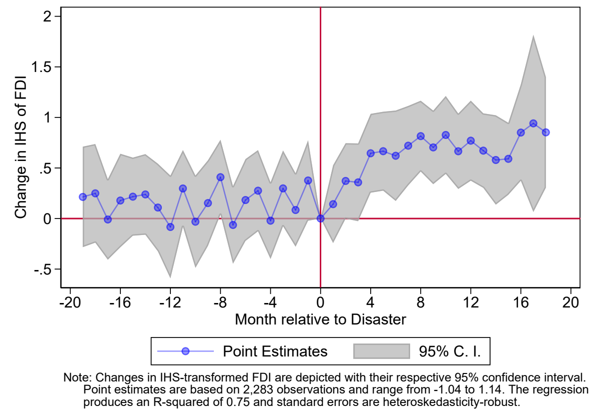
Lastly, both sets of results provide evidence in support of the parallel paths assumption underlying our baseline estimates. In both affected and unaffected regions, there is no evidence of a pre-trend for 18 month prior to the disasters. While our point estimates fluctuate around the excluded reference month, only one of the 36 pre-treatment coefficients is statistically significant at the 5%. The absence of these trends provides further evidence that we are indeed capturing the causal effect of the disasters.

5.3 Spillover Effect Heterogeneity

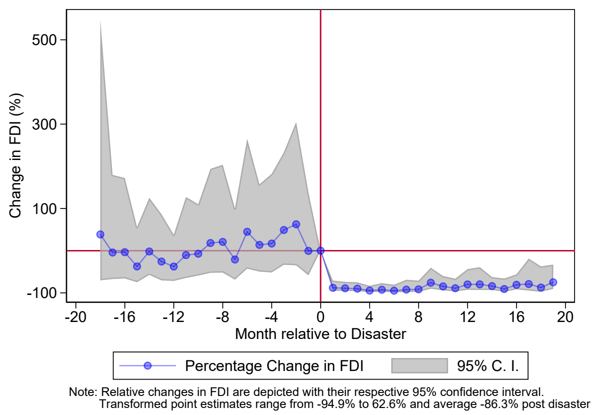
Given the presence of large positive investment spillovers into unaffected Indian regions, we ask whether these re-locations are equally distributed across unaffected areas, or are instead concentrated in regions with certain attributes. To explore this potential heterogeneity, we adopt a modified version of the fixed effects model discussed in section 5.1. Specifically, we expand Equation 8 by interacting each of the five



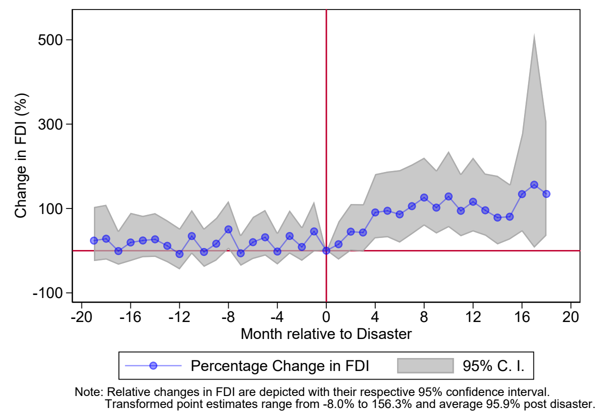
(a) Event Study Affected Regions (IHS Estimates)



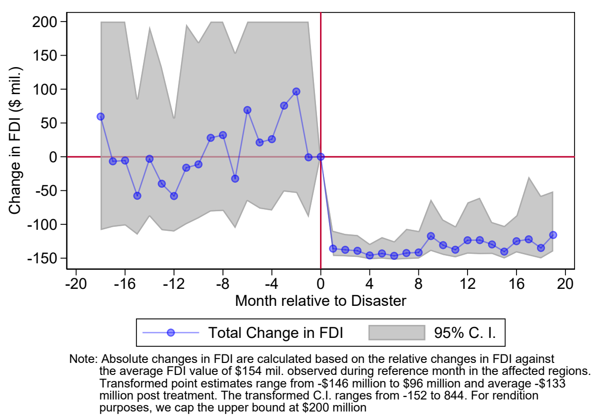
(b) Event Study Unaffected Regions (IHS Estimates)



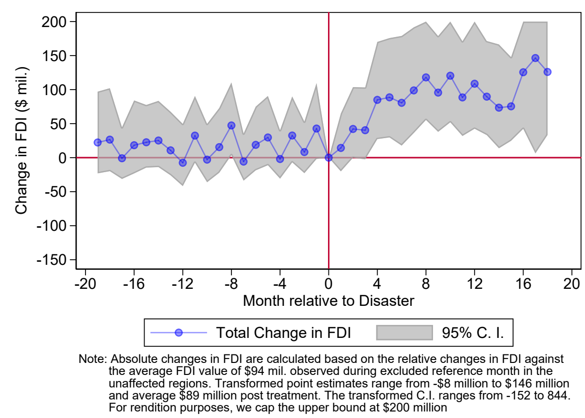
(c) Event Study Affected Regions (% Change)



(d) Event Study Unaffected Regions (% Change)



(e) Event Study Affected Regions (Total FDI)



(f) Event Study Unaffected Regions (Total FDI)

Figure 4: Event Study Estimates for Affected and Unaffected Regions

disaster dummies (D_{tk}) with a regional weight (W_i) and an indicator variable identifying the unaffected regions for each disaster (U_{ik}). The resulting estimation equation is given as follows:

$$F_{it} = \sum_{k=1}^{5} \gamma_k D_{tk} * A_{ik} + \sum_{k=1}^{5} \delta_k * W_i * D_{tk} * U_{ik} + \beta X_{it} + \alpha_i + \omega_t + \epsilon_{it}. \tag{10}$$

where F_{it} represents the IHS of FDI inflows into region i in month t and X_{it} gives the control variable matrix and intercept. As before, α_i and ω_t represent the region- and time-specific fixed effects, and ϵ_{it} is the random error component.

Similar to Equation 8, the terms $D_{tk} * A_{tk}$ identify the five direct treatment effects on affected regions and these ATEs are captured by γ_k. Under this specification, the coefficients of particular interest are δ_k for $k = 1, \ldots, 5$, which reveal whether regional characteristic W, such as market potential, level of development, or labor skill, strengthens or weakens the spillover effect for disaster k. The specific weights included in our analysis are 1) contiguity status with respect to at least one of the affected regions; 2) density; 3) population share living in urbanized areas; 4) population share that has access to a latrine within premises; 5) access to a major Indian seaport; 6) literacy rate; 7) share of manufacturing employment; and 8) similarity in industry composition relative to the affected area.[14] Because any these variables (except contiguity) may be affected by the occurrence of a natural disaster (i.e. through evacuee migration), we fix them at their respective 2001 values, predating any of the disasters observed during our sample.

Columns (1) through (8) of Table 3 present the results for our eight regional weights. Panel A provides the direct ATEs of the five disasters for affected regions. As expected, these treatment effect estimates are unaffected by the inclusion of spillover weights and are qualitatively and quantitatively similar to the baseline estimates reported in column (6) of Table 2.

The coefficients in Panel B of Table 3 represent the attribute-specific spillover effects. We observe a few noteworthy patterns that align with some of the findings in the previous literature and fit with our theoretical framework. First, market potential seems to play a positive role in determining the multinational's re-location decision. Higher levels of density, for example, are associated with greater FDI inflow spillovers

[14] The similarity weight follows a specification proposed by Boarnet (1998). Essentially, we compare an unaffected region's employment share in a particular industry (s_{ij}) against the average employment share of the affected regions in that industry (s_{aj}) relative to all other unaffected regions' similarity. Greater similarity in employment shares receive higher weights. Finally, we sum these similarity weights across all 2-digit industries identified in the Census dataset. The specific weight specification is given as follows: $W_i = \sum_j \frac{1/|s_{ij} - s_{aj}|}{\sum_i 1/|s_{ij} - s_{aj}|}$.

Table 3: Spillover Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Geography	Market Potential		Development		Skill & Industry Composition		
	Contiguity	Density	Urban	Latrines	Ports	Literacy	Manu. (%)	Similarity
Panel A - Direct Effects:								
Disaster 1 ATE	-2.682	-2.480	-2.295	-2.235	-2.522	-1.745	-3.061	-3.239
	(0.211)	(0.196)	(0.215)	(0.225)	(0.205)	(0.509)	(0.406)	(0.242)
Disaster 2 ATE	-2.342	-2.239	-2.496	-2.285	-2.445	-1.638	-3.035	-2.300
	(0.145)	(0.151)	(0.189)	(0.178)	(0.144)	(0.422)	(0.362)	(0.160)
Disaster 3 ATE	-3.055	-3.169	-3.343	-3.233	-2.954	-3.086	-3.298	-3.023
	(0.143)	(0.167)	(0.178)	(0.170)	(0.141)	(0.180)	(0.182)	(0.141)
Disaster 4 ATE	-2.307	-2.275	-1.825	-1.909	-2.519	-1.952	-1.912	-2.616
	(0.120)	(0.098)	(0.122)	(0.113)	(0.139)	(0.140)	(0.151)	(0.132)
Disaster 5 ATE	-1.726	-2.094	-1.634	-2.216	-1.751	-1.981	-1.662	-1.698
	(0.226)	(0.223)	(0.233)	(0.238)	(0.229)	(0.242)	(0.238)	(0.234)
Panel B - Indirect Effect Patterns:								
Spillover Pattern ND 1	-0.333	0.005	0.007	0.010	0.078	0.014	-0.019	-0.989
	(0.158)	(0.002)	(0.003)	(0.004)	(0.149)	(0.008)	(0.013)	(0.202)
Spillover Pattern ND 2	0.194	0.001	-0.001	0.003	-0.134	0.013	-0.013	0.212
	(0.142)	(0.002)	(0.003)	(0.004)	(0.140)	(0.007)	(0.012)	(0.106)
Spillover Pattern ND 3	0.040	0.121	-0.007	-0.005	0.434	-0.002	-0.016	0.384
	(0.155)	(0.026)	(0.004)	(0.004)	(0.150)	(0.003)	(0.006)	(0.080)
Spillover Pattern ND 4	0.128	0.022	0.016	0.017	-0.100	0.008	0.011	-0.221
	(0.113)	(0.002)	(0.002)	(0.003)	(0.137)	(0.002)	(0.005)	(0.138)
Spillover Pattern ND 5	-1.047	-0.005	-0.002	-0.004	-0.199	-0.002	-0.000	-0.276
	(0.186)	(0.002)	(0.002)	(0.003)	(0.149)	(0.002)	(0.005)	(0.126)
Panel C - Control Variables								
Lagged ln(GDP)	1.844	0.788	0.880	1.131	1.788	1.408	1.551	1.844
	(0.382)	(0.331)	(0.338)	(0.336)	(0.342)	(0.354)	(0.379)	(0.350)
Lagged ln(Pop.)	-0.043	-0.134	-0.087	-0.052	-0.239	-0.160	-0.010	-0.266
	(0.110)	(0.094)	(0.100)	(0.098)	(0.108)	(0.098)	(0.102)	(0.118)
Constant	-18.708	-4.452	-6.119	-9.906	-15.954	-13.196	-14.487	-15.844
	(4.926)	(4.172)	(4.258)	(4.262)	(4.274)	(4.475)	(4.798)	(4.346)
N	2688	2688	2688	2688	2688	2688	2688	2688
R^2	0.812	0.820	0.815	0.815	0.811	0.813	0.812	0.813
Region FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Standard errors, reported in parenthesis, are heteroskedasticity-robust. Each column presents the full set of direct average treatment effects on affected regions and spillover patterns experienced by unaffected regions across all five disasters. The results in column (1) present geographic spillover patterns based on contiguity of unaffected regions to at least one affected region. Coefficients presented in columns (2) and (3) explore spillover patterns based on market potential, which we measure using population density and percentage of people living in urbanized areas. Coefficients presented in columns (4) and (5) explore spillover patterns based the unaffected region's level of development, as measured by the population share with access to a latrine within premises and whether it hosts one of the major Indian seaports. Results presented in columns (6) through (8) investigate spillover patterns based on the labor skill and industrial composition of unaffected regions. Labor skill is measured via the literacy rate, whereas industry composition is captured via the manufacturing share among the employed as well as the overall similarity between the industry composition of an unaffected region relative to the average composition of the affected regions.

for three of the five disasters, while only one shows a negative spillover pattern with respect to density (see column (2)). With respect to urbanization (column (3)), only two coefficients are statistically significant at the 5% level. Both carry a positive sign indicating that greater urbanization is not only associated with greater economic growth (Sachs et al., 2002), but also larger FDI spillovers.

Similarly, a region's level of development appears to matter in the multinational's decision making process. In column (4) of Table 3, we report the coefficient estimates for the share of a region's population with in-home latrine access and find two statistically significant coefficients, both of which point to a positive correlation between this development indicator and the disasters' FDI spillovers. The same holds true if we proxy for development using access to tap water or electricity (not shown in Table 3).

Somewhat surprisingly, access to infrastructure, such as seaport access, matters less in the re-location decision (see column (5)). The coefficients have mixed signs and tend to be statistically insignificant. Only FDI spillovers resulting from the Northern Indian Floods (disaster 3) appear to be significantly higher in unaffected regions with a major seaport.

Similar to infrastructure, geography seems to matter less to the multinational relocation process. If anything, contiguity, or closeness to the affected areas, appears to be negatively correlated with FDI spillovers (see column (1) of Table 3).[15] The negative and significant coefficients for the Bihar Floods (disaster 1) and Kerala Floods (disaster 5) indicate that multinationals may avoid relocating near the affected regions for some disasters, but this pattern does not appear consistent.

Lastly, we evaluate the impact of labor skill and industry composition on FDI spillovers. Labor skill, which we measure via the literacy rate, exerts a positive influence on investment relocation decisions (column (6)). Three of the five coefficients are statistically significant at the 10% and carry a positive sign, indicating that firms look to locate near areas with a higher level of human capital.[16] In contrast, the effects of industry composition in unaffected regions seem to be mixed across the five disasters. Spillovers resulting from the Northern Indian Floods, for example, are negatively correlated with the size of the manufacturing sector in the unaffected region, while the opposite is true for spillovers resulting from the South Indian Floods.

We also find mixed results with respect to economic similarity. In a framework where a multinational originally intended to invest in the region struck by a disaster, but chooses to reinvest elsewhere, we would

[15]This results is also consistent across other measures of distance to disaster.

[16]We also explore the role of the share of college graduates among workers and find a similarly positive influence.

expect the next best choice to be similar to the affected region. However, of the four statistically significant coefficients, two indicate a negative correlation with FDI spillovers and the other two indicate a positive correlation. The former may be indicative of intra-national supply chain linkages that transmit the negative disaster impact into otherwise unaffected regions and cause unfavorably relocation conditions, whereas the latter may capture the particular suitability of unaffected regions as a new investment location with a similar employment mix. As a result, the exact nature of the impact of economic similarity on FDI spillovers (and other attributes as well) may critically hinge on the industry composition of the directly affected areas. That being said, regions affected by disasters 1 and 5, for which similarity in industry composition seems to dampen FDI spillovers, tend to be specialized in manufacturing of household and non-household products, whereas regions affected by disasters 3 and 4, for which similarity exerts a positive influence on investment relocation, seem to be less specialized in manufacturing and more concentrated in retail, transportation, and other service industries.

Overall, most of these estimated FDI spillover patterns are broadly consistent with our theoretical framework, while some are more difficult to reconcile. On the one hand, multinationals that are forced to relocate may look to more developed and densely populated regions, where healthier workers imply lower marginal costs and greater urbanization offers a larger and more accessible market. Moreover, the negative correlation of FDI inflows with respect to contiguity gets at an important tension in relocation decisions, where multinationals must weigh disaster risk against other location-based concerns. Through this lens, the estimated effects suggest that risk factors may be a more important concern than the ease of reinvestment in a nearby regions. On the other hand, our seaport results point to the fact that international transport costs, which are surely influenced by access to this type of infrastructure, may be a less important determinant of relocation decisions.

6 Discussion and Limitations

Together, our findings provide evidence in support of the hypothesis that natural disasters can have a significant and lasting impact on the "risk factor" of investing in directly affected regions. Consequently, this study provides a window into the decision making of multinational firms under conditions of risk. Relative disaster risk between regions appears to be a significant consideration in location decisions, as multinationals shift over 60 percent of lost investment flows from affected to unaffected regions following a disaster. Moreover, the longevity of our measured effects indicates that the salience of disaster risk does not quickly dissipate. These results are consistent with our theoretical framework, where a past disaster lowers expected profits in future periods and leads to reinvestment decisions within a foreign country.

Past studies on the role of disaster risk in multinational location decisions have found little impact (e.g. Oh and Oetzel, 2011). However, because these analyses were conducted at the country-level, the presence of large and offsetting *within-country* investment shifts found in this paper may be weakening their estimates. For example, an analysis of our data at the country level would only capture a $40 million impact on monthly FDI inflows, less than two-thirds of the true $130 million monthly impact in affected regions.

Our results also suggest an element of path dependence in location decisions. In India, where regional divergence in living standards and growth rates has become a significant concern for policymakers, we provide a channel through which these disparities can emerge and endure. Indeed, the persistence of our direct and indirect effect estimates indicates that affected regions can become "left behind" following a major disaster, leading to a long-run exit of multinational firms. At the same time, they can cause FDI inflows in some unaffected regions to thrive. Consequently, a disaster shock can lead to a reversal of the "lock-in" effect in the affected regions (see, for example, Fujita and Mori (1996) or Behrens (2007)) and amplify agglomeration economies in unaffected regions. For example, the destruction and displacement of productive capacity following a disaster might initially lead to only a short-run fall in FDI, but once multinationals locate elsewhere and economies of scale emerge, they are dissuaded from returning even after the affected region has physically recovered.

Finally, given that the majority of the lost FDI in affected regions is allocated to other regions within India rather than overseas, our findings imply significant cross-country relocation costs, driven by lost access to the Indian market, India's superior cost advantage, or a combination of both.

6.1 Limitations

Although our estimates deliver consistent and compelling evidence to support these arguments, there are three noteworthy limitations to our analysis. First, given that our study focuses solely on India, there are 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. It may also be the case 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.[17]

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 shocks that occur simultaneously. For this reason, it is possible that differential policy responses to a disaster could challenge the validity of the findings. For a significant bias to take hold, affected and/or unaffected regions would need to enact a similar type of policy following each of the five disasters in our analysis, such that the policy-induced impacts on FDI inflows consistently bias our estimates in same direction. For example, it would need to be the case that unaffected regions systematically adopt some FDI incentivizing policy immediately after each disaster or that affected regions adopt similar recovery efforts that aim to prevent FDI relocation. The latter set of policies seems more likely, but would also have to be implemented immediately following each of the five disasters. If such policies did exist, our results would have to be reinterpreted as the residual disaster impact on FDI inflows in the presence of recovery policies, and could help to evaluate the efficacy of such efforts.

Finally, our mixed results regarding spillover patterns and industry composition may suggest significant diversity across multinationals in their reinvestment decisions. An analysis at the industry or firm level could shed light on which type of foreign investment is more affected by a natural disaster and which is more prone to locate. It is entirely possible that our aggregated regional data is missing some diverse industry patterns, providing the opportunity for future research when such data become available.

7 Conclusion

This paper finds significant impacts of natural disasters on FDI. The magnitude and persistence of our estimated disaster effects show that shifts in multinational firm location are a significant and understudied mechanism through which natural disasters impact the economy. Additionally, the dominance of within-country investment relocations from affected to unaffected regions emphasizes the fact that country-level

[17] FDI data at the regional level, which is currently rarely reported, will be important for this type of analysis.

analyses are not sufficient for understanding the relationship between natural disasters and FDI. Our results show that the application of country-level data will cause researchers to severely underestimate the effects of natural disasters on FDI in the affected regions and miss the considerable intra-national reallocation of these foreign investments.

These findings have important implications for the future. Given that some regions directly benefit from natural disasters, due to positive investment spillovers, our results highlight the challenge of building broad consensus around disaster mitigating policies, such as climate change prevention. Furthermore, our findings reveal the sensitivity of multinational firms' location decisions to disaster risk. Ultimately, the results of this paper tell a pessimistic story, predicting underinvestment in disaster prevention at the national level, a long-run exit of multinational firms from the areas most affected by climate change, and continued divergence across Indian regions, reinforced by the persistent disaster-induced effects on foreign direct investment.

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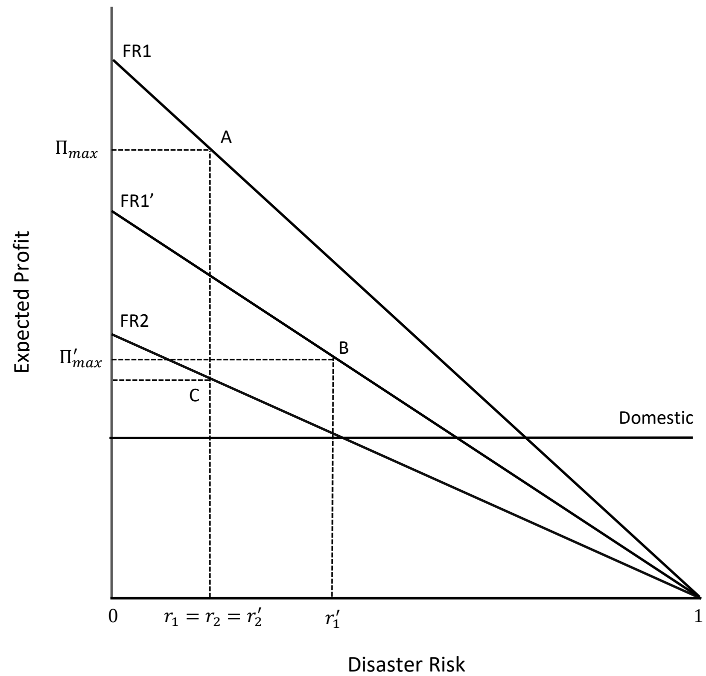
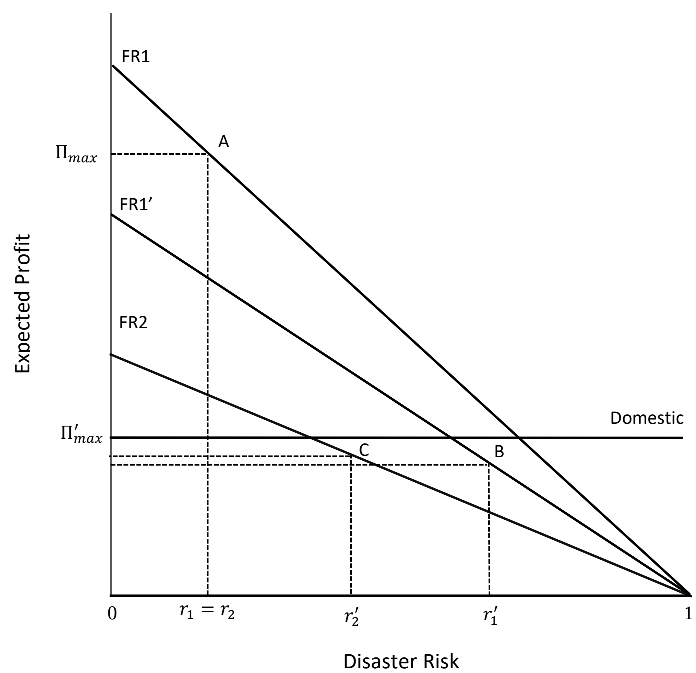
Appendix



(a) No Location Switching



(b) Disaster-induced Location Switching from FR1 to Domestic Option

Figure A1: Potential Disaster Effects on Multinationals' Location Choice

Table A1: Region-to-State Concordance

Region	States
Ahmedabad	Gujarat
Bangalore	Karnataka
Bhopal	Chhattisgarh, Madhya Pradesh
Bubaneshwar	Odisha
Chandigarh	Chandigarh, Haryana, Himachal Pradesh, Punjab
Chennai	Puducherry, Tamil Nadu
Guwhati	Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Tripura
Hyderabad	Andhra Pradesh
Jaipur	Rajasthan
Kanpur	Uttar Pradesh, Uttarakhand
Kochi	Kerala, Lakshadweep
Kolkata	Sikkim, West Bengal
Mumbai	Dadra and Nagar Haveli, Daman and Diu, Maharashtra
New Delhi	Delhi
Panaji	Goa
Patna	Bihar, Jharkhand