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# Natural disasters, intra-national FDI spillovers, and economic divergence: Evidence from India[☆]

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ABSTRACT

This paper studies the effects of natural disasters on foreign direct investment, considering the case of India. We document large and persistent investment reductions in affected regions following a disaster as well as lasting positive spillovers into otherwise unaffected Indian regions. Intra-national relocations account for more than two-thirds of the losses in affected areas, explaining the puzzlingly small country-level findings of previous works. Furthermore, we show that these investment shifts tend to flow into more developed, less disaster-prone regions, fueling the prominent divergence in India's economic growth. Combined, our results suggest that multinational firms consider both local cost and region-specific disaster risk when selecting locations for production.

## 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 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. This investment, however, has been uneven across Indian regions, and the resulting spatial disparities in development have become a real concern for policymakers (New York Times, 2005; The Economist, 2017). 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, it 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 (Dilley et al., 2005; World Bank, 2014).

The goal of this paper is to connect these trends, identifying the effect of natural disasters on FDI inflows into directly affected regions and quantifying the resulting intra-national investment spillovers into

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

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unaffected areas. Using data from 16 regions within India, we consider the impact of the five most destructive disasters between 2006 and 2019 and uncover three key insights. First, we find evidence that FDI falls substantially in 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, showing that multinational firms shift investment intra-nationally away 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 the disaster impacts are immediate and persist over six years after a disaster.

We further investigate why foreign firms move and where these multinationals choose to relocate their investments. Fixed capital declines in response to natural disasters, whereas new business life insurance premiums tend to rise in affected areas. Accordingly, both production costs and the assessed risk of future disasters appear to increase in affected regions, helping to explain the persistent decline in FDI. Exploring the predictors of where multinationals choose to reinvest within India, we find that urbanization, physical development, labor skill, and the perceived risk of future disasters are key determinants of these spillovers. Consequently, we provide a channel through which regional disparities can persist, as multinationals shift investment away from the areas most affected by natural disasters and into more developed regions. We show that these results are consistent with a model of multinational location choice in which firms consider both local cost and region-specific disaster risk when selecting locations for production.

Our findings contribute to several related literatures. Most immediately, we add to the evidence on the economic impacts of natural disasters. While there has been significant work on the 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 longer-term impacts (Skidmore and Toya, 2002; Rasmussen, 2004; Cuaresma et al., 2008; Raddatz, 2009; Anttila-Hughes and Hsiang, 2013; Hsiang and Jina, 2014; 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. All of these works are at the country-level and examine either the cross-sectional correlation between number of natural disasters and FDI (Escaleras and Register, 2011) or the impact of one disaster over time (Kukułka, 2014; Anuchitworawong and Thampanishvong, 2015). Such studies tend to find modest reductions in countrywide FDI.

While these works have improved our understanding of disaster impacts on national FDI flows, we are the first to consider effects at the intra-national level. Given that the physical impacts of disasters are localized, this allows us to consider effects in a more narrowly defined area struck by the disaster. Moreover, it enables us to examine where multinationals choose to reinvest within a country—a topic that cannot be addressed with national-level data. Identifying these intra-national responses in multinational location choice matters for several reasons.

First, our results show that previous country-level estimates may only represent the "tip of the iceberg." The magnitude and persistence of our direct and indirect effect estimates provide strong evidence that *within-country* investment shifts are critical to understanding the full scope of a disaster's impact. Indeed, given that more than two-thirds of investment losses are reallocated to other regions within India, our findings suggest that studies at the national level will severely underestimate a disaster's impact in directly affected regions and therefore mislead policy efforts.[2]

Second, the within-country analysis adds to an emerging literature considering firm location decisions at this disaggregated level (see Peng and Lebedev (2017) for a review). Our research is one of the first to consider intra-national patterns of FDI in any context, and the only to measure within-country investment responses to natural disasters. Our findings indicate that relative disaster risk may be a significant concern for multinational firms settling on a location within a chosen country—even after a region has physically recovered from a disaster. Additionally, the persistence of our measured effects indicates that the salience of the disaster effects does not quickly dissipate.[3]

Third, our use of within country panel data represents a methodological advance. Much of the previous literature relies on using the cross-sectional correlation between the number of natural disasters in a country and its FDI inflows to identify causality (e.g. Escaleras and Register, 2011). Due to unmeasured cross-country variation, this specification raises significant concerns. To combat this problem, we instead utilize panel data, allowing us to control for time invariant factors at the regional level. Other studies, which look at only one disaster or country, implement difference-in-differences style designs that use nearby countries as the control group. By constructing a control group made up of unaffected regions in the *same* country, we argue that our design is able to create a more credible counterfactual. Additionally, because we observe multiple disasters over a 13 year period, we are able to implement an event study specification to check for parallel pre-disaster trends and capture time-varying treatment effects.

Finally, our results contribute to work on agglomeration effects and regional divergence (Fujita and Mori, 1996; Quah, 2002; Rossi-Hansberg, 2005; Kline and Moretti, 2013; Alfaro and Chen, 2014; Davis et al., 2014), providing a channel through which such disparities can emerge and endure. The persistence of our estimates six years post-disaster emphasizes an element of path dependence in the location decisions of multinational firms, where businesses 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 growth, becoming 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.

Given that we show significant and persistent disaster-induced changes in the location decisions of *foreign* firms, this paper raises the question of how *domestic* firms respond to natural disasters and what the differences might be between foreign and domestic firms' responses. Based on our findings, the old concern over "footloose" foreign multinationals switching investment locations across countries (Görg and Strobl, 2003; Alvarez and Görg, 2009) appears to be equally important across regions within the same country. While we discuss several hypotheses for why domestic firms may be considerably less responsive to natural disasters than multinationals, this is an important topic for future research.

The remainder of the 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 develop a theoretical framework for the location decisions of multinational firms under conditions of disaster risk. In Section 4, we discuss the economic and disaster data used in our analysis. Our empirical results are presented in Section 5 and detail 5.1) the baseline difference-in-differences estimates of each disaster's impact on FDI; 5.2) the dissection of these effects into direct FDI disruptions and indirect intra-national spillovers; and 5.3) an investigation into the mechanisms driving the direct FDI reductions and indirect 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] See, for example, Oh and Oetzel (2011), who find insignificant effects of disasters on multinational location choice at the national level.

[3] As such, this research also adds to the literature on the decision making of multinational firms under conditions of risk.

## 2. Economic growth, natural disasters and FDI inflows in India

India's development, particularly post-reform, has been characterized by considerable economic divergence across regions (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 initial economic size. Common explanations for these disparities include differing rates of urbanization (Sachs et al., 2002), variation in physical and social infrastructures (Lall, 1999, 2007), state-level policy reforms (Ghosh, 2012), and differences in FDI inflows (Ghosh, 2012).

Over the more recent time period, India has not only experienced growing regional inequalities, but has suffered from multiple natural disasters. Given that only the most disruptive events have significant economic ramifications (Felbermayr and Gröschl, 2014), we focus our analysis on India's five most destructive disasters over the 2006 to 2019 sample period. According to the Dartmouth Flood Observatory, which classifies disasters according to their physical severity, these were the only five disasters to be classified as "extreme events" and were much more destructive than any other calamity during this time period.[4]

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, 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 major 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). Moreover, anecdotal accounts from the region document a significant exit of multinational firms in the post-disaster period, with one source citing a 97% investment decline in West Bengal (Business Standard, 2013a,b).

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, 2013). 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). Additionally, the storm led to the displacement of a number of automotive plants in the region, a key source of international investment.

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, in terms of physical severity, these disasters are the five most significant such events over the period of analysis and are orders of magnitude more extreme than any of the smaller disasters that hit India during this time. Finally, the disasters are not concentrated in one region (see Fig. 1(a)) and therefore make our identification strategy more credible.[5]

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 Fig. 1(b), 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.[6]

To produce preliminary insight into whether these natural disasters exerted any influence over regional FDI inflows, we plot FDI inflows over time, differentiating across six types of regions: those affected by natural disasters (ND) 1 and 2[7], those only affected by ND 2, 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. Fig. 2(a) depicts FDI inflows simultaneously for all region types and indicates that average monthly foreign investments 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 appears to be influenced by the occurrence of major natural disasters.

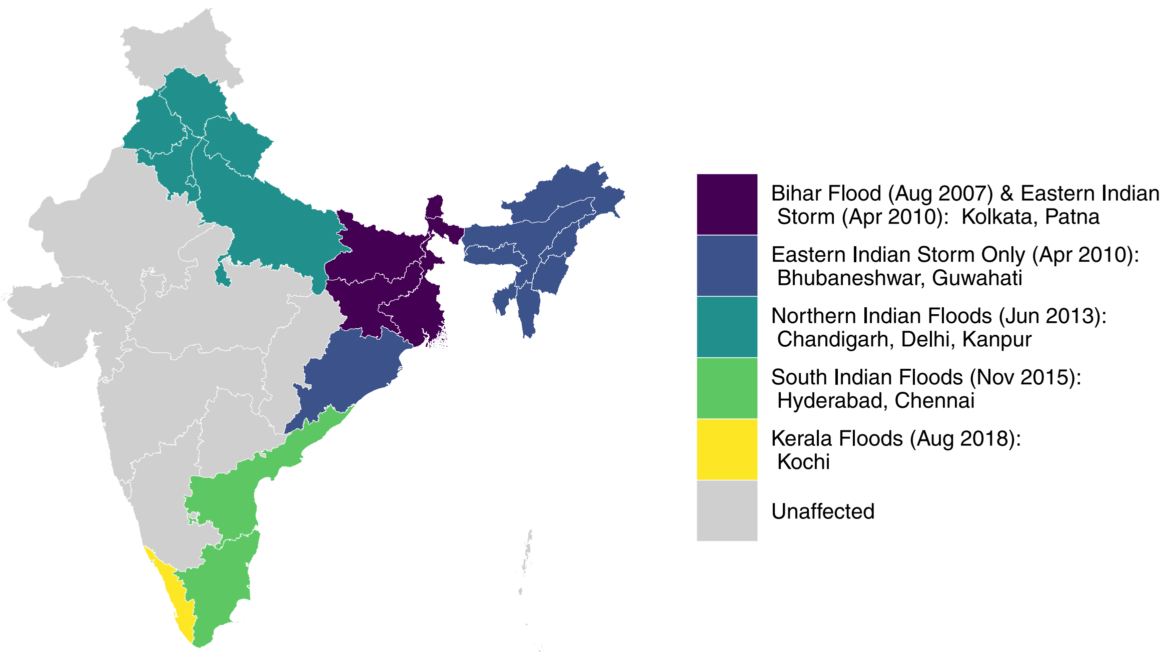
To take a closer look at these individual disaster effects, we plot each group of affected regions separately. Figs. 2(b) through 2(f) illustrate that each of the disasters had a notable impact on FDI inflows in the directly affected regions. The Northern Indian Floods (ND 3), for example, coincide with a drastic reduction of around $200 million per month in average FDI inflows in the affected regions (see Fig. 2(d)). 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 (see Fig. 2(e)). Interestingly, the timings of the other disasters in other Indian regions appear to coincide with uncharacteristic increases in foreign investment inflows both in the unaffected regions (see Fig. 2(a)) and to some extent those regions affected by other disasters (see Figs. 2(c), 2(d), 2(e), and 2(f)). These investment patterns provide first evidence of disaster-induced FDI disruptions in affected regions, combined with intra-national substitution into unaffected areas.

[4] We select the natural disasters used in our analysis based on their physical characteristics. This is preferable to severity measures based on human or monetary costs, given that these outcomes are endogenous to level of development and may also suffer from significant measurement error due to reporting differences across regions. We test the sensitivity of our results against the inclusion of additional, less damaging disasters in Appendix B. As expected, we find consistent but smaller effects.

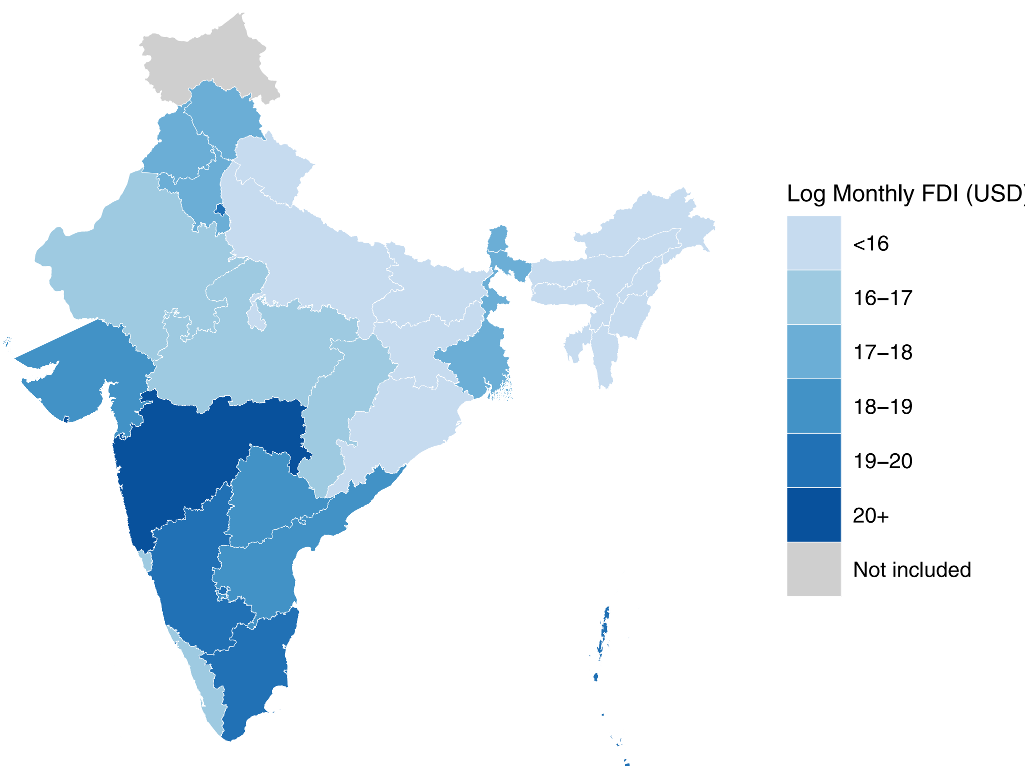
[5] One potential concern with our selection is that the 2004 Indian Ocean earthquake and tsunami occurred only a year before our data begins and is therefore not included in our analysis. In India, it affected the Andaman and Nicobar Islands, which are not included in our panel, and the southern state 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.

[6] One might be concerned that our results are driven entirely by the dominant investment flows into the unaffected regions of Maharashtra (which includes Mumbai) and Karnataka (which includes Bangalore). Reassuringly, our findings remain consistent when we exclude these regions (see Fig. B.1 in Appendix B).

[7] The districts Patna and Kolkata were affected by both disasters 1 and 2, while regions Bhubaneshwar, and Guwahati were only affected by the second disaster.

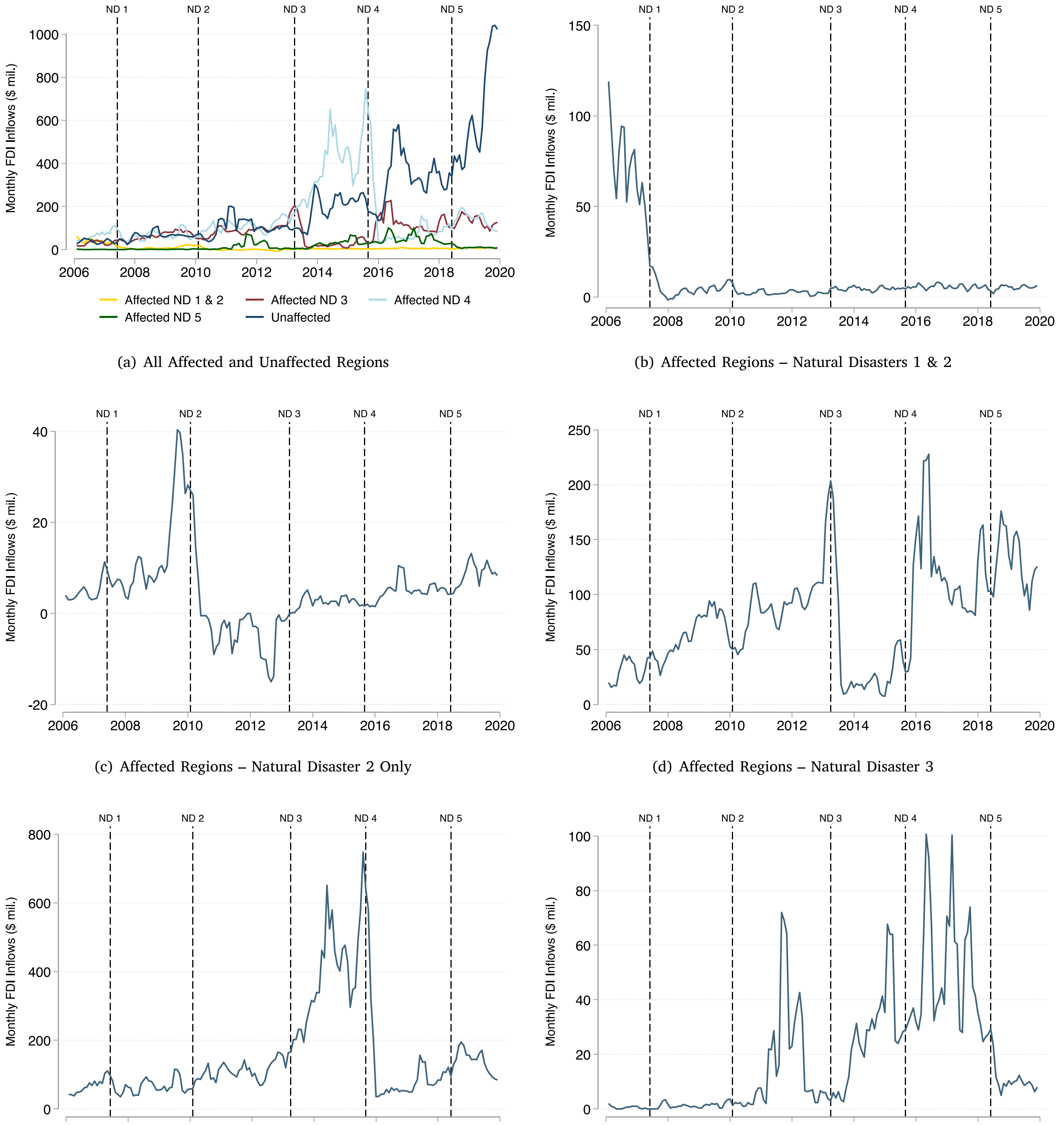



(a) Affected Regions for the Five Disasters




(b) Average FDI Inflows by Region

**Fig. 1.** Affected Regions for the Five Natural Disasters and Regional FDI Inflows (2006–2019).
*Notes:* Panel (a) maps the affected regions for the five main natural disasters. The Bihar Flood in August of 2007 is the first disaster included in our analysis and struck the regions of Kolkata and Patna. Second, the April 2010 Eastern Indian Storm hit the regions of Bhubaneshwar, Guwahati, Kolkata and Patna (the last two had already been affected by the earlier Bihar floods). Third, the Northern Indian Floods struck the regions of Chandigarh, Delhi, and Kanpur in June of 2013. Fourth, in November 2015 the South Indian Floods affected the south-eastern regions of Hyderabad and Chennai. Finally, the Kerala Floods struck India's southern region of Kerala on Augest 2018. Panel (b) shows average log monthly FDI inflows for the 16 Indian regions included in our analysis over the period 2006-2019. Investment tends to be concentrated in India's western and southern regions, as well as Delhi in the north.




(a) All Affected and Unaffected Regions

(b) Affected Regions – Natural Disasters 1 & 2

(c) Affected Regions – Natural Disaster 2 Only

(d) Affected Regions – Natural Disaster 3

(e) Affected Regions – Natural Disaster 4

(f) Affected Regions – Natural Disaster 5

**Fig. 2.** FDI Inflows by Disaster-Affected Regions (2006–2019).
*Notes:* This figure shows raw monthly FDI inflows by disaster-affected regions. Panel (b) shows regions hit by both the Bihar FLood and Eastern Indian Storm, panel (c) shows regions struck only by the Eastern Indian Storm, panel (d) shows regions affected by the Northern Indian Floods, panel (e) shows regions affected by the South Indian Floods, and panel (f) shows regions affected by the Kerala Floods. Panel (a) plots all these series together, along with inflows for regions unaffected by any of these five disasters. The FDI statistics come from the Reserve Bank of India's regional branches and are in millions of U.S. dollars. As we discuss in Section 2, the FDI inflow data include only equity capital inflows and do not include re-invested earnings or intra-company loans. Additionally, they only reflect multinational corporations, and therefore do not include government aid or investment from NGOs.

## 3. Theory of multinational firm location

### 3.1. Motives for FDI

Motivated by the potential influence of natural disasters on these striking foreign investment patterns, we extend a simple model of multinational location choice (Head, 2007; Neary, 2009) to help explain the observed phenomena and guide 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 our study focuses on FDI in India, we build on the vertical framework.[8]

### 3.2. Potential impact channels of a natural disaster

Natural disasters are a significant concern for global firms looking to invest in India (Dilley et al., 2005; World Bank, 2014). We begin by considering the channels through which a past disaster can influence present and future FDI location choices. The most prominent explanation in the context of vertical FDI is the disaster-induced rise in the cost of production. With the displacement of workers, destruction of factories, and disruption of critical infrastructure, such as roads, electricity grids, water, and sanitation, a natural disaster can raise the cost of labor and capital and thereby undermine the competitive advantage of a potential investment location. Accordingly, we assume that the location-specific marginal cost of production ($c_j^s$) can take on two distinct values depending on the state of the world:

$$c_j^s = \begin{cases} c_j^0 & \text{if } D_j = 0 \\ c_j^1 & \text{if } D_j = 1. \end{cases} \tag{1}$$

In the first state, region $j$ does not experience a disaster ($D_j = 0$), while in the second state region $j$ suffers from the effects of a natural disaster ($D_{jt} = 1$) and marginal costs rise to $c_j^1 > c_j^0$.[9]

The second potential mechanism through which natural disasters can influence the location decisions of multinationals is by altering the perceived risk of such an event. 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.[10] For this reason, we make the assumption that firms update their beliefs about the probability of a disaster in a region after it has experienced a shock.[11] More formally, if $D_t$ is the event of a natural disaster in period $t$, we assume that when making location decisions at some future time period $t+i$, firms take into account the fact that

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

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 the price of reinsurance for regions that have experienced a natural disaster.[12] Although the risk calculations of other firms are less transparent, it is reasonable to assume that they similarly update their forecasts. Furthermore, survey results from multinational firms indicate that disaster risk is an important factor in their location decisions (World Bank, 2014). Following this intuition, we define the "risk factor" of investing in region $j$ as follows:

$$r_j^s = \begin{cases} r_j^0 & \text{if } D_j = 0 \\ r_j^1 & \text{if } D_j = 1. \end{cases} \tag{3}$$

where $r_j^1 > r_j^0$. Because a disaster increases the perceived probability of a future disaster in region $j$, the risk factor of investing in region $j$ rises from $r_j^0$ to $r_j^1$ following a disaster.[13]

Importantly, these two mechanisms of cost and risk have differing implications for the persistence of a disaster's effects. While cost increases may dominate in the short run, evidence of continued impacts on location choice after a region has physically recovered would imply that perceived disaster risk may be more important in the long-run.

### 3.3. Model

To incorporate these features, we extend a simple static model of multinational location choice (as in Neary (2009)) 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.[14] Critically, the probability of a disaster can differ between the foreign regions (even within a single foreign country). For simplicity, we assume that the fixed costs of setting up production are identical across all possible locations.[15] We define the expected operating profits for each region as follows:

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

[9] Of course, this cost increase for foreign multinational corporations could last for multiple time periods until the local economy has recovered. For simplicity, we develop a static model of the multinational's location choice, while the extensions to a dynamic framework go beyond the scope of this study.

[10] 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 that do not fit this pattern.

[11] It is possible, of course, that firms "overreact" to past disasters, à la Bordalo et al. (2020). Nonetheless, whether firms update risk expectations correctly or overreact, the predictions of the model remain the same; indeed, given that changes in *perceived* risk are the key mechanism through which natural disaster influence FDI inflows, overreaction would increase the importance of this channel.

[12] Reinsurance is insurance for insurance companies, where multiple insurance companies share risk by purchasing insurance policies from other insurers to limit their own losses in case of a disaster. Consequently, reinsurance prices are very sensitive to disaster risk.

[13] One interpretation of this disaster risk factor is as the cost of insuring the firm's physical capital investment.

[14] 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.

[15] This is an assumption of convenience. Foreign locations may further differentiate themselves from the domestic investment option through non-symmetric fixed costs of setting up production. Like marginal costs, the fixed cost may change with the occurrence of a disaster. Including these costs, however, will not change the theoretical conclusions, but clutter the exposition.

*Domestic Production:*

$$\Pi_d = PQ - c_d Q \tag{4}$$

*Foreign Production Region 1:*

$$E(\Pi_1) = PQ - c_1^s Q - tQ - r_1^s \tag{5}$$

*Foreign Production Region 2:*

$$E(\Pi_2) = PQ - c_2^s Q - tQ - r_2^s \tag{6}$$

where $c_j^s$ is the marginal costs in region $j$ in state $s$ (with and without a natural disaster), $t$ is the per-unit trade cost (identical across foreign regions within a foreign country) and $r_j^s$ is the "risk-factor" of investing in region $j$ in state $s$.[16]

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 $a$:

*Domestic Production:*

$$\Pi_d^{max} = \frac{1}{4}\left(a - c_d\right)^2 \tag{7}$$

*Foreign Production Region 1:*

$$E(\Pi_1)^{max} = \frac{1}{4}\left(a - c_1^s - t\right)^2 - r_1^s \tag{8}$$

*Foreign Production Region 2:*

$$E(\Pi_2)^{max} = \frac{1}{4}\left(a - c_2^s - t\right)^2 - r_2^s \tag{9}$$

From these equations one can derive the multinational's location decision rule, revealing that a disaster-induced rise in the perceived risk ($r_1$ or $r_2$) or cost of production ($c_1$ or $c_2$) reduces the expected profits earned by investing in foreign regions 1 or 2 and makes these less desirable investment locations.[17] These relationships can be expressed graphically by plotting expected profits against the perceived risk of a disaster, where movements along the curves represent changes in risk and shifts indicate changes in the cost of production. Consider, for example, the initial (pre-disaster) scenario, where foreign disaster risks are equal ($r_1^0 = r_2^0$) 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 Fig. 3(a) and following Section 3.2, the shock acts through two channels, increasing the marginal cost of production (from $c_1^0$ to $c_1^1$) and causing multinationals to update their beliefs about the perceived risk of future disasters in FR1 ($r_1^1 > r_1^0 = r_2^0$). Consequently, FR1's competitive advantage erodes in the short-run and expected profits from investing in FR1 fall from point A to point B. Over time, the local economy of FR1 may recover and marginal costs may return to their previous state (see the shift back from FR1' to FR1 in Fig. 3(b)). Whether or not the disaster has an investment impact that outlasts these cost adjustments depends on the multinational's risk assessment and how quickly the added fear of future disasters dissipates (moving back from $r_1^1$ to $r_1^0$).

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

[17] The actual disaster-induced changes in the multinational investment decision rule, of course, depend on the relative magnitudes of marginal costs, trade costs, and demand, as well as the firm's risk assessment. Moreover, the transitions between the preferred investment locations are a dynamic process that depends on the recovery of production costs and adjustments in perceived risk in the aftermath of a natural disaster. In absence of a fully dynamic model that specifies these transitions, the key theoretical insights can be visualized graphically.

Conditional on the assumption that the expected profits from the domestic location remain unchanged, several potential location choice adjustments are possible. First, if the immediate cost or disaster risk adjustments are large, expected profits from locating in FR1 will fall below those attainable in FR2, such that multinationals will locate in FR2, rather than FR1, in the short-run (see Fig. 3(a)). 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. Over time, FR1 may recover economically and/or the perceived risk of future events may decline, but whether this region will regain its competitive advantage as a foreign investment location depends on the size of the these long-run adjustments.

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 Fig. A.1 in Appendix A) both in the short-run and in the long-run. Nonetheless, expected profits will decline and one would expect less FDI inflows in FR1 in the short-term as a result of the disaster. Lastly, it is possible that the disaster-induced increases in costs and perceived risk in FR1 spillover into FR2. Depending on the relative size of these cost and risk increases, it is possible that the domestic option becomes the preferred location choice in the short-run and FDI inflows fall for both foreign regions (see Fig. A.1).

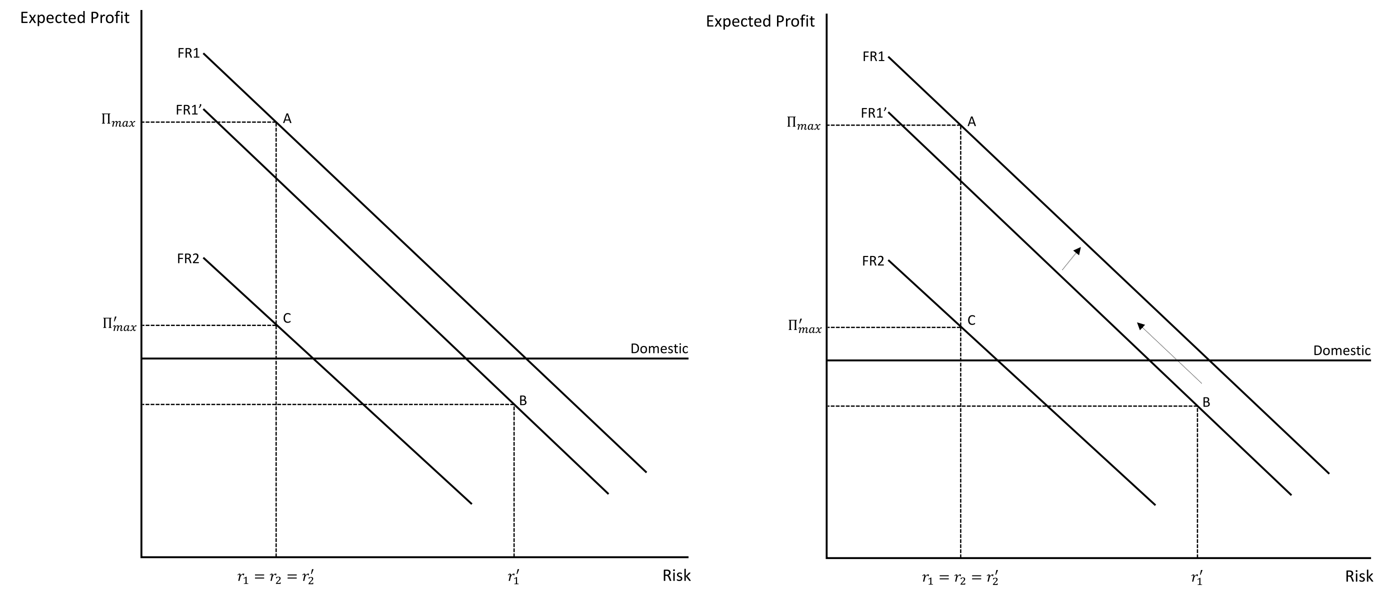
Combined, this framework provides several testable hypotheses regarding the impact of a disaster on firm investment in the foreign country. First, our model predicts that a disaster will lead to an immediate fall in foreign direct investment in the affected regions and that the size of this short-run FDI reduction depends on the rise in the cost of production and adjustments in perceived disaster risk. Second, our model predicts that the disaster may lead to intra-national spillovers in investment into otherwise unaffected regions. The size of these spillovers depends on the unaffected region's competitive advantage. Lastly, the model shows that there are two distinct mechanisms (cost and risk) through which disasters influence investment location decisions. Importantly, these mechanisms offer differing predictions regarding the persistence of FDI relocations, with cost concerns likely dominating in the aftermath of a disaster and risk perceptions dominating in the longer-run.

### 3.4. Potential extension to domestic firms

One potential extension is to consider why a disaster's impact on location choice might differ for domestic businesses compared to foreign multinationals. To explore this potential heterogeneity through the lens of the model, we must revisit our initial assumptions regarding the impact of disasters on cost and risk. While the destruction of firm capital and infrastructure is likely similar across domestic and foreign firms, there are three potential distinctions by firm type one could incorporate.

First, all else equal, the fixed cost of relocating from an affected to unaffected region may be greater for domestic firms. Domestic businesses, for example, may be owner operated and thus tied to their current location through the owner's personal preferences and social connections. In contrast, foreign multinationals are unlikely to face these non-business considerations in their location decision. Moreover, domestic firms may lack experience in making relocation decisions, further raising the costs of a location switch. Survey evidence suggesting that multinationals employ considerably more management expertise lends support to this argument (Bloom and Van Reenen, 2010).

Second, it is conceivable that domestic firms experience a different change in marginal costs. On the one hand, foreign multinationals may be able to negotiate greater government support in disaster affected regions, such that recovery efforts are concentrated around foreign firm




(a) Short-term Adjustment (b) Long-term Adjustment

**Fig. 3.** Disaster-Induced Location Switching.
*Notes:* This figure shows the firm's location decision problem following a natural disaster in foreign region 1 (FR1). In the short-run, shown in panel (a), expected profits in FR1 shift left due to disaster-induced cost increases. Simultaneously, the perceived disaster risk increases from $r_1$ to $r_1'$. Consequently, the profit-maximizing location switches from FR1 to FR2, moving the firm from point A to point C. In the long run, shown in panel (b), production costs return to their previous level. The persistence of the disaster effects then depends on whether the perceived risk of future disasters remains elevated or returns to $r_1$.

locations (Polk et al., 2014). On the other hand, domestic firms may be more deeply embedded in the local supplier network and experience greater support. Given these competing theories, it is unclear a priori how disaster-induced changes in marginal costs will differ between domestic and foreign firms.

Third, domestic firms may face different risk factor adjustments after a disaster strikes. Domestic firms, for example, may have more information ex ante regarding the likelihood of a disaster, and thus may update their perceived risk less than foreign firms. Additionally, multinationals' increased sophistication may make them more likely to consider disaster risk at all in their location choices (Fillat and Garetto, 2015).

Each of these mechanisms may drive a wedge between the responses of foreign and domestic firms, and on net suggest that the investment responses of domestic firms may be considerably less extreme. While this study focuses on the consequences of disasters for FDI location, we note that the response of domestic firms is an important consideration and deserving of future research.

## 4. Data

### *4.1. Economic data*

To study the effects of the five disasters and test the theoretical predictions, we construct a monthly panel of 16 Indian regions running from January 2006 to December 2019. These regions are based on the Reserve Bank of India branches, which collect monthly FDI inflow statistics for their respective districts.[18] The FDI data are restricted exclusively to multinational corporations, and therefore do not include any foreign aid, military aid, or other sources of investment. Consequently, this paper studies only the private sector investment response to natural disasters and does not capture any offsetting aid efforts from the Indian government, foreign governments, or NGOs. Additionally, the FDI data reflect only equity capital inflows and do not include reinvested earnings or intra-company loans.[19]

We combine these data with commonly used controls, such as annual statistics on regional domestic product and population (Chakrabarti, 2001; Di Giovanni, 2005; Bergstrand and Egger, 2007; Head and Ries, 2008; Blonigen and Piger, 2014), which are publicly available from India's Central Statistical Organisation.[20] Additionally, we include annual state-level observations on principal economic indicators from a variety of sources to explore the mechanisms driving the direct effect on FDI. Finally, we use 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 regional sample averages for these statistics and supports 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.

18 The states included in each region are listed in Table A.1 in Appendix A. Given that only 16 districts cover all of India, our regions are large, and for many of the disasters in our analysis only parts of a region are affected by the disaster. However, given that the FDI data is not recorded at a more granular level, we necessarily treat an entire region as affected if any part of the region is hit by a disaster. To the extent that there may be intra-regional shifts in FDI, our regional disaster effect estimates may attenuate towards zero and our conclusions regarding total intra-national FDI spillovers may therefore be conservative.

19 Our FDI data is therefore composed of both greenfield investment and international mergers and acquisitions.

20 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. All of our results are robust against the exclusion of these control variables.

**Table 1**
Regional Sample Averages.

| | Monthly FDI Inflows ($ mil) | Natural Disaster | GDP ($ mil) | Population (millions) | Density (100/km$^2$) | % Urban Population | Access to Latrine | Major Seaport | Literacy Rate | % College Graduate | % Manufacturing Employment |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Ahmedabad | 123.7 | 0 | 768.4 | 61.7 | 2.6 | 37.4 | 35.3 | 0 | 58.9 | 3.7 | 32.9 |
| Bangalore | 447.6 | 0 | 727.9 | 48.3 | 2.8 | 34.0 | 22.9 | 1 | 57.6 | 4.2 | 28.6 |
| Bhopal | 19.3 | 0 | 413.5 | 74.4 | 2.8 | 46.8 | 13.8 | 0 | 52.7 | 3.1 | 28.4 |
| Bubaneshwar | 2.7 | 2 | 267.7 | 41.9 | 2.4 | 15.0 | 9.6 | 0 | 53.9 | 3.2 | 28.5 |
| Chandigarh | 29.3 | 3 | 765.0 | 61.7 | 3.6 | 24.2 | 40.4 | 1 | 60.1 | 4.0 | 26.9 |
| Chennai | 216.2 | 4 | 866.1 | 59.7 | 4.8 | 43.9 | 21.2 | 1 | 65.0 | 3.6 | 34.2 |
| Guwahati | 7.3 | 2 | 254.7 | 44.9 | 0.8 | 23.4 | 25.8 | 0 | 54.1 | 2.8 | 18.0 |
| Hyderabad | 83.0 | 4 | 470.9 | 55.4 | 2.8 | 27.8 | 20.8 | 1 | 52.4 | 3.7 | 30.8 |
| Jaipur | 17.0 | 0 | 502.7 | 70.1 | 1.6 | 23.4 | 21.9 | 0 | 49.0 | 2.6 | 25.8 |
| Kanpur | 5.1 | 3 | 980.4 | 214.7 | 4.2 | 23.2 | 23.5 | 0 | 46.3 | 3.1 | 38.7 |
| Kochi | 19.1 | 5 | 412.4 | 33.9 | 8.2 | 26.0 | 65.1 | 1 | 80.0 | 4.5 | 21.1 |
| Kolkata | 26.0 | 1 & 2 | 646.2 | 92.2 | 9.0 | 28.0 | 23.5 | 1 | 58.9 | 4.0 | 33.8 |
| Mumbai | 662.6 | 0 | 1478.7 | 92.8 | 3.1 | 42.4 | 28.3 | 1 | 66.0 | 5.0 | 31.0 |
| New Delhi | 209.5 | 3 | 399.8 | 17.5 | 92.9 | 93.0 | 68.0 | 0 | 69.8 | 12.7 | 26.0 |
| Panaji | 9.3 | 0 | 44.6 | 1.5 | 3.6 | 49.8 | 45.8 | 1 | 73.1 | 7.3 | 17.5 |
| Patna | 1.5 | 1 & 2 | 296.4 | 106.5 | 6.1 | 16.4 | 13.8 | 0 | 39.0 | 2.7 | 33.1 |

*Notes:* Monthly information on regional FDI inflows is collected by the regional branches of the Reserve Bank of India and published from January 2006 through December 2019. Annual state-level GDP and population data are from India's Central Statistics Organization and 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. Information on natural disaster location is from the Geocoded Disasters (GDIS) Dataset.

### 4.2. Natural disaster selection and data sources

We select the natural disasters used in our analysis based on their physical characteristics. As emphasized by Felbermayr and Gröschl (2014) and others, this is preferable to severity measures based on human or monetary costs, given that these outcomes are endogenous to the level of development and may suffer from significant measurement error due to reporting differences across regions. Specifically, we use data from the Dartmouth Flood Observatory (DFO), which catalogs the magnitude and timing of natural disasters in the Global Active Archive of Large Flood Events. The DFO database provides a disaster severity index that is constructed using a combination of duration (in days), intensity (in centimeters of rainfall), and affected area (in square kilometers):

$$\text{Severity}_k = \log\left(\text{Duration}_k * \text{Affected Area}_k * \text{Intensity}_k\right) \tag{10}$$

The five disasters included in our main analysis are by this measure the most severe over our sample period; in particular, they are the only Indian disasters to be classified by the DFO as "extreme events", reserved for calamities with a greater than 10-year expected recurrence interval for a particular region. We explore the robustness of our disaster selection in Appendix B, where we extend our analysis to include disasters categorized as "large events", the next level down in destructiveness.

Our information on the location of natural disasters comes from the Geocoded Disasters (GDIS) Dataset, which provides granular data on the precise regions struck by a disaster. We use these data to determine whether each of the 16 regions in our panel is included in any of the five disaster's respective affected areas. As discussed, our regions are necessarily large and we treat an entire region as affected if any portion was hit by the disaster. This assumption of equal treatment across all affected regions can be imprecise. Unfortunately, neither the DFO nor the GDIS databases provide information on region-specific disaster severity. Without further details on the intensity of individual disasters by region, our assumption of treating two or more regions as equally affected yields the average treatment effect across the full range of disaster severity. We test the sensitivity of our primary findings against this assumption by restricting treatment solely to the region identified as containing the centroid of a given disaster and excluding all other affected regions. These results, shown in Table B.1 in Appendix B, are quantitatively and qualitatively similar.

## 5. Empirical strategy and results

To identify the impacts of the five disasters and investigate the mechanisms driving the direct effects and intra-national spillover patterns, we take four complementary approaches. We begin by estimating static and dynamic difference-in-differences (DD) models (Section 5.1). Typically, these estimates yield the average treatment effect on the treated (ATT) and provide a useful baseline for the overall disaster impact. However, unlike a traditional DD setting, we do not expect our "control group" to be unaffected by the disasters; on the contrary, our theoretical framework and raw descriptive statistics predict that positive investment spillovers into unaffected regions are possible. Consequently, the disaster-specific DD estimates capture the sum of the direct and indirect effects.

Given that the DD estimates likely 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 (Section 5.2.1). By grouping observations by months to disaster and estimating separate time-to-disaster coefficients for affected and unaffected regions, we are able to dissect the DD estimates into direct effects and spillovers. Similar to the dynamic DD analysis, 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.[21]

We supplement the event study analysis with a spatial difference-in-differences design (Section 5.2.2), which allows us to estimate spillover effects separately for each disaster as well as account for spatial autocorrelation in both FDI and the error term. Specifically, we estimate a spatial autocorrelation combined (SAC) model (LeSage and Pace, 2009), where we specify spatial weight matrices using both first order contiguity and inverse distance weighting schemes.

Lastly, we explore the channels through which natural disasters influence investment decisions in both directly affected regions (Section 5.3.1) and unaffected areas (Section 5.3.2). Specifically, we contrast the disaster-induced response in FDI to adjustments in other principal economic indicators and test whether the estimated direct

[21] The time plot in Fig. 2 also allows us to evaluate these parallel pre-treatment trends. 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 trend observed for regions affected by disasters 3 and 4, as well as the unaffected regions.

and spillover effects vary with regional characteristics. Our results point to several policy-relevant patterns in multinationals' investment relocation decisions and highlight the fact that natural disasters can alter the perceived riskiness of investing in an affected location and contribute to lasting regional inequalities.

Across most of our specifications, we transform the FDI data using the inverse hyperbolic sine (IHS). The IHS transformation adjusts for skewness in regional investment inflows and retains useful information in zero or negative-valued observations.[22] Our results are robust to estimating the effects on untransformed FDI inflows or the alternative $\log(y+1)$ transformation commonly used in the related literature.

For each of the analyses, we adjust the standard errors of our point estimates for the presence of clustered correlations. Our panel is comprised of 16 regions and 168 months, which presents a challenge when considering a clustered standard error structure. Angrist and Pischke (2008), for example, suggest that 42 clusters are sufficient for reliable inference. Cameron and Miller (2015) argue that although there is no clear definition of what constitutes too few clusters, the threshold may range from 20 to 50 for balanced groups. While Colin Cameron et al. (2011) recommend the use of two-way clustering across regions and time with a panel of either ten or more regions and/or ten or more months, a clustered standard error approach is further complicated by the presence of few treated clusters in our dataset. The number of treated regions in our analysis varies from one to ten, depending on whether we consider the individual or average effects of the five disasters, and we therefore utilize the wild cluster bootstrap (Cameron et al., 2008; Roodman et al., 2019). The reported p-values in Tables 2–4 as well as confidence intervals (C.I.) shown in Figs. 4, 5(a), and 5(b) are based on two-way clustered (region and time) standard errors obtained via the wild cluster bootstrap routine developed by Roodman et al. (2019). We test the sensitivity of our inference against this specification. One-way clustered standard errors produce qualitatively consistent results. Finally, our spatial difference-in-differences results, discussed in Section 5.2.2, reveal that spatial dependency in the error term is relatively small.

### 5.1. Baseline estimates

We first estimate the static DD treatment effect for each of the five disasters separately.[23] To capture these impacts, we estimate a fixed effects model of the form:

$$f_{jt} = \sum_{k=1}^{5} \gamma_k D_{tk} * A_{jk} + \beta X_{jt} + \alpha_j + \omega_t + \epsilon_{jt} \tag{11}$$

where $f_{jt}$ represents FDI inflows into region $j$ in month $t$, $D_{tk}$ is a dummy for whether the $k$th disaster occurred before or during period $t$, and $A_{jk}$ is an indicator for whether region $i$ was in the affected area of disaster $k$. The interaction between $D_{tk}$ and $A_{jk}$ identifies post-disaster periods in the treatment group, and $\gamma_k$ captures the coefficients of interest, namely the disaster-specific impact on FDI inflows. The inclusion of region and time fixed effects, $\alpha_j$ and $\omega_t$, 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 $A_{jk}$. The matrix $X_{jt}$ represents the constant term and the control variables, while $\epsilon_{jt}$ 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 effect on FDI 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.

We present our baseline estimates in columns (1) through (7) of Table 2 (the final two columns show our spatial DD estimates, which we discuss in Section 5.2.2). 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, but the last, of the five 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. These estimates suggest that the occurrence of each disaster, including the fifth disaster, is associated with an economically and statistically significant divergence in investment between affected and unaffected regions.[24] Our baseline results are in line with anecdotal accounts from the period, discussed in Section 2, which documented a shift in multinational investment following the disasters.[25]

When we estimate the disaster impacts on total FDI inflows (column (7)) the results remain largely consistent and indicate considerable investment responses. Changes in FDI between treatment and control group range from −109 to −293 million dollars per month. 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: (1) the direct reduction in FDI in affected regions and (2) any potential spillovers into unaffected regions. The estimated treatment effect of around -\$110 million for Disaster 1, for example, 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

[22] 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 commonly used tool when working with skewed data containing many zero-valued observations (e.g. Zhang et al., 2000; Bellemare and Wichman, 2020).

[23] Since we include each disaster as a separate treatment, we are not identifying off the difference in timing of the five calamities. Consequently, the Goodman-Bacon decomposition would yield a single $2 \times 2$ DD pair holding all the weight (Goodman-Bacon, 2021). Nonetheless, it is possible that a disaster's effect on FDI evolves dynamically and is poorly represented by the average DD estimate. We also conduct an event study that allows us to evaluate the short-run dynamics of the disaster impacts in the following subsection.

[24] As previously discussed, two-way clustered standard errors (and the resulting p-values shown in Table 2) are obtained via wild cluster bootstrap (Cameron et al., 2008; Roodman et al., 2019). We scrutinize these standard error estimates by conducting randomization tests. 5,000 re-sampling replications yield generally consistent p-values for each of our five treatment effect estimates. The largest change in $p$-value is observed for the fifth disaster which is found to have a statistically significant impact at the 10% rather than 5% level.

[25] Across all specifications in Table 2 we include one year lagged controls for log GDP and log population. In general, the coefficients estimates on our control variables carry the expected sign, but are statistically indistinguishable from zero. Importantly, our primary disaster effect estimates do not hinge on the inclusion of these or other potential control variables. In addition, we test the sensitivity of our findings against the inclusion of alternative control variables, such as cumulative or one-year lagged FDI inflows, finding similar results. We also estimate the model using $\log(FDI+1)$ as the dependent variable. Because some months have negative inflows, the $\log(FDI+1)$ transformation is undefined in some cases and the number of observations falls. Regardless, the results are consistent and show a reduction in FDI between a 77.8 and 95.4 percent relative to unaffected regions.

**Table 2**
Difference-in-Differences Estimates.

| | *Baseline estimates* | | | | | | | *Spatial difference-in-differences* | |
|---|---|---|---|---|---|---|---|---|---|
| | IHS FDI (1) | IHS FDI (2) | IHS FDI (3) | IHS FDI (4) | IHS FDI (5) | IHS FDI (6) | Total FDI (7) | Contiguity (8) | Inverse Distance (9) |
| Disaster 1 | −3.709 | | | | | −2.554 | −109.3 | −2.733 | −2.656 |
| | (0.012) | | | | | (0.024) | (0.038) | (0.000) | (0.000) |
| Disaster 2 | | −2.212 | | | | −2.499 | −130.0 | −3.003 | −3.019 |
| | | (0.003) | | | | (0.004) | (0.038) | (0.000) | (0.000) |
| Disaster 3 | | | −2.254 | | | −3.094 | −146.4 | −3.477 | −3.393 |
| | | | (0.016) | | | (0.004) | (0.112) | (0.000) | (0.000) |
| Disaster 4 | | | | −1.413 | | −2.297 | −293.1 | −2.340 | −2.274 |
| | | | | (0.017) | | (0.011) | (0.143) | (0.000) | (0.000) |
| Disaster 5 | | | | | −0.642 | −1.609 | −234.5 | −1.696 | −1.616 |
| | | | | | (0.379) | (0.015) | (0.417) | (0.000) | (0.000) |
| Disaster 1 - indirect | | | | | | | | 0.623 | 1.122 |
| | | | | | | | | (0.000) | (0.000) |
| Disaster 2 - indirect | | | | | | | | 0.707 | 1.300 |
| | | | | | | | | (0.011) | (0.000) |
| Disaster 3 - indirect | | | | | | | | 0.806 | 1.463 |
| | | | | | | | | (0.004) | (0.000) |
| Disaster 4 - indirect | | | | | | | | 0.539 | 0.972 |
| | | | | | | | | (0.002) | (0.000) |
| Disaster 5 - indirect | | | | | | | | 0.318 | 0.692 |
| | | | | | | | | (0.002) | (0.000) |
| Ln(GDP$_{t-1}$) | 2.255 | 1.298 | 2.241 | 2.409 | 2.229 | 1.722 | 78.89 | 1.305 | 1.329 |
| | (0.225) | (0.409) | (0.294) | (0.249) | (0.283) | (0.235) | (0.893) | (0.331) | (0.318) |
| Ln(Pop$_{t-1}$) | 0.633 | 0.427 | 0.424 | 0.715 | 0.707 | −0.142 | 448.4 | −0.005 | −0.020 |
| | (0.187) | (0.345) | (0.355) | (0.245) | (0.191) | (0.720) | (0.075) | (0.987) | (0.946) |
| $N$ | 2688 | 2688 | 2688 | 2688 | 2688 | 2688 | 2688 | 2688 | 2688 |
| $R^2$ | 0.722 | 0.729 | 0.729 | 0.704 | 0.696 | 0.811 | 0.475 | 0.291 | 0.251 |
| # of Affected Regions | 2 | 4 | 3 | 2 | 1 | 10 | 10 | 10 | 10 |
| Regional FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\rho$ | | | | | | | | −0.553*** | −0.877*** |
| $\lambda$ | | | | | | | | 0.230 | 0.100 |

*Notes:* *P*-values are reported in parentheses. For columns (1) through (7) these are based on two-way wild cluster bootstrapped standard errors. Columns (1) through (7) show the baseline estimates, while columns (8) and (9) report the results of the spatial difference-in-differences analysis (discussed in section 5.2.2). Columns (1) through (5) show the separately estimated disaster impacts, whereas the results in columns (6) through (9) are based on jointly estimated disaster effects. The dependent variable underlying the regressions reported in all columns except (7) is the inverse hyperbolic sine of FDI, whereas the results given in column (7) are based on raw FDI inflows. For columns (8) and (9), the parameter $\rho$ reflects spatial correlation in FDI inflows, whereas $\lambda$ captures potential spatial dependence in the error term. The sample consists of a total of 16 Indian regions.

effect on unaffected regions. Because the baseline DD estimates cannot distinguish between these two components, we are careful not to mistake them for the causal ATT.

We conclude our baseline empirical investigation with a dynamic DD analysis. The dynamic model allows us to identify the timing of the disaster effects and evaluate the persistence of the disaster-induced investment shifts. To this end, we amend Eq. (11) by aligning the timing of multiple disasters and integrating common pre- and post-treatment indicators ($I_{t^*+i}$); one for each month prior to and after a disaster's landfall:

$$f_{jt} = \sum_{i=\underline{i}}^{\bar{i}} \gamma_{t^*+i} I_{t^*+i} * A_j + \beta X_{jt} + \omega_t + \alpha_j + \epsilon_{jt}, \tag{12}$$

Consequently, we can no longer identify the effects of each disaster separately, and instead focus on the average dynamic effects across events. Based on our sample period and the timings of the disasters, the model includes 153 pre-treatment periods ($\underline{i}$) and 117 post-treatment periods ($\bar{i}$) each evaluated against the excluded reference period ($t^*$), which represents the month prior to a disaster's landfall. Similar to the static model, the dynamic indicators are interacted with a dummy that identifies the affected regions for each disaster.[26] Again, we control for lagged regional GDP and population ($X_{jt}$) as well as time and region-specific fixed effects ($\omega_t$ and $\alpha_j$).

The coefficient vector $\gamma_{t^*+i}$ indicates the dynamic pre- and post-treatment effects on IHS-transformed regional FDI inflows. We present these estimates for 72 pre-treatment and 72 post-treatment months in Fig. 4.[27] The results show negligible differences in FDI inflows between affected and unaffected regions in India prior to a natural disaster and a clear divergence in new foreign investment thereafter. Compared to unaffected regions, affected regions experience around a 90% reduction in FDI inflows one month after a disaster's landfall, relative to the excluded pre-treatment period. Most importantly, Fig. 4 shows that this divergence persists for over six years after the disaster. Again, we are careful to note that these effects are composed of both direct impacts and spillovers, given that they represent the difference between affected and unaffected regions.

### 5.2. Direct effects and spillovers

Our baseline estimates are large, and likely represent a combination of the reduction in FDI experienced by directly affected regions as well as potential investment spillovers into otherwise unaffected areas. To disentangle these two components, we utilize both an event study design and a spatial difference-in-differences analysis.

[26] The affected regions of Patna and Kolkata must be excluded because these districts get hit by two of our five major disasters and would therefore have overlapping pre- and post-treatment periods.

[27] Because the timings of the disasters vary over our sample period, the average dynamic effects are identified by a varying set of affected regions. That is, the estimate for the pre-treatment period one month prior to a disaster is based on the changes in FDI (with respect to $t^*$) in all of the affected regions relative to unaffected regions. In contrast, the estimate for the pre-treatment period of 153 months prior to a disaster's landfall is only identified by the changes in FDI observed for Kochi, which experiences the last disaster in our sample. To avoid the potential influence of compositional changes in the treatment group, we focus the exposition on a six-year window before and after the disasters' landfalls, which includes at least five treated regions.

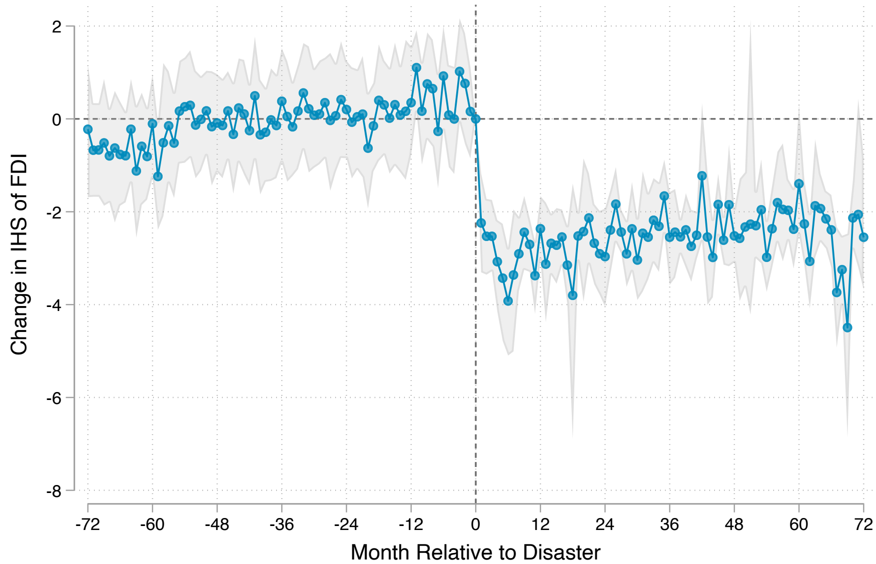



**Fig. 4.** Dynamic Difference-in-Differences Estimates.
*Notes:* Dynamic difference-in-difference estimates for the five disasters. Changes in IHS-transformed FDI are depicted with their respective 95% confidence interval. Point estimates are based on 2,352 observations and range from −4.49 to 1.10. We include controls for lagged log GDP and population as well as region fixed effects. The regression produces an $R^2$ of 0.81 and the C.I. is based on two-way wild cluster bootstrapped standard errors.

### 5.2.1. *Event study*

We begin with the event study, where we estimate a separate model for affected and unaffected regions, identifying off the temporal variation in disasters. Similar to the dynamic DD analysis, 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:

$$f_{jt} = \sum_{i=\underline{i}}^{\bar{i}} \gamma_{t^*+i} I_{t^*+i} + \beta X_{jt} + \alpha_j + \epsilon_{jt}, \tag{13}$$

where $f_{jt}$ represents the IHS of FDI inflows into region $j$ in month $t$, $\alpha_j$ controls for time-invariant regional characteristics, and the control variable matrix $X_{jt}$ includes an intercept, lagged regional GDP and population as before. The random error component is given by $\epsilon_{jt}$.

The key distinction from the previous dynamic 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.[28] 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 includes 18 pre- and 18 post-treatment periods [$\underline{i} = -18, \bar{i} = 18$].

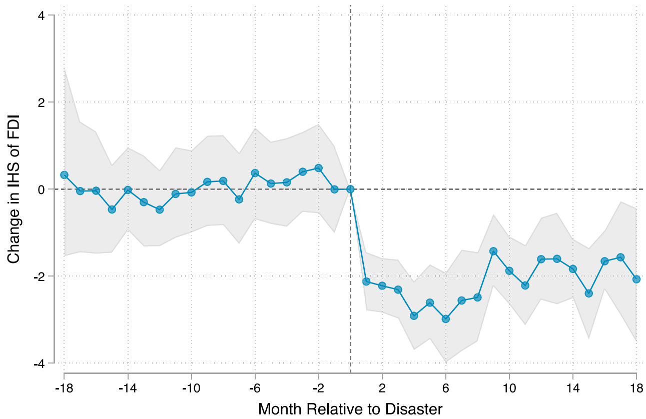
[28] This prohibits the inclusion of time fixed effects. An alternative to these fixed effects may be the inclusion of a time trend, and our results are robust to this inclusion.

The critical explanatory variables in Eq. (12) are given by the set of indicators $I_{t^*+i}$, which mark the time periods relative to the disaster. The first post-treatment period, for example, is identified by ($I_{j,t^*+1}$) and equals one at different points in time for regions affected by different disasters (i.e. $I_{j,t^*+1} = 1$ for Guwahati in April 2010 and for Kanpur in June 2013). The coefficients of interest are given by $\gamma_{t^*+i}$ 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.

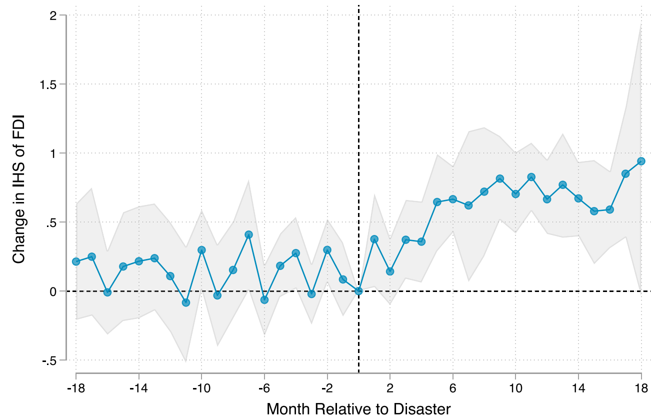
We present the pertinent coefficient estimates of these event studies in Figs. 5(a) and 5(b), and translate these results into percentage changes (Figs. 5(c) and 5(d)) as well as adjustments in total monthly inflows (Figs. 5(e) and 5(f)). The estimates provide compelling evidence in support of our baseline findings and emphasize that the treatment effects measured in the static and dynamic DD specifications represent a combination of FDI inflow reductions in directly affected regions and positive investment spillovers into otherwise unaffected regions.

The direct effect estimates (Figs. 5(a), 5(c), and 5(e)) show a significant and immediate reduction in FDI inflows at the time of the disaster. In relative terms, foreign investment falls by 86.3% 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, reiterating the dynamic DD findings that natural disasters cause lasting damage to a region's competitiveness in multinational location decisions.

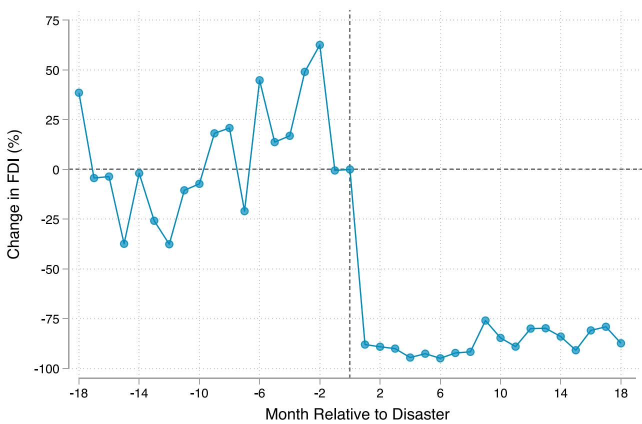
The indirect effect estimates (Figs. 5(b), 5(d), and 5(f)) demonstrate that an economically and statistically significant portion of lost FDI inflows are reallocated towards unaffected areas in India. Relative to inflows observed during the excluded reference month, these positive spillovers amount to 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



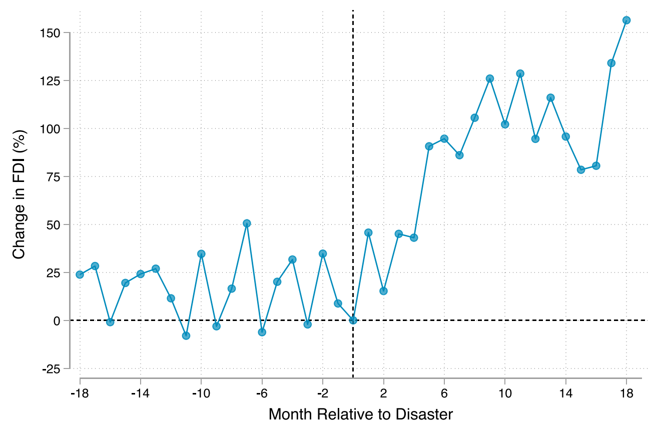

(a) Event Study Affected Regions (IHS Estimates)



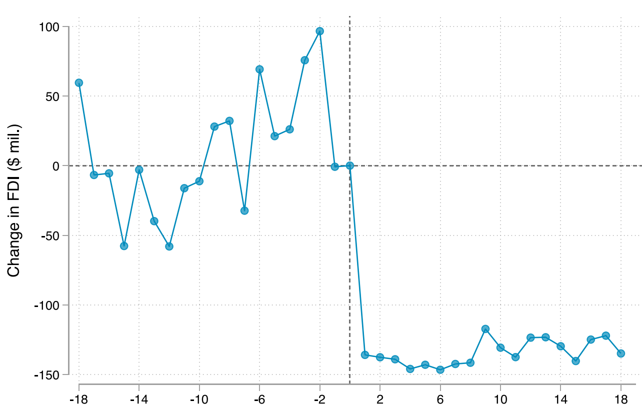

(b) Event Study Unaffected Regions (IHS Estimates)



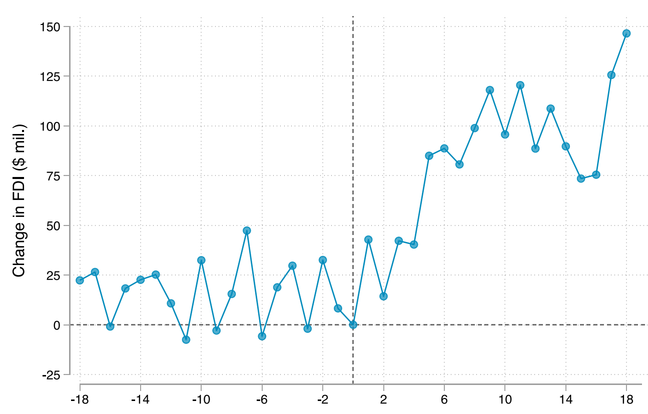

(c) Event Study Affected Regions (% Change)




(d) Event Study Unaffected Regions (% Change)




(e) Event Study Affected Regions (Total FDI)




(f) Event Study Unaffected Regions (Total FDI)

**Fig. 5.** Event Study Estimates for Affected and Unaffected Regions.
*Notes:* Panels (a) and (b) show results for IHS FDI, where the coefficients are relative to the excluded reference period and the gray shading indicates 95% confidence intervals. Panels (c) and (d) show the transformed point estimates for the percent change in FDI, while panels (e) and (f) show point estimates for the absolute change in FDI. All specifications include controls for lagged log GDP and population as well as region fixed effects.

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.[29]

Combined, the event studies 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 three of the 18 pre-treatment coefficients are statistically significant at the 5% level. The absence of these pre-treatment trends provides further evidence that we are indeed capturing the causal effect of the disasters.

### 5.2.2. Spatial difference-in-differences

We supplement our event study analysis with a spatial difference-in-differences design, which allows us to identify spillovers from each disaster separately and account for spatial correlation in FDI inflows over time. Specifically, we estimate a spatial autocorrelation combined (SAC) model (LeSage and Pace, 2009), which allows for spatial correlation in both the dependent variable and disturbance process $\epsilon$. This enables us to account for potential correlation in the unexplained portion of FDI across regions and directly evaluate the indirect spillover effects into unaffected Indian regions.

We specify the nature of the spatial spillovers via spatial weight matrix $W$. Commonly used weighting schemes include the first-order contiguity (or nearest-neighbor) matrix, which allows for spillovers and feedback across neighboring regions, and the inverse distance matrix, which allows for spillovers and feedback across all regions with an exponential decay over space. We estimate the following SAC model using both types of spatial weight matrices:

$$f_{jt} = \rho W f_{jt} + \sum_{k=1}^{5} \gamma_k D_{tk} * A_{jk} + \beta X_{jt} + \alpha_j + \omega_t + u_{jt}; \qquad (14)$$
$$\text{where} \quad u_{jt} = \lambda W u_{jt} + \epsilon_{jt}$$

The autoregressive process over space is captured by $\rho W f_{jt}$, whereas spatial correlation of the error term is captured by $\lambda W u_{jt}$. Estimates of $\rho$ and $\lambda$ can thus be used to evaluate the severity of spatial dependencies.

Our spatial DD results are shown in columns (8) and (9) of Table 2. First, we note that the estimates point to spatial competition for foreign investment across Indian regions. In both specifications, the estimate for the parameter $\rho$ is negative and statistically significant at the 1% level; a shock to FDI in one region tends to have an inverse effect on FDI in other regions. Second, the estimate for $\lambda$ is statistically insignificant, suggesting that spatial correlation in the error term is less of a concern.

The point estimates of interest represent the direct and indirect effects of each of the five natural disasters. As expected, the direct effect estimates are qualitatively consistent with the earlier baseline results (columns (1) through (6)) and demonstrate the negative impact of natural disasters on foreign investment in directly affected regions. In absolute magnitude, the direct spatial DD coefficients tend to be larger than the corresponding standard linear estimates shown in column (6). The cause of this difference is a feedback effect. Once a disaster strikes, FDI falls in the affected region and the inverse spatial dependence leads to an upwards adjustment in FDI in unaffected regions. This reallocation of FDI towards unaffected regions, in turn, has a compounding negative feedback effect on foreign investments in the disaster-struck location.

Indeed, consistent with the event study evidence, the indirect effect estimates presented in columns (8) and (9) of Table 2 illustrate statistically significant positive spillover effects arising from each of the five disasters. The magnitude of these spillovers is nontrivial and varies by disaster. The Eastern Indian storm in April 2010 and Northern Indian floods in June 2013 appear to have caused the largest investment spillovers in otherwise unaffected regions. A comparison of the indirect effect estimates across columns (8) and (9) shows larger spillovers when spatial autocorrelations are not limited to the nearest neighboring regions, indicating that significant investment relocations flow to regions located at greater distances from affected locations.

## 5.3. Mechanisms

To summarize, we have found consistent evidence of substantial FDI reductions in directly affected regions, accompanied by positive investment relocations into otherwise unaffected Indian regions. This raises two questions: Why exactly do foreign firms change investment locations in response to a natural disaster? And, what regions are likely recipients of relocated FDI? To shed light on these questions, we next consider the channels through which these post-disaster shifts emerge.

### 5.3.1. Direct effect mechanisms

We begin by considering the mechanisms through which a natural disaster can cause investment reductions in directly affected regions. Following the theory, two potential causes stand out: (1) an immediate cost increase in affected regions in the aftermath of the disaster; and (2) a rise in the perceived risk of future disasters that will erode the affected location's competitive advantage. In the absence of direct measurements of production costs and/or risk assessments, we lean on other economic indicators to gain insights into these factors. A plausible assumption is that a disaster increases the cost of production not only for foreign multinationals, but also domestic businesses. As such, one would expect the local economy as a whole to experience a downturn in the aftermath of each of these calamities. Evidence to the contrary would suggest that the economic conditions remain largely unscathed and/or that the cost-increasing effects of the disaster have dissipated quickly. In the latter case, the significant and lasting effects on FDI are unlikely attributable to changes in local economic conditions, and are instead likely to be caused by changes in perceived risk.

To test this hypotheses, we obtain data on multiple principle economic indicators available through several sources, including the Annual Survey of Industries (ASI), published by the Indian Ministry of Statistics and Programme Implementation, the Indian Labor Bureau, and the Reserve Bank of India. Unlike the FDI data, most of these statistics are available at the state level and are reported annually from 2006 through 2017, rather than monthly. The data include information on factor inputs, such as the stock of fixed capital and the number of workers, as well as factor prices, including wages and rents. Other outcomes considered include consumer prices, as well as state-level data on new business life insurance policy premiums, published by the Insurance Regulatory and Development Authority of India. While the data on inflation as well as factor inputs and prices offer a broad view of

[29] For robustness, we explore whether the disaster spillovers are driven entirely by investment flows into the unaffected regions of Maharashtra (which includes Mumbai) and Karnataka (which includes Bangalore). This is an important robustness check given that these are two of India's most economically important cities, and because these regions have attracted significant investment from the tech sector in recent years, which is less likely to shift based on natural disasters. To do so, we re-estimate Eq. (12) excluding the regions of Maharashtra and Karnataka. The estimated spillover effects, shown in Fig. B.1 in Appendix B, remain positive and significant on this restricted sample, although slightly smaller in magnitude, as expected. This exercise shows that while Maharashtra and Karnataka are key recipients of the investment spillovers, they do not alone drive our results, with other regions receiving a significant portion of the redirected FDI.

the disaster-induced adjustments in regional economies, the latter time-series allows us to gain some insight on whether insurance companies have updated their beliefs about the riskiness of investments in the directly affected regions after a disaster strikes.

To analyze the impact across these economic indicators and compare our findings against the foreign investment response, we turn towards the static difference-in-differences model for each outcome variable ($y_{st}$) that compares differences in means across affected and unaffected states ($s$) during the post-disaster period relative to the difference in means observed prior to each disaster. The empirical specification follows the static DD setup (Eq. (11)) and can be expressed as follows:

$$y_{st} = \sum_{k=1}^{5} \gamma_k D_{tk} * A_{sk} + \beta X_{st} + \alpha_s + \omega_t + \epsilon_{st}. \tag{15}$$

As before, we control for lagged state-level population and GDP as well as state and time fixed effects. The point estimates of interest ($\gamma_k$) are reported in Table 3 and capture the disaster-induced economic adjustments in directly affected states relative to unaffected ones for each of the four major disasters that occurred during the shortened 2006–2017 sample period.

Overall the results are mixed and notably less statistically significant than the estimated effects on FDI (see Table 2). Factor prices, for example, indicate negligible adjustments in response to each of the four major disasters (see coefficient estimates in columns (3) and (4) of Table 3). The estimated effects on the # of workers tend to switch signs across the disasters and only one is statistically significant at the 10% level suggesting an influx of workers in affected regions after the East Indian Storm (see column (2) of Table 3). Column (5) also shows sign switching coefficient estimates with respect to the disaster effects on CPI which matches some of the evidence presented by the previous literature (Noy, 2009).

**Table 3**
Difference-in-Differences Estimates for Economic Indicators.

| | Fixed Capital (1) | Number of Workers (2) | Hourly Wages (3) | Rent Prices (4) | Consumer Price Index (5) | Insurance Premiums (6) |
|---|---|---|---|---|---|---|
| Disaster 1 | −0.199 | −0.121 | −0.230 | 0.166 | 0.030 | −0.047 |
| | (0.527) | (0.287) | (0.286) | (0.516) | (0.284) | (0.739) |
| Disaster 2 | 0.251 | 0.206 | 0.136 | −0.006 | −0.017 | 0.257 |
| | (0.288) | (0.065) | (0.248) | (0.976) | (0.463) | (0.083) |
| Disaster 3 | −0.187 | 0.040 | 0.014 | 0.014 | −0.048 | 0.009 |
| | (0.096) | (0.744) | (0.884) | (0.934) | (0.014) | (0.947) |
| Disaster 4 | −0.268 | −0.239 | −0.175 | −0.439 | 0.008 | 0.187 |
| | (0.049) | (0.268) | (0.253) | (0.201) | (0.658) | (0.150) |
| $N$ | 348 | 348 | 348 | 348 | 276 | 348 |
| $R^2$ | 0.810 | 0.408 | 0.894 | 0.448 | 0.993 | 0.435 |
| # of Affected States | 20 | 20 | 20 | 20 | 20 | 20 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Notes:* P-values, reported in parentheses, are based on two-way wild cluster bootstrapped standard errors. The dependent variables underlying all regressions are logged. The sample consists of a total of 29 Indian states and runs from 2006 through 2017.

The effects on fixed capital and new business life insurance premiums are more consistent in terms of their sign and provide some evidence into the potential mechanisms that may drive the persistent decline in FDI inflows. Across disasters 1, 3, and 4, the coefficient estimates presented in column (1) of Table 3, for example, suggest that the stock of fixed capital in affected regions declines by around 20% in response to a major natural disaster. This destruction of transport infrastructure and public utilities, among other fixed capital, can help explain the reduction in FDI inflows and are in line with the long-run disaster-induced reductions in economic growth found by Hsiang and Jina (2014).

The estimated disaster effects on premiums for new business life insurance, shown in column (6) of Table 3, tend to suggest a rise in insurance rates after a calamity's landfall, although only one of three positive coefficient estimates is statistically significant at the 10% level. The uptick in insurance premiums in affected relative to unaffected states may indicate that premiums on new policies must cover the heightened perceived risk of future calamities. If foreign multinationals update their beliefs about future disaster risks similar to these insurance companies, this finding helps explain the prolonged reduction in FDI inflows.

### 5.3.2. Indirect spillover patterns

Our final analysis focuses on the presence of large positive investment spillovers into unaffected Indian regions. We ask whether these disaster-induced relocations 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 Eq. (11) by interacting each of the five disaster dummies ($D_{tk}$) with a regional weight ($W_j$) and an indicator variable identifying the unaffected regions for each disaster ($U_{jk}$). The resulting estimation equation is given as follows:

$$f_{jt} = \sum_{k=1}^{5} \gamma_k D_{tk} * A_{jk} + \sum_{k=1}^{5} \delta_k * W_j * D_{tk} * U_{jk} + \beta X_{jt} + \alpha_j + \omega_t + \epsilon_{jt}. \tag{16}$$

where $f_{jt}$ represents the IHS of FDI inflows into region $j$ in month $t$ and $X_{jt}$ gives the control variable matrix and intercept. As before, $\alpha_j$ and $\omega_t$ represent the region- and time-specific fixed effects, and $\epsilon_{jt}$ is the random error component.

Similar to Eq. (11), the terms $D_{tk} * A_{jk}$ differentiate the directly affected regions for each disaster and $\gamma_k$ captures the post-disaster changes in the difference in means of FDI inflows between affected and unaffected regions. The interaction terms $D_{tk} * U_{jk}$ identifies the unaffected regions for each disaster and can only be included interacted with regional weights $W_j$. Under this specification, the coefficients of particular interest are given by $\delta_k$ for $k = 1, \ldots, 5$, and reveal whether regional characteristic ($W$), such as perceived disaster risk, market potential, level of development, or labor skill, strengthens or weakens the spillover effect for disaster $k$. To be clear, we cannot separately identify the size of the spillover effects via this specification; instead, with the interaction of regional characteristics we explore whether these investment spillovers tend to be positively or negatively correlated with $W_j$.

The specific regional characteristics 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 electricity within premises; (5) access to a major Indian seaport; (6) population share that has a college degree; (7) share of manufacturing employment; (8) similarity in industry composition relative to the affected area;[30] and (9) perceived future disaster risk as measured by previous disaster damages accumulated over a 20 year period from 1985 to 2005 and the count of major disasters over this same period. Because any of these variables (except contiguity and ex ante risk measures) may be affected by the occurrence of a natural disaster (i.e. through evacuee migration), we fix them at

[30] The similarity weight follows a specification proposed by Boarnet (1998), where 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: $W_i = \sum_j \frac{1/|s_{ij}-s_{aj}|}{\sum_i 1/|s_{ij}-s_{aj}|}$.

their respective 2001 values, predating any of the disasters observed during our sample.[31]

Columns (1) through (10) of Table 4 present the results for our ten regional weights. Panel A provides the treatment estimates of the five disasters for affected regions relative to unaffected ones. As expected, these coefficients are largely 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 4 represent the attribute-specific spillover patterns. We observe a few noteworthy trends that align with some of the findings in the previous literature and shed light on the determinants of FDI relocation decisions after a major natural disaster.

First, market potential seems to play a positive role in determining the multinational's relocation decision. Higher levels of density, for example, are associated with greater FDI inflow spillovers for four of the five disasters. Two of these coefficients indicate a statistically significant positive spillover pattern with respect to density (see column (2)). Similarly, with respect to urbanization (column (3)) two of the coefficients are statistically significant at the 10% level. Both are positive suggesting that market potential, as measured via greater urbanization, is not only associated with greater economic growth (Sachs et al., 2002), but also larger FDI spillovers in the aftermath of a natural disaster.

Similarly, a region's level of development appears to matter in the multinational's decision making process. In column (4) of Table 4, we report the coefficient estimates for the share of a region's population with in-home electricity 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 latrine (not shown in Table 4).

Somewhat surprisingly, access to infrastructure (column (5)), such as seaport access, and contiguity to affected regions (column (1)) do not seem to influence a multinational's investment relocation decision. For both of these regional characteristics, coefficient estimates have mixed signs and are statistically insignificant for all five of the disasters.[32]

We also evaluate the impact of labor skill and industry composition on FDI spillovers. Labor skill, which we measure via the share of the population with a college degree, exerts a positive influence on investment relocation decisions (column (6)). Two of the five coefficients are statistically significant at the 10% level and carry a positive sign, indicating that firms look to locate near areas with a higher level of human capital.[33] In contrast, the effects of industry composition in unaffected regions (column (7)) and similarity thereof to the economy of affected areas (column (8)) matter less to investment relocation. Across the five disasters, only one coefficient is found to be statistically significant at the conventional levels and indicates a negative correlation between investment spillovers and economic similarity. This is somewhat surprising. In a framework where a multinational originally intended to invest in the region struck by a disaster, but chooses to reinvest elsewhere, we would expect the next best choice to be similar to the affected region. However, of the five coefficients, three indicate a negative correlation with FDI spillovers and only in the case of the first disaster is the point estimate statistically significant. A potential explanation for the negative correlation could be the presence of intra-national supply chain linkages that transmit the negative disaster impact into otherwise unaffected regions and cause unfavorable conditions for investment relocation. Of course, this explanation critically hinges on the industry composition of the directly affected areas. Regions affected by disasters 1, for which similarity in industry composition seems to dampen FDI spillovers, tend to be specialized in manufacturing of household and non-household industries, which indeed make use of supply chain networks.

Lastly, we explore the influence of perceived risk of future natural disasters on foreign firms' investment relocation decisions. According to the theory, in an environment of imperfect information, firms may base their assessment of the risk of future natural disasters on the occurrence of previous events. In line with this assumption, we test whether investment spillover patterns are shaped by the occurrence of past major disasters and the related damages accumulated between 1985 and 2005 prior to our sample. A priori, one would expect that a region that is unaffected by the disasters in our 2006 through 2019 sample, but has experienced significant calamities and economic damages in the past may be a less attractive candidate for investment relocation than an unaffected region with few previous disasters and/or relatively low historical economic damages. The coefficient estimates with respect to cumulative historical disaster damages tend to carry the expected negative sign (4 out of 5) and one is statistically significant at the 5% level. This estimate suggests that in response to Disaster 1 an unaffected region experienced 7% less spillovers for every 1% rise in cumulative damages from previous disasters. The interaction with the number of previous disasters exceeding $1 billion in damages echo this finding with respect to Disaster 1 and show that multinationals avoided relocating investment in regions with prior exposure to major calamities.

Overall, most of these estimated FDI spillover patterns are broadly consistent with our theoretical framework. Economic costs and perceived risk of future disasters matter to some extent, while some estimates are more difficult to reconcile. On the one hand, multinationals that are forced to relocate may look to more developed and densely populated regions with lower perceived disaster risk, where healthier workers imply lower marginal costs and greater urbanization offers a larger and more accessible market. On the other hand, our seaport and industry composition results point to the fact that international transport costs, which are surely influenced by access to this type of infrastructure, as well as the share of manufacturing may be less important determinants of investment relocation decisions in India after the strike of a natural disaster.

## 6. Discussion and limitations

Together, our findings provide evidence that natural disasters have a significant and lasting impact on FDI, both in directly affected and unaffected regions. We show that the resulting relocation decisions are driven by considerations of both economic costs and the "risk factor" of investing in regions previously hit by a disaster. Consequently, this study provides a window into the decision making of multinational firms under conditions of risk. Market potential, level of development, and relative disaster risk between regions appear to be significant determinants of relocation 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 FDI disruptions indicates that the salience of these factors does not quickly dissipate. These results are consistent with our theoretical framework, where a disaster raises the cost of production in the short run, indirectly lowers expected profits through adjustments in the perceived risk of future calamities, and ultimately leads to long-term reallocation 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

[31] We also explore the variation of spillover effects with respect to pre-existing cumulative FDI inflows and the interaction of the pre-existing foreign investment stock with our measure of economic similarity, producing insignificant estimates. This indicates that the volume of previous investments does not help predict disaster-induced investment relocation decisions.

[32] The insignificant contiguity results are also consistent across other measures of distance to disaster.

[33] We also explore the role of the literacy rate among workers and find a similarly positive influence.

**Table 4**
Investment Spillover Patterns.

| | *Geography* | *Market Potential* | | *Development* | | *Skill & Industry Composition* | | | *Perceived Disaster Risk* | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Contiguity (1) | Density (2) | Urban (3) | Electricity (4) | Ports (5) | College (6) | Manu. (%) (7) | Similarity (8) | Past Damages (9) | Past Disasters (10) |
| **Panel A – Direct Effects** | | | | | | | | | | |
| Disaster 1 | −2.682 | −2.480 | −2.295 | −2.169 | −2.522 | −2.231 | −3.061 | −3.239 | −3.570 | −2.749 |
| | (0.022) | (0.022) | (0.012) | (0.008) | (0.021) | (0.015) | (0.005) | (0.009) | (0.004) | (0.018) |
| Disaster 2 | −2.342 | −2.239 | −2.496 | −2.593 | −2.445 | −2.607 | −3.035 | −2.300 | −3.190 | −2.341 |
| | (0.009) | (0.012) | (0.012) | (0.003) | (0.006) | (0.006) | (0.076) | (0.013) | (0.060) | (0.005) |
| Disaster 3 | −3.055 | −3.169 | −3.343 | −3.254 | −2.954 | −3.394 | −3.298 | −3.023 | −3.273 | −3.029 |
| | (0.006) | (0.002) | (0.002) | (0.002) | (0.004) | (0.002) | (0.005) | (0.004) | (0.006) | (0.004) |
| Disaster 4 | −2.307 | −2.275 | −1.825 | −1.885 | −2.519 | −1.851 | −1.912 | −2.616 | −2.096 | −2.450 |
| | (0.006) | (0.005) | (0.009) | (0.010) | (0.001) | (0.011) | (0.003) | (0.000) | (0.002) | (0.002) |
| Disaster 5 | −1.726 | −2.094 | −1.634 | −1.936 | −1.751 | −1.780 | −1.662 | −1.698 | −1.637 | −1.588 |
| | (0.017) | (0.003) | (0.028) | (0.024) | (0.011) | (0.006) | (0.035) | (0.047) | (0.067) | (0.165) |
| **Panel B – Indirect Spillover Patterns** | | | | | | | | | | |
| Spillover pattern ND 1 | −0.333 | 0.005 | 0.007 | 0.011 | 0.078 | 0.069 | −0.019 | −0.989 | −0.071 | −0.166 |
| | (0.352) | (0.072) | (0.076) | (0.049) | (0.718) | (0.062) | (0.199) | (0.017) | (0.026) | (0.048) |
| Spillover pattern ND 2 | 0.194 | 0.001 | −0.001 | −0.005 | −0.134 | −0.030 | −0.013 | 0.212 | −0.047 | 0.099 |
| | (0.600) | (0.905) | (0.857) | (0.653) | (0.732) | (0.570) | (0.764) | (0.571) | (0.611) | (0.464) |
| Spillover pattern ND 3 | 0.040 | 0.121 | −0.007 | −0.007 | 0.434 | −0.065 | −0.016 | 0.384 | −0.009 | 0.072 |
| | (0.934) | (0.291) | (0.644) | (0.614) | (0.349) | (0.600) | (0.506) | (0.193) | (0.840) | ( 0.667) |
| Spillover pattern ND 4 | 0.128 | 0.022 | 0.016 | 0.016 | −0.100 | 0.142 | 0.011 | −0.221 | 0.014 | −0.069 |
| | (0.741) | (0.002) | (0.059) | (0.089) | (0.747) | (0.018) | (0.485) | (0.665) | (0.522) | (0.681) |
| Spillover pattern ND 5 | −1.047 | −0.005 | −0.002 | −0.003 | −0.199 | −0.031 | −0.000 | −0.276 | −0.007 | 0.032 |
| | (0.273) | (0.067) | (0.488) | (0.292) | (0.496) | (0.105) | (0.974) | (0.301) | (0.640) | (0.864) |
| $N$ | 2688 | 2688 | 2688 | 2688 | 2688 | 2688 | 2688 | 2688 | 2688 | 2688 |
| $R^2$ | 0.812 | 0.820 | 0.815 | 0.814 | 0.811 | 0.816 | 0.812 | 0.813 | 0.812 | 0.811 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Region FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Notes:* P-values, reported in parentheses, are based on two-way wild cluster bootstrapped standard errors. Each column presents the full set of disaster impact estimates 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 electricity 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 share of the population that holds a college degree, 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. Coefficients presented in columns (9) and (10) investigate the sensitivity of spillover patterns with respect to perceived risk of future disasters, which we measure via historical economic damages (column (9)) and counts of previous major disasters exceeding $1 billion in economic damages (column (10)).

in this paper qualify their estimates. For example, an analysis of our data at the country level would capture only a $40 million impact on FDI inflows, less than two-thirds of the true $130 million 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 economic 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 (Fujita and Mori, 1996; 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 otherwise 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.

Although our estimates deliver consistent and compelling evidence to support these arguments, there are four 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.[34]

The second limitation is the possibility of simultaneous policy responses. While our event study and dynamic DD frameworks rule out the presence of diverging pre-disaster trends or other region-specific time-variant factors that do not occur in the same month as the disaster, they are unable to control for unmeasured shocks that occur simultaneously with a disaster. Disaster-induced policy responses to aid reconstruction and recovery, for example, may influence investment decisions and attenuate our disaster effect estimates on FDI. In this case, a conservative interpretation would view our results as the residual disaster impact on FDI inflows in the presence of recovery policies. For there to be a significant concern, however, affected regions would

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

need to enact a similar type of policy following each of the five disasters in our analysis. For example, it would need to be the case that affected regions adopt similar recovery efforts that successfully limit the attraction of FDI inflows.

The evidence regarding the existence and efficacy of such policies points to the contrary. A 2017 Post Disaster Needs Assessment by the Indian Ministry of Home Affairs evaluates the efficacy of post disaster policy responses in India. The report concludes that "while the existing system enables the prompt disbursing of assistance to disaster-affected people, it does not enable the comprehensive and systematic estimation of overall disaster impact nor the estimation of financial requirements. The data collected is insufficient to enable a full and scientific analysis of the consequences of the disaster on living conditions, quality of life and on the socioeconomic development of those who are affected" (PDNA Report, Disaster Management Division, 2017).

Third, our mixed results regarding spillover patterns and industry composition may suggest significant diversity across multinationals in their reinvestment decisions. In the absence of region-sector-level FDI data, we are limited to investigate the variation of FDI disruptions in directly affected regions with respect to local industry composition. If regional industry composition mirrors the makeup of FDI inflows, this analysis may provide some insights into the sector-specific responses of multinationals. Point estimates suggest that FDI disruptions are larger for regions with greater agricultural and mining sectors, while larger employment shares in retail and manufacturing limit the disaster-induced FDI disruptions. However, since the identifying variation is based on only two to four affected regions (depending on the disaster), we deem these findings preliminary. An analysis at the industry or firm level could shed light on which types of foreign investment are most affected by a natural disaster and which industries are more prone to relocate. It is entirely possible that our aggregated regional data miss some diverse industry patterns, providing the opportunity for future research when such data become available.

Finally, given the strong response of foreign firms to natural disaster risk, our results also raise the question of how *domestic* firms react to these same calamities. While data constraints require us to leave an empirical investigation of this question to future research, the theoretical considerations laid out in Section 3.4 suggest that multinationals' investment decisions may be considerably more sensitive to natural disasters than those of domestic firms.

## 7. Conclusion

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

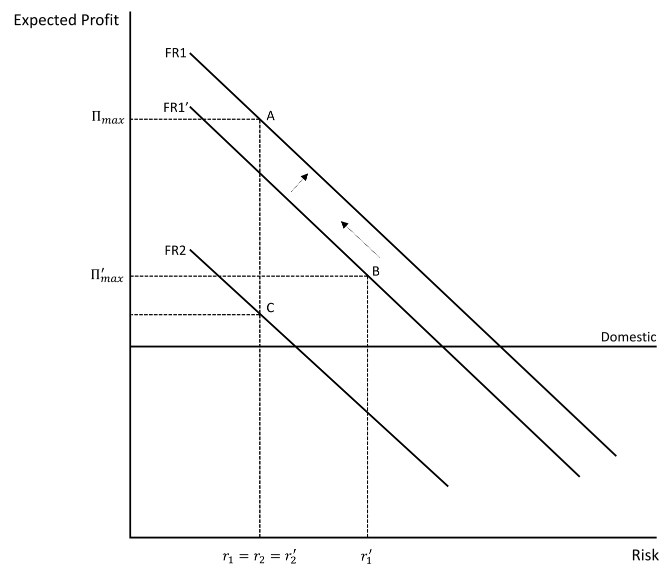
We find that intra-national FDI relocation decisions are driven by considerations of economic development, market potential, and the risk of future calamities. Among the potential beneficiaries of relocated investment, districts with greater urbanization, better access to electricity, a more skilled labor force, and a history of few and less harmful natural disasters experience the greatest FDI spillovers. The persistent and systematic divergence in FDI inflows from less developed, disaster-prone regions to more developed, urban, and unaffected regions has considerable policy relevance and may contribute to the growing regional inequalities in India.

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. 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 regions.

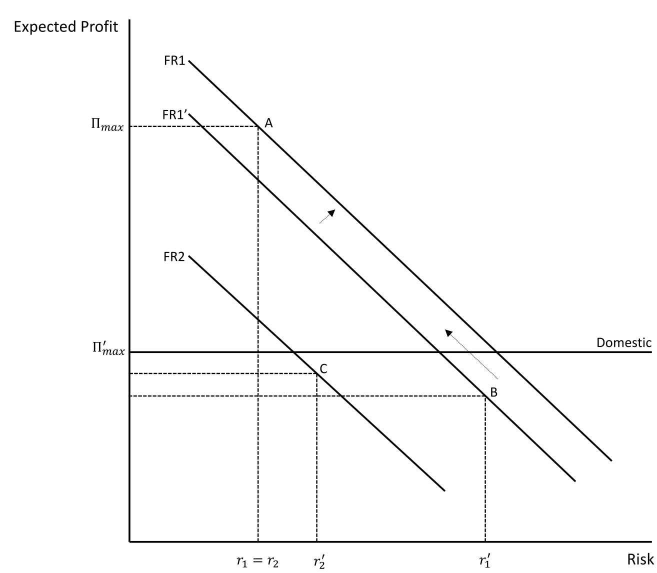
## Data availability

Data will be made available on request.

## Appendix A. Additional tables and figures




(a) No Location Switching




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

**Fig. A.1.** Potential Disaster Effects on Multinationals' Location Choice.

**Table A.1**
Region-to-State Concordance.

| *Region* | *States* |
|---|---|
| Ahmedabad | Gujarat |
| Bangalore | Karnataka |
| Bhopal | Chhattisgarh, Madhya Pradesh |
| Bubanesh. | Odisha |
| Chandigarh | Chandigarh, Haryana, Himachal Pradesh, Punjab |
| Chennai | Puducherry, Tamil Nadu |
| Guwahati | Arun. Pradesh, Assam, Manipur, Meghal., Mizoram, Nagal., 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 |

*Notes:* Our regions are based on the Reserve Bank of India districts, which are named after the major city in each respective region. This table shows the Indian states in each region.

## Appendix B. Robustness

### *B.1. Exclusion of large cities*

As part of our robustness checks, we test whether our spillover effect estimates hinge on the investment dynamics of the regions of Mumbai and Bangalore, which are the largest recipients of FDI inflows in India. This robustness analysis is particularly important given that these regions host two of India's largest cities and because they are key recipients of FDI from the technology sector, which might be less responsive to natural disasters. Fig. B.1 plots the spillover effect estimates, akin to Fig. 5(b), when we exclude the regions of Mumbai and Bangalore. These unaffected region event study estimates appear highly robust to the exclusion of these two regions, indicating that investment relocation is not solely concentrated in a few large cities.

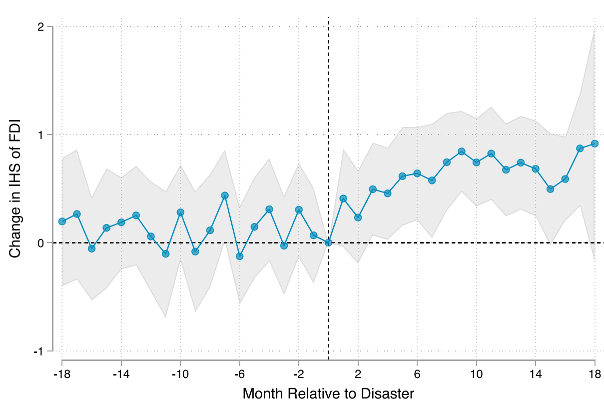


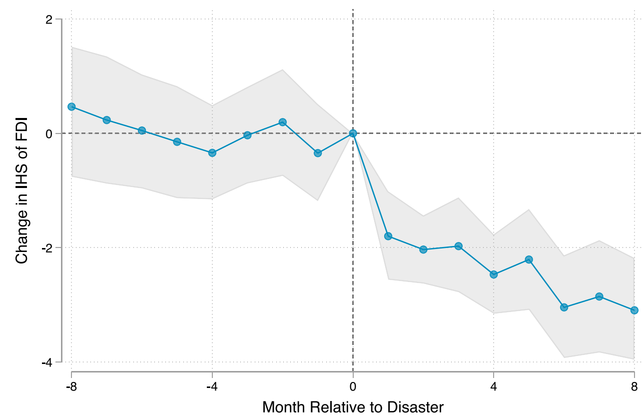

**Fig. B.1.** Spillover Effect Estimates Excluding Regions of Mumbai and Bangalore.

### *B.2. Changes to disaster selection criteria*

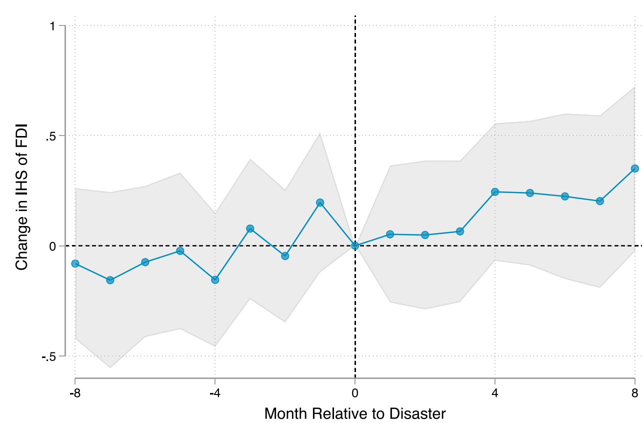
We also explore the sensitivity of the results with respect to our disaster selection. The primary results include the five most destructive Indian disasters over our sample period, where these events are chosen based on physical severity as outlined in Section 4.2. According to the DFO database, each of these disasters is classified as an "extreme event", reserved for disasters with an estimated recurrence rate greater than 10 years.

This section tests how our results change if we weaken this threshold to additionally include disasters classified as "large events", the next level down in severity. This adds four new disasters to our sample for a total of nine events. The newly included disasters are the Surate Flood in July 2006, the Indian Floods in July 2009, the India–Pakistan Floods in September 2014, and the South Asia Floods in July 2019.

Fig. B.2 shows our event study estimates for affected and unaffected regions when we expand the selection to include these less severe disasters.[35] In general, the results are consistent with our baseline results. First, the pre-treatment trends remain flat and statistically insignificant for both affected and unaffected regions. In affected regions (Fig. B.2(a)), the estimated magnitude and significance of the post-disaster effects is very similar to our five disaster sample. For spillovers into unaffected regions (Fig. B.2(b)), our estimates tend to be smaller in magnitude and less significant, but still show a noticeable rise following a disaster. This is not unexpected; since our expanded sample includes 9 disasters, the unaffected regions are now comprised of districts that may have more recently experienced a disaster of their own, dampening the size of the spillovers.




(a) Event Study with More Disasters, Affected Regions (IHS Estimates)




(b) Event Study with More Disasters, Unaffected Regions (IHS Estimates)

**Fig. B.2.** Robustness Against the Inclusion of More Disasters.

### *B.3. Affected regions based on disaster centroids*

Due to data limitations, our primary estimates rest on the assumption that all affected regions experience the same disaster severity. In reality some directly hit regions may be more devastated by a given

[35] Given that our sample now include 9 disasters over the 15 year period, we are only able to estimate time-to-event coefficients for 8 months before and 8 months after a disaster.

disaster than others. The Northern Indian Floods of June 2013, for example, has been reported to have affected the Indian regions of Chandigarh, Delhi, and Kanpur. The center of this flood, however, was concentrated in Kanpur. Treating all affected regions as equally affected delivers treatment effect estimates that average the disaster impact across the full spectrum of disaster intensities and destructiveness. The less some "affected" regions are actually impacted, the more our primary estimates attenuate to zero.

To test the sensitivity of our findings against this assumption we conduct a robustness analysis that restricts the treatment group to affected regions where the centroid of a given disaster was located (i.e. one affected region per disaster). All other (possibly partially) affected regions are excluded. As a result, the estimation sample is restricted to five affected centroid regions and five regions unaffected by any of the five disasters.

A priori, one would expect the magnitude of the coefficient estimates to increase. The exclusion of potentially less affected areas shifts all the weight onto the comparison between the arguably most affected centroid region and completely unaffected investment locations. One potential drawback from this restriction, however, is the reduction in sample size and number of treated regions.

Table B.1 shows the coefficient estimates when imposing this sample restriction and focusing the impact estimates on centroid regions only. As expected, the coefficient estimates remain negative and increase in absolute magnitude when each of the five disaster effects are estimated separately. The change in coefficient estimates varies by disaster and ranges from as little as 2% to as high as 40%. The joint estimation shown in column (6) of Table B.1 delivers similar point estimates as those shown in column (6) of Table 2. Qualitatively, the results are very consistent with the primary estimates and lend further support to our initial analysis.

**Table B.1**
DD Estimates with Only Centroid Regions as Treated and Other Affected Regions Excluded.

| | IHS FDI (1) | IHS FDI (2) | IHS FDI (3) | IHS FDI (4) | IHS FDI (5) | IHS FDI (6) |
|---|---|---|---|---|---|---|
| Disaster 1 | −4.560 | | | | | −3.689 |
| | (0.000) | | | | | (0.000) |
| Disaster 2 | | −2.473 | | | | −1.429 |
| | | (0.005) | | | | (0.039) |
| Disaster 3 | | | −3.003 | | | −3.258 |
| | | | (0.001) | | | (0.000) |
| Disaster 4 | | | | −1.443 | | −1.727 |
| | | | | (0.012) | | (0.000) |
| Disaster 5 | | | | | −0.893 | −1.444 |
| | | | | | (0.326) | (0.016) |
| Ln($GDP_{t-1}$) | 0.501 | 0.536 | −1.697 | −0.533 | −0.557 | −0.125 |
| | (0.766) | (0.730) | (0.185) | (0.759) | (0.759) | (0.889) |
| Ln($Pop_{t-1}$) | 0.078 | −0.003 | −0.045 | 0.465 | 0.225 | −0.196 |
| | (0.890) | (0.996) | (0.927) | (0.460) | (0.737) | (0.627) |
| *N* | 1680 | 1680 | 1680 | 1680 | 1680 | 1680 |
| $R^2$ | 0.812 | 0.801 | 0.814 | 0.789 | 0.784 | 0.860 |
| # of Affected Regions | 1 | 1 | 1 | 1 | 1 | 5 |
| Regional FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Notes:* P-values, reported in parentheses, are based on two-way wild cluster bootstrapped standard errors. Columns (1) through (5) show the separately estimated disaster impacts, whereas column (6) is based on jointly estimated disaster effects. The dependent variable is the inverse hyperbolic sine of FDI. The analysis underlying the coefficients shown here mirrors the analysis underlying point estimates shown in Table 2 but we restrict the set of treated locations to the region where the centroid of a given disaster is located and exclude all other affected regions. Consequently, the sample consists of a total of 10 Indian regions – five affected and five unaffected – rather than 16 total regions as in the primary baseline analysis.

## References


Alfaro, Laura, Chen, Maggie Xiaoyang, 2014. The global agglomeration of multinational firms. J. Int. Econ. 94 (2), 263–276.

Alvarez, Roberto, Görg, Holger, 2009. Multinationals and plant exit: Evidence from Chile. Int. Rev. Econ. Finance 18 (1), 45–51.

Amei, Amei, Fu, Wandong, Ho, Chih-Hsiang, 2012. Time series analysis for predicting the occurrences of large scale earthquakes. Int. J. Appl. Sci. Technol. 2 (7).

Angrist, Joshua D., Pischke, Jörn-Steffen, 2008. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press.

Anttila-Hughes, Jesse, Hsiang, Solomon, 2013. Destruction, disinvestment, and death: Economic and human losses following environmental disaster. Working Paper.

Anuchitworawong, Chaiyasit, Thampanishvong, Kannika, 2015. Determinants of foreign direct investment in thailand: Does natural disaster matter? Int. J. Disaster Risk Reduct. 14, 312–321.

Behrens, Kristian, 2007. On the location and lock-in of cities: Geography vs. transportation technology. Reg. Sci. Urban Econ. 37 (1), 22–45.

Bellemare, Marc F., Wichman, Casey J., 2020. Elasticities and the inverse hyperbolic sine transformation. Oxf. Bull. Econ. Stat. 82 (1), 50–61.

Benson, Charlotte, Clay, Edward J., 2003. Disasters, Vulnerability, and the Global Economy. World Bank Disaster Risk Management Series.

Bergstrand, Jeffrey H., Egger, Peter, 2007. A knowledge-and-physical-capital model of international trade flows, foreign direct investment, and multinational enterprises. J. Int. Econ. 73 (2), 278–308.

Berlemann, Michael, Wenzel, Daniela, 2016. Long-term growth effects of natural disasters - empirical evidence for droughts. Econ. Bull. 36, 464–476.

Biharprabha News, 2014. 2008 Kosi flood victims in bihar still await rehabilitation.

Blonigen, Bruce A., Piger, Jeremy, 2014. Determinants of foreign direct investment. Can. J. Econ. 47 (3), 775–812.

Bloom, Nicholas, Van Reenen, John, 2010. Why do management practices differ across firms and countries? J. Econ. Perspect. 24 (1), 203–224.

Boarnet, Marlon G., 1998. Spillovers and the locational effects of public infrastructure. J. Reg. Sci. 38 (3), 381–400.

Bordalo, Pedro, Gennaioli, Nicola, Ma, Yueran, Shleifer, Andrei, 2020. Overreaction in macroeconomic expectations. Amer. Econ. Rev. 110 (9), 2748–2782.

Boustan, Leah Platt, Kahn, Matthew, Rhode, Paul, Yanguas, Maria Lucia, 2020. The effect of natural disasters on economic activity in US counties: A century of data. J. Urban Econ. 118 (103257).

Business Standard, 2013a. Emami and shrachi to move operational headquarters out of Kolkata.

Business Standard, 2013b. West Bengal saw 97% decline in industries since 2010.

Cameron, A. Colin, Gelbach, Jonah B., Miller, Douglas L., 2008. Bootstrap-based improvements for inference with clustered errors. Rev. Econ. Stat. 90 (3), 414–427.

Cameron, A. Colin, Miller, Douglas L., 2015. A practitioner's guide to cluster-robust inference. J. Hum. Resour. 50 (2), 317–372.

CBS News, 2013. India raises flood death toll.

Chakrabarti, Avik, 2001. The determinants of foreign direct investments: Sensitivity analyses of cross-country regressions. Kyklos 54 (1), 89–114.

Colin Cameron, A., Gelbach, Jonah B., Miller, Douglas L., 2011. Robust inference with multiway clustering. J. Bus. Econom. Statist. 29 (2), 238–249.

Coronese, Matteo, Lamperti, Francesco, Keller, Klaus, Chiaromonte, Francesca, Roventini, Andrea, 2019. Evidence for sharp increase in the economic damages of extreme natural disasters. Proc. Natl. Acad. Sci. 116 (43), 21450–21455.

Cuaresma, Jesús Crespo, Hlouskova, Jaroslava, Obersteiner, Michael, 2008. Natural disasters as creative destruction? Evidence from developing countries. Econ. Inq. 46 (2), 214–226.

Dahlen, Sebastian, Peter, Goetz, 2012. Natural catastrophes and global reinsurance – exploring the linkages. BIS Q. Rev.

Davis, Morris, Fisher, Jonas, Whited, Toni, 2014. Macroeconomic implications of agglomeration. Econometrica 82 (2), 731–764.

Deccan Herald, 2015. Tamil Nadu's deadly rains hit industries hard.

Di Giovanni, Julian, 2005. What drives capital flows? The case of cross-border M&A activity and financial deepening. J. Int. Econ. 65 (1), 127–149.

Dilley, Maxx, Chen, Robert, Lerner Lam, Arthur, Arnold, Margaret, 2005. Natural Disaster Hotspots: A Global Risk Analysis. World Bank Group.

Escaleras, Monica, Register, Charles A., 2011. Natural disasters and foreign direct investment. Land Econom. 87 (2), 346–363.

Felbermayr, Gabriel, Gröschl, Jasmin, 2014. Naturally negative: The growth effects of natural disasters. J. Dev. Econ. 111, 92–106.

Fillat, José L., Garetto, Stefania, 2015. Risk, returns, and multinational production. Q. J. Econ. 130 (4), 2027–2073.

Fujita, Masahisa, Mori, Tomoya, 1996. The role of ports in the making of major cities: Self-agglomeration and hub-effect. J. Dev. Econ. 49 (1), 93–120.

Ghosh, Madhusudan, 2012. Regional economic growth and inequality in India during the pre-and post-reform periods. Oxf. Dev. Stud. 40 (2), 190–212.

Ghosh, Madhusudan, Ghoshray, Atanu, Malki, Issam, 2013. Regional divergence and club convergence in India. Econ. Model. 30, 733–742.

Ghosh, Buddhadeb, Marjit, Sugata, Neogi, Chiranjib, 1998. Economic growth and regional divergence in India, 1960 to 1995. Econ. Political Wkly. 33 (26), 1623–1630.

Goodman-Bacon, Andrew, 2021. Difference-in-differences with variation in treatment timing. J. Econometrics 225 (2), 254–277.
Görg, Holger, Strobl, Eric, 2003. 'Footloose' multinationals? Manch. Sch. 71 (1), 1–19.
Goud, S. Limba, 2011. Causality between foreign direct investment (FDI) and economic growth (GDP) in India during 1991-92 to 2009-10. Int. J. Appl. Bus. Econ. Res. 9 (2), 167–176.
Hallegatte, Stéphane, 2014. Natural Disasters and Climate Change: An Economic Perspective. Springer International.
Head, Keith, 2007. Elements of Multinational Strategy. Springer Science & Business Media.
Head, Keith, Ries, John, 2008. FDI as an outcome of the market for corporate control: theory and evidence. J. Int. Econ. 74 (1), 2–20.
Hindustan Times, 2010. More bodies found in Bihar, West Bengal, toll 129.
Hsiang, Solomon M., Jina, Amir S., 2014. The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence from 6,700 Cyclones. NBER Working Paper 20352.
Kline, Patrick, Moretti, Enrico, 2013. Local economic development, agglomeration economies, and the big push: 100 years of evidence from the Tennessee valley authority. Q. J. Econ. 129 (1), 275–331.
Kukułka, Agnieszka, 2014. Natural Disasters and FDI Inflow in the Developing Countries Of South-Eastern Asia. Research Papers of WrocłAw University of Economics, (370), pp. 208–216.
Lall, Somik V., 1999. The role of public infrastructure investments in regional development: Experience of Indian states. Econ. Political Wkly. 717–725.
Lall, Somik V., 2007. Infrastructure and regional growth, growth dynamics and policy relevance for India. Ann. Reg. Sci. 41 (3), 581–599.
LeSage, James, Pace, Robert Kelley, 2009. Introduction to Spatial Econometrics. Chapman and Hall/CRC.
Neary, J. Peter, 2009. Trade costs and foreign direct investment. Int. Rev. Econ. Finance 18 (2), 207–218.
New York Times, 2005. In India, economic prosperity is spreading slowly.
Noy, Ilan, 2009. The macroeconomic consequences of disasters. J. Dev. Econ. 88 (2), 221–231.
Oh, Chang Hoo, Oetzel, Jennifer, 2011. Multinationals' response to major disasters: How does subsidiary investment vary in response to the type of disaster and the quality of country governance? Strategic Manag. J. 32 (6), 658–681.
PDNA Report, Disaster Management Division, 2017. Handbook: Post Disaster Needs Assessment India. Technical report, Ministry of Home Affairs.
Peng, Mike, Lebedev, Sergey, 2017. Intra-national business. Asia Pacific J. Manag. 34, 241–245.
Polk, Andreas, Schmutzler, Armin, Müller, Adrian, 2014. Lobbying and the power of multinational firms. Eur. J. Political Econ. 36, 209–227.
Quah, Danny, 2002. Spatial agglomeration dynamics. Amer. Econ. Rev. 92 (2), 247–252.
Raddatz, Claudio, 2009. The wrath of God: Macroeconomic costs of natural disasters. World Bank Policy Research Working Paper 5039.
Rasmussen, Tobias N., 2004. Macroeconomic implications of natural disasters in the Caribbean. IMF Working Papers, 04, (224).
Reuters, 2010. Indian tornado deaths rise, survivors wait for aid.
Roodman, David, Nielsen, Morten Orregaard, MacKinnon, James G, Webb, Matthew D, 2019. Fast and wild: Bootstrap inference in stata using boottest. Stata J. 19 (1), 4–60.
Rossi-Hansberg, Esteban, 2005. A spatial theory of trade. Amer. Econ. Rev. 95 (5), 1464–1491.
Sachs, Jeffrey D., Bajpai, Nirupam, Ramiah, Ananthi, 2002. Understanding regional economic growth in India. Asian Econ. Pap. 1 (3), 32–62.
Skidmore, Mark, Toya, Hideki, 2002. Do natural disasters promote long-run growth? Econ. Inq. 40 (4), 664–687.
The Economist, 2017. The gap between India's richer and poorer states is widening.
The Independent, 2018. Worst floods in nearly a century kill 44 in India's Kerala state amid torrential monsoon rains.
Thorne, Nigel J., 1984. Reinsurance and natural disasters. Geneva Pap. Risk Insur. 9 (31), 167–174.
World Bank, 2014. World bank India disaster risk management program.
Zhang, Mingliang, Fortney, John C., Tilford, John M., Rost, Kathryn M., 2000. An application of the inverse hyperbolic sine transformation: A note. Health Serv. Outcomes Res. Methodol. 1 (2), 165–171.