Firm Adaptation in Production Networks: Evidence from Extreme Weather Events in Pakistan

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Abstract

This paper considers how far private adaptation may reduce future vulnerability to climate change. Firms' climate risk exposure depends not only on the location of production, but also on network effects via the flood risk profile of suppliers and transportation links connecting trading partners. We use data on monthly firm-to-firm transactions for the near-universe of formal sector manufacturing firms in Pakistan, and more than six billion observations from commercial trucks traveling on the road network from 2011 to 2018, to study adaptation of firms in production networks. We find that firms affected by major floods relocate to less flood-prone areas, and shift the composition of their suppliers towards those located in less flood-prone regions and reached via less flood-prone roads. Identification strategies that exploit both firm- and route-level flooding suggest that these responses reflect forward-looking actions to reduce future vulnerability to flood risk, and are consistent with experience-based updating. We develop a quantitative spatial model of endogenous production network formation among firms that learn about flood risk from realized flood events. We estimate the model to quantify the importance of the adaptive responses identified for the aggregate vulnerability of the economy to future flooding. The results suggest that the impacts of climate change will be mediated as firms learn from the experience of increasingly frequent climate disasters.

Keywords: flooding, adaptation, firms, production networks, environment, transportation, remote sensing, climate change, Pakistan

JEL Codes: L25, O14, O18, O53, Q52, Q54, R11, R41

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1 Introduction

Climate change presents a global threat to human populations and economic growth. Despite growing policy and research focus on mitigating climate risks, it is now clear that mitigation efforts will be insufficient to prevent many of their damaging effects. Foremost among these is the increased likelihood and severity of extreme weather events (IPCC, 2021). Estimating the costs of climate change, and designing appropriate policies to moderate damages, requires an understanding of how those affected by climate disasters respond to these changing circumstances (Carleton et al., 2022; Bilal and Rossi-Hansberg, 2023). In particular in developing economies, where capacity for centralized policymaking is often weak (Greenstone and Jack, 2015), the burden of adaptation often lies disproportionately with private actors. This paper considers how firms—which represent the central locus for the location of economic activity and are of first-order importance for the welfare of populations—anticipate and adapt to climate-related shocks.

Estimating firm adaptation to climate change, and its role in shaping aggregate growth trajectories, is challenging because both risk exposure and adaptation margins may involve complex network effects. Firms are exposed to spatially concentrated disaster risk not only directly because of their production taking place in risky locations, but also indirectly via exposure of their suppliers or buyers (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021), or transportation infrastructure that links firms to their trading partners (Korovkin et al., 2024). Adaptive behavior—actions taken by firms to reduce their risk exposure—can therefore take place along several margins: firms may exit or contract activities in risky locations, relocate towards less disaster-prone regions, adjust their mix of trading partners, or shift routes towards those less exposed to disaster risk. Capturing exposure and adaptation margins therefore requires detailed knowledge of production linkages, as well as a convincing methodology to distinguish changes in expectations over supply partners' outcomes from changes in costs or other determinants of supply chain formation.

Our empirical analysis provides evidence that firms affected by natural disasters undertake adaptive production and sourcing decisions along *all* of the margins of location, supplier and supply route choice in the aftermath of major floods. We leverage detailed data on transactions between firms, as well as measures of both firm- and supply route-level exposure to natural disasters, to attribute these adjustments to forward-looking decisions over future risk exposure rather than the direct disruptive impacts of flooding. This finding has crucial implications for our understanding of the role of climate risk in firm decision-making, complementing a recent literature examining individual decision-making and learning in relation to climate risks (Deryugina, 2013; Kala, 2017; Patel, 2023). While a worsening trajectory of natural disaster risk will have damaging impacts for firms, our results suggest that these will be mediated by firms responding adaptively as more information becomes available. More broadly, the complex adaptive behavior we identify is informative about the forward-looking behavior of firms in the presence of risk, which plays a central role in a large range of economic and policy questions.

The context of our study is Pakistan, one of the countries most exposed to extreme weather worldwide (Eckstein et al., 2021). We study firm and production network adaptation in Pakistan from 2011 to 2018 at a highly granular spatial and temporal scale using a series of novel datasets. We leverage georeferenced monthly microdata on the near-universe of formal firm-to-firm sales transactions to capture the key adaptation margins available to firms at a high frequency and level of precision. We complement the transaction records with data on over six billion observations from GPS trackers installed on more than 15,000 commercial trucks over the same period to measure the extent to which supply routes are affected by natural disasters. Flood disruptions to firm activities and the road network are measured by intersecting these with satellite-derived data on major flood events. To capture how far responses to these events may reduce vulnerability to future floods, we supplement this data with high-resolution measures of flood risk derived from a global flood hazard model.

We first document severe but short-lived disruption of firm activities and traffic induced by flooding of firm premises and roads. Sales and purchases of the mean flooded firm decline by 1.32% and 0.41% respectively in the month of recorded flooding, though both recover within six months. Pronounced increases in the probability of exit are observed following severe flood events. Flooding of roads also leads to large but brief disruptions to traffic flows: mean truck speeds decline by 0.8km/hr and truck-day counts by 16-20% immediately following floods, with reversion of both outcomes to pre-exposure levels within a month. The core of our analysis then turns to the question of whether these significant but temporary flooding disruptions induce firms to undertake longer term adaptive changes in order to reduce their vulnerability to future flooding.

We provide the first micro-level evidence of firm-level adaptive relocation by studying whether flooded firms relocate towards areas less prone to flooding. The results suggest that the average flooded firm sees a 1.79% increase in the odds of relocating more than 10km away over the ten-year study period relative to those that are not flooded. Importantly, this relocation is adaptive in the sense that flooding induces firms to relocate systematically towards less flood-prone locations: the average flooded firm that relocates more than 10km sees a 3.79cm reduction in the expected flood depth it would experience during a 1-in-100 year flood. District-level gravity specifications also suggest that relocating firms respond to recent flooding in deciding on a destination location, substantively avoiding locations that have recently been flooded within origin-destination district pair moves. These firm-level findings complement a recent climate migration literature which considers the response to extreme weather events of populations (Boustan et al., 2012; Mueller et al., 2014), night lights (Kocornik-Mina et al., 2020; Elliott et al., 2015), and employment (Indaco et al., 2021).

Given that firms may be exposed to climate risk not only directly but also via vertical linkages, we use transaction-level data to examine adaptation through supplier choice. Diversification may ameliorate expected flood losses by reducing dependence on individual suppliers, and spreading risk across suppliers with uncorrelated shocks (Cole et al., 2013; Meltzer et al., 2021; Boehm and Sonntag, 2022; Castro-Vincenzi et al., 2024). Consistent with this, we find that firms increase the number of suppliers from which they source following flooding of their suppliers, but that this response endures for less than a year. Combining transaction-level data with data on flood risk reveals that these firms more persistently shift the *composition* of their supplier base towards less flood-prone suppliers. This adaptive behavior is also evident among a firm's non-flooded suppliers – suggesting a role for forward-looking adaptation rather than simply the mechanical effect of no longer being able to source from flood-affected sellers – and persists for at least four years after flood exposure.[1] These results suggest that accounting for network-based adaptation margins is important, and demonstrate the sophisticated nature of firms' adaptive responses beyond the direct flood exposure of production sites.

The vulnerability of the firm network is predicated not only on the flood risk of firms, but also on the riskiness of the trading links connecting them. We use data on flood-induced road disruptions to examine adaptation via firms' choice of supply routes. Route-level specifications leverage the bilateral nature of the transaction-level data to fully isolate adaptive behavior by using buyer-seller, buyer-

[1]This is consistent with extensive margin evidence from financial data that temperature and flood shocks at supplier locations that exceed expectations may induce customers to terminate relationships and choose replacement suppliers with lower expected climate risk (Pankratz and Schiller, 2022).

time and seller-time fixed effects. These control for any direct effects of floods on firms and rule out potentially confounding shocks that may affect flooded firms even after their sales and purchases have recovered, such as local labor market disruptions or correlated cost shocks. The results suggest that firms respond to short-lived flood-induced disruptions to road transportation by reducing their dependence on supply partners reached via flood-prone routes. Despite pre-flood traffic flows being restored within a month, firms do not switch back to sourcing from these suppliers once access is restored. This provides our most cleanly identified evidence of firms undertaking long-term adaptation in response to transient shocks, and highlights the importance of accounting for route- as well as firm-level adaptation margins.

Taken together, these results provide evidence that firms anticipate future flood risk and undertake adaptive actions following exposure to major flood events. Quantifying the economy-wide implications of this adaptation for the vulnerability of the production network is challenging given that aggregate effects will reflect firm connections via multi-step linkages and general equilibrium forces. We therefore develop a quantitative spatial model of endogenous production network formation that captures firm-to-firm linkages and general equilibrium forces in order to estimate aggregate impacts.

The model features firms that are subject to both idiosyncratic and aggregate flood shocks that reduce firm productivity. Firms are imperfectly informed about the (joint) distribution of these risks, but update their beliefs in response to flood shocks. The framework builds on recent advances in modeling production network formation under uncertainty (Kopytov et al., 2022) to incorporate this imperfect information. Before flood shocks are realized, firms search for suppliers in different locations, taking into account their beliefs over potential partners' flood risk. These search decisions affect the distribution of supplier draws that the firm receives. Once shocks have been realized, firms make production and sourcing decisions conditional on these draws to minimize costs. We incorporate insights from the spatial trade literature, leveraging extreme value distributions to yield tractable gravity equations describing sourcing shares (following Eaton and Kortum, 2002; Oberfield, 2018; and Boehm and Oberfield, 2020, 2022). These gravity equations allow us to parameterize flood-induced productivity shocks and identify adaptive changes in firms' supplier search decisions from observed changes in sourcing shares, without imposing parametric assumptions about the belief-updating process. The structure of the model therefore allows us to estimate the aggregate impacts of adaptive changes in firms' supplier choice and to simulate policy counterfactuals.

We parameterize flood-induced productivity shocks at the level of locations comprising proximate firms with similar supplier flood exposure, which update their beliefs in a similar way following flood events. Accounting for direct productivity losses as well as general equilibrium impacts of supplier disruption, the estimated economy-wide increase in the household cost index for the floods in our sample ranges from 0.05% to 0.3%. We use the model to estimate the impacts of adaptation undertaken in the aftermath of these floods via counterfactual simulations that consider how damages from subsequent floods change if we remove adaptation following previous floods. This exercise reveals that adaptation following the 2012 floods helped reduce damages from subsequent floods affecting similar locations in 2013 and 2015, which would have been 5% and 1% higher respectively under sourcing shares that prevailed before the 2012 floods. However, adaptation in the aftermath of the 2012 floods is estimated to have *worsened* the impacts of the 2014 floods, which affected spatially disjoint regions in lower flood risk areas. This highlights that post-flood adaptation need not always ameliorate damages from future flood events, especially when idiosyncratic flooding affects areas that are not particularly flood-prone, which may become increasingly pertinent as flooding incidence responds to climate change.

The paper's findings suggest that natural disaster risk plays an important role in firm decision-making and that the realization of climate shocks influences firm expectations in a meaningful way. This manifests via adaptation along location, supplier and route choice margins, with complex system-wide effects as a result of manifold inter-linkages in production networks. A significantly worsening trajectory of flood events is predicted in Pakistan (World Bank and ADB, 2021) and globally (Kirezci et al., 2020) over the coming decades as climate change unfolds. As such, these responses will have profound implications for how firms will adapt to an increasingly risky environment, a key factor informing assessments of the costs of climate change. Our results indicate that firms are imperfectly informed about climate-related disaster risk, highlighting the potential for policies addressing such frictions to ameliorate climate damages.

The remainder of the paper proceeds as follows. Section 2 describes the datasets used in the analysis. Section 3 provides evidence for the disruptive impacts of flood events on firm production and road transportation in Pakistan. Section 4 examines firm and supply chain adaptation in the aftermath of flood events. Section 5 uses a quantitative model of production network formation and adaptation under supply chain uncertainty in our empirical setting to understand the importance of adaptive decisions for aggregate outcomes. Section 6 concludes.

2 Data

The empirical setting for our analysis is Pakistan, one of the world's most vulnerable countries to the effects of extreme weather worldwide (Eckstein et al., 2021), where rapid industrialization is proceeding alongside increasing vulnerability to the effects of climate change. Floods are preeminent among these: the country frequently ranks in the top deciles for per capita flood losses globally (Guha-Sapir et al., 2022), with major floods involving severe disruption to firms and infrastructure. The 2022 floods alone are estimated to have resulted in damages of $40 billion (PMO, 2022) (roughly 11.5% of 2021 GDP), 30% of which are accounted for by damages to infrastructure and non-residential structures (World Bank, 2022). Transportation infrastructure is especially affected by flooding: the 2022 floods damaged over 8000 miles of roads and 392 bridges (Congressional Research Service, 2022), while the 2010 floods are reported to have damaged 10% of the country's road network (World Bank, 2010).

In this context, the analysis draws on four novel georeferenced micro-datasets from 2011-2018 in order to characterize flood-induced disruption to firms and production network linkages, and identify adaptive adjustments at a fine temporal and spatial resolution. Firm-to-firm transaction data allows us to identify production network linkages, disruption to firms and relationships, and examine adaptation via firm location and supplier choice. We use GPS tracker signals from commercial trucks to identify disruption to transportation routes and examine adaptation via trading route choice. We identify the flood exposure of firms and roads in the data by intersecting these geocoded datasets with satellite images of flood extents. Finally, detailed data on flood risk from an advanced flood hazard model helps us to characterize adjustments as adaptive to the extent they reduce the flood risk of firms' premises and supply network dependencies.

2.1 Firm transactions data

Data on firm outcomes comes from the near-universe of formal firm-to-firm monthly sales transactions for all VAT-registered firms over July 2011-June 2018 from Pakistan's Federal Board of Revenue (FBR). At the firm level, these data contain information on reporting firms' name, industry and address at the beginning and end of the study period. The data also contain monthly information on all transactions where at least one party is registered for VAT, as well as total sales, purchases, exports and imports as reported monthly by each firm. We construct three firm-level monthly sales and purchases variables: one given by the firm's reported sales (purchases); a second given by the sum of transaction-level sales (purchases) reported by the firm; and a third which aggregates the union of transaction-level purchases (sales) reported by the firm and its trading partners.

The data contains reports of all firms in Pakistan registered to pay VAT, which is required for all importers, wholesalers and distributors, as well as manufacturers and retailers with revenue exceeding 10 million rupees in the previous tax reporting period and an annual utility bill above 800,000 rupees.[2] This yields a raw dataset containing information on 419,517 firms which either self-report or are reported upon in the reports of VAT-registered firms.

We take a number of steps to exclude incomplete or potentially misreported transaction data. We exclude firms that have been identified as—or transact exclusively with—'invoice mills', firms that exploit breaks in the supply chain to purchase and sell VAT invoices without conducting any real business (Waseem, 2019; Keen and Smith, 2006). This removes 4% of firms in the sample. Also excluded are 29% of firms for which there is insufficient address information to geocode the firm's location and therefore for which we cannot identify flood exposure. A large fraction of the remaining firms report very infrequently or not at all (the latter appearing in the dataset only by virtue of having transactions reported upon by their VAT-registered transaction partners). Given that measurement for such firms is likely to be poor and that singleton observations will not be informative for studying the effects of flooding, we also exclude firms that report at most twice in any transaction measure.[3] The full set of sample restrictions reduces the firm count considerably to 73,336, but excludes firms that account for only 2.9% of aggregate sales and 3.4% of aggregate purchases.

The resulting data represents a large fraction of the economic aggregates reported in national accounts. In the restricted sample, aggregate manufacturing value added accounts for 89% of reported manufacturing GDP in the last year of the sample.[4] To capture entry and exit of firms while allowing for the potentially confounding effect of irregular reporting, we define a firm as entering on the date of their first report (self-reported or reported by a transaction partner) if this is more than a year since the beginning of our panel, and as exiting on the date of their last report if this is more than a year from the end of our panel. All observations for a given firm before their date of entry or after their date of exit are set to missing. Summary statistics describing the firms and transactions in the restricted sample are included in Tables A.1 and A.2, respectively.

Address information for firms in the sample was used to geocode firm locations using the Google Maps API.[5] The location of firms in the sample is shown in Panel (a) of Figure 1 and displays a strong concentration of firms in Pakistan's major industrial provinces of Punjab and Sindh. For 60% of firms, sufficient address information is available to geocode addresses in 2011 and 2019 separately.

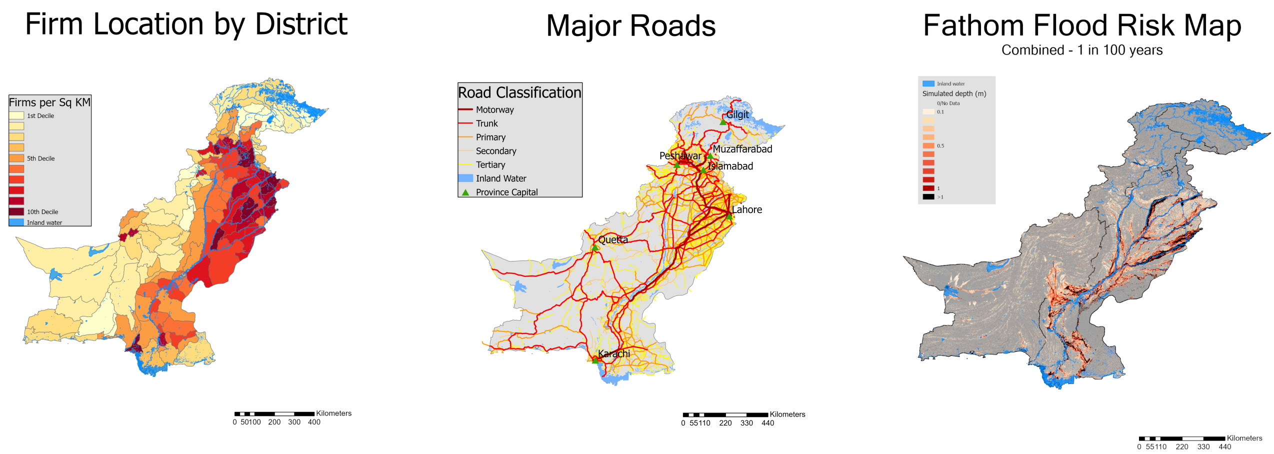
[2] These thresholds were raised from 5 million rupees in July 2016 and from 700,000 rupees in July 2015, respectively.

[3] For the same reason, all transaction-level specifications restrict attention to firm-pairs for which we observe at least one transaction across the study period.

[4] Total value added in our restricted sample accounts for approximately 20% of total GDP. This is likely because the reported aggregates include sectors which are not subject to VAT—agriculture, certain services, and the informal sector.

[5] For those firms for which no address information was available from the FBR's firm transactions data, where possible we used address information scraped from the FBR's Active Taxpayer Lookup Portal. Where multiple addresses are available for a firm, we use the primary 'business' address. We drop a small number of firms reporting two business addresses which are more than 5km apart.

Figure 1. Spatial distribution of firms, roads, and flood risk



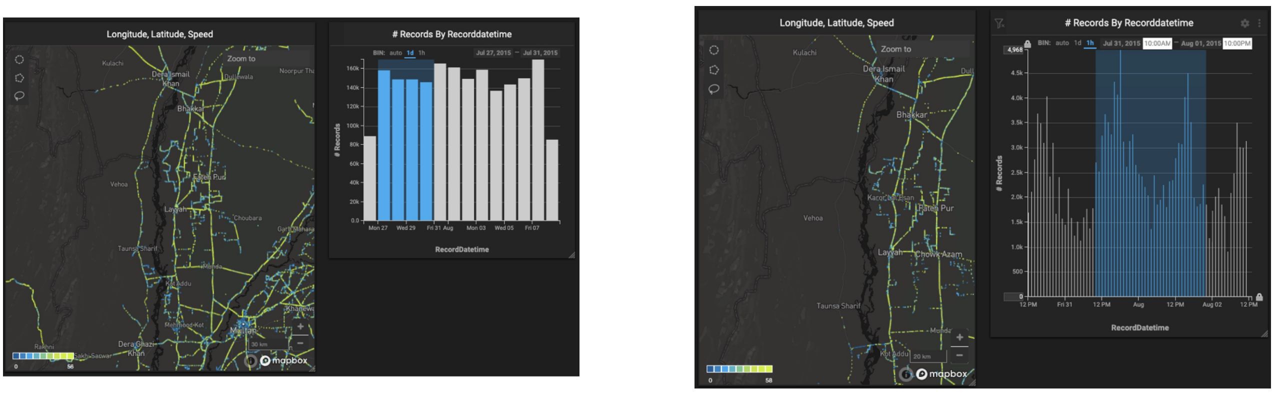
(a) Firms (b) Roads (c) Flood risk

Notes: Flood risk in panel (c) is defined as the maximum across fluvial and pluvial flood risk, both measured as the expected flood depth in meters for a 1 in 100 year return period.

2.2 GPS tracker data from commercial trucks

In order to study the disruptive effects of flooding on firm-to-firm trade via transportation network disruptions, we obtain high-frequency data from GPS trackers installed in more than 15,000 commercial trucks in Pakistan from a large original equipment manufacturer. The data provider sells tracking devices and associated tracking and fleet management solutions to truck manufacturers, logistics providers, industrial and insurance companies. The data comprises more than six billion observations showing the precise location, timestamp, and speed of trucks traveling on Pakistan's road network from 2012 to 2018. As such, the data yield accurate information on truck supply routes, traffic conditions, and disruptions.

Figure 2. N-55 Indus Highway flooding disruption



(a) Jul 27-30, 2015 (b) Jul 31-Aug 1, 2015

Notes: The maps display the location and speed of trucks from GPS tracker data in the area surrounding the N55 highway near Vehova in Punjab Province before (panel (a)) and after (panel (b)) reported flooding.

Figure 2 displays the capacity of this data to capture flood-induced disruption to roads at an extremely fine spatial and temporal resolution. The Figure shows the area surrounding the N55 highway near Vehova in Punjab Province, which at 09:15 on 31 July 2015 was reported by Pakistan's

National Disaster Management Authority (2015) to have been hit by "floodwater coming from Koh-e-Suleman Range" which "swept away a 300-foot portion of the highway" (Dawn.com, 2015). The left hand panel shows normal traffic running along the north-south highway directly to the left of the Indus River in the four days leading up to the flood from 27-30 July. The right hand panel shows the abrupt cessation of traffic along the route in the direct aftermath of the flooding from 10:00 on 31 July to 10:00 on 1 August. In Section 3.2, we use weekly road edge level regressions to document a systematic pattern of such flood-induced disruptions to road traffic in our sample.

We study flood-induced disruption to firm-to-firm supply routes by constructing firm-pair-route level measures of travel speeds and disruption over time. To do so, we obtain Open Street Map data on Pakistan's road network comprising motorways, trunk roads, primary, secondary and tertiary roads and their links, shown in Figure 1b. These are split at road endpoints and intersections to yield an edge-level dataset onto which we project the GPS tracker observations according to the closest edge within 10 meters of the observation coordinates.[6] Consecutive observations are filtered out where the between-observation elapsed time is more than 30 minutes (periods during which the truck is likely parked) or the Euclidean distance is more than 20km (from which sensible route information cannot be inferred). Using the remaining data observations, we find the shortest distance between each consecutive pair of observations along the edge network and—based on the observations' timestamps at both points—infer the average speed at which the truck traveled on all edges between them. We aggregate speeds first to the day-truck-edge level, and then by taking the mean to the week-edge level, also taking note of the number of truck-day observations within each week-edge ("day-truck count").

Figures A.1 and A.2 suggest that the resulting edge-time level dataset captures travel speeds well. Figure A.1 compares calculated speeds in the full sample to speeds reported by the trackers themselves at the time of each observation, for each road type in 2012. This comparison demonstrates that calculating travel speeds using the method described above overcomes selection bias in the reported speeds arising from the fact that GPS trackers are disproportionately likely to report when vehicles are starting, stopping, braking, or turning, which accounts for the mass of observations at very low reported travel speeds. In contrast, calculated speeds follow a smooth distribution with a sensible distribution by road type. Figure A.2 compares calculated speeds for an area of Lahore in 2015 to those reported for 2010 in Japan International Cooperation Agency (2012), and finds a high degree of overlap in both the magnitude and spatial distribution of reported speeds.

The edge-week level data are used to construct the least-time route and travel time between each buyer-seller pair on average across non-flooded weeks, and during each week when flood events are recorded. Buyer and seller firm locations are projected onto the road network and the least-time route between them calculated using average edge-level speeds over the relevant period, weighting by edge length.

2.3 Flooding data

Data on flood events in Pakistan from 2011-2018 are obtained from the United Nations Satellite Centre (UNOSAT) flood portal.[7] This service provides satellite imagery of major flood events generated in response to requests from organizations such as UN entities, member states, government offices and NGOs, most often to aid disaster response efforts.[8] These images allow us to map the exact location

[6] All observations with coordinates more than 10 meters from any road edge in our data are discarded.

[7] http://floods.unosat.org/geoportal/catalog/main/home.page.

[8] We cross-reference the floods identified from this source with major flood events identified in other key natural disaster datasets (the EM-DAT dataset of the Centre for Research on the Epidemiology of Disasters, the Dartmouth

of floods as detected from satellites, from which we extract a reference water layer.[9] Flood-affected firms and roads are identified by intersecting the resulting flood areas with georeferenced firm and road locations.

For firm-level specifications, we aggregate satellite images to the monthly level, which yields a total of 7 monthly flood events over 2011-2018. The aggregate extent of flooding during years in which we observe flood events during our sample is shown in Figure A.3. We capture flooding of firm locations using the maximum share of a 2km buffer surrounding the firm's geocoded location that is flooded during a given flood event. As described in Table A.1, using this definition 28% of firms in the sample are ever flooded during the sample period and 4% are flooded more than once.

Given that roads are often disrupted by floods for shorter durations, and the extremely fine temporal resolution of the GPS tracker data, we consider flood-induced road disruption at the weekly level. Satellite images grouped at the weekly level yield a total of 11 flooded weeks during the sample period for which we observe GPS network data (2012-2018). Road network edges are intersected with the union of flood polygons observed in each week. At the buyer-seller level, 46% of ordinary-time shortest routes experience flooding at least once during the sample period.

2.4 Flood risk data

Given our focus on adaptation to flood risk, we supplement our data on flood exposure with data on flood risk. These data come from Fathom-Global, which uses a global flood hazard model combined with detailed terrain and hydrography data. The resulting datasets comprise rasters at a resolution of 90 meters representing fluvial and pluvial flood risk (measured as the expected flood depth in meters) with return periods of 1 in 10 years, 1 in 50 years and 1 in 100 years.[10] For each return period, we take the maximum of the projected fluvial and pluvial flood risk. Panel (c) of Figure 1 maps the Fathom flood risk across Pakistan for a return period of 1 in 100 years; equivalent maps for return periods of 1 in 10 and 1 in 50 years are shown in Figure A.4. These maps demonstrate a significant degree of overlap between flood-prone locations and areas with a high density of firms, which are shown in Panel (a) of Figure 1.

The flood risk of a firm location is calculated as the weighted average Fathom flood risk depth index in the 2km buffer surrounding a firm's geocoded location, cropped to erase the baseline water layer. The distribution of firms' flood risk for each return period is shown in Figure A.5. As expected, longer return periods are associated with more density in the right tail, and in each case the distribution for firms that are ever flooded during the sample is rightward shifted. Similar patterns are evident for the distribution of flood risk of routes connecting firm pairs, calculated as the average Fathom flood risk depth index of all edges along the route, weighted by edge length, as shown in Figure A.6.

Flood Observatory and Sentinel Asia) to confirm that major flood events described in these sources are captured in our data. Relative to these sources, the UNOSAT data provides the advantage of exact flood locations and extents as observed from satellites during our study period.

[9] The reference water layer comprises rivers, lakes and other existing bodies of water obtained from https://download.geofabrik.de/asia/pakistan.html.

[10] Fathom-Global 2.0 is based on LISFLOOD-FP, a two-dimensional hydrodynamic model designed to simulate floodplain inundation over complex topography (Bates, 2010). The key datasets used are the MERIT-Hydro global hydrography dataset and the MERIT-DEM global terrain dataset, which have been corrected for urban developments (Yamazaki et al., 2017; Yamazaki et al., 2019), as well as a database of flood defense infrastructure.

3 Floods and supply chain disruption

In this section, we present motivating evidence for the disruptive impacts of flooding on firm and network activity. Understanding how flooding of firms and roads disrupts firm operations is an important outcome in its own right that has received limited empirical attention in developing country contexts (Hu et al., 2019; Rentschler et al., 2021; Zhou and Botzen, 2021). This is especially pertinent in Pakistan given the country's extreme vulnerability to acute flooding (Eckstein et al., 2021) and under-developed disaster insurance market.[11] Analyzing the dynamic effects of floods on firm operations will also be informative for our subsequent examination of firm adaptation. If firms undertake long-term actions in response to floods, this may reflect adaptive behavior or mirror persistent direct impacts of flooding on firm operations. We use evidence on the duration of direct impacts of floods from these specifications to help disentangle these two effects in Section 4.

3.1 Direct impacts of firm flooding

We first consider the direct impact of flooding of a firm's premises on its operations, as measured by sales and purchases, using the following specification:

$$y_{it} = \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_\tau \text{FloodExtent}_{i,t-\tau} + \alpha_{im(t)} + \alpha_{iy(t)} + \alpha_t + \varepsilon_{it} \tag{1}$$

where y_{it} denotes log declared aggregate monthly sales or purchases for firm i in month-year t; and FloodExtent_{it} is the maximum share of firm i's 2km buffer that is flooded during month-year t. $\alpha_{im(t)}$, $\alpha_{iy(t)}$, and α_t are firm-month, firm-year and month-year fixed effects respectively, which control for firm-specific seasonality, firm-specific yearly shocks, and aggregate time trends.[12] Standard errors are clustered at the firm level. As we observe multiple instances of flooding for a small share of firms, we restrict attention to each firm's first observed flooding event-month during the study period in this and all subsequent specifications unless otherwise noted. We choose the period two months before the firm's first recorded flood as the omitted reference period, and shade the period from $\tau = -1$ to $\tau = 0$ as the period during which the firm is likely to have first experienced flooding. This reflects the fact that there is a lag between the onset of flooding and the date at which UNOSAT satellites capture flood extents.[13]

The results of estimating this specification, shown in Figure 3, display intuitive reductions in both the sales and purchases of flood-hit firms in the direct aftermath of flooding events. The immediate impacts are statistically significant and economically large: during the month of impact, sales decline by 1.32% and purchases by 0.41% for the mean treated firm, which sees 1.31% of its 2km buffer flooded.[14] These large impacts are, however, relatively short-lived, with recovery of both sales and purchases to levels close to their pre-flooding levels within six months.[15] Reassuringly, trends are flat

[11] An estimated 3% of damages caused by flooding and earthquakes is covered by insurance and risk retention funds in any given year (ADB, 2021).

[12] Results are robust to replacing month-year fixed effects with district-month-year fixed effects or Fathom flood risk decile-month-year fixed effects, as demonstrated in Figures A.7 and A.8, respectively.

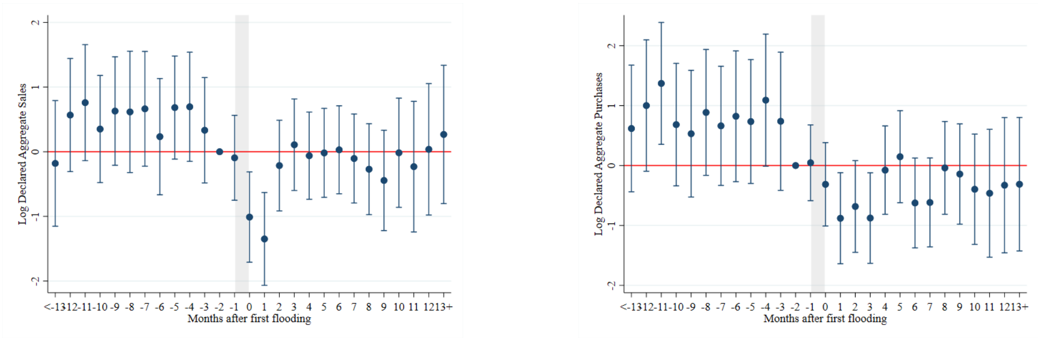
[13] In Appendix C.1, we consider the robustness of results to using alternative estimators to address potential challenges associated with two-way fixed effects regressions including treatment lags and leads with variation in treatment timing.

[14] Results where FloodExtent_{it} is replaced by an indicator variable capturing whether a firm sees 0-5%, 5-10% or more than 10% of its buffer flooded are shown in Figures A.9 and A.10. These results suggest that estimated effects are driven by firms that see a large share of their buffer flooded.

[15] The fact that sales and purchases appear not to fully recover to pre-purchase levels is consistent with firms incurring

in the full pre-treatment window for sales outcomes and in the period up to two months before recorded flooding for purchases outcomes. The slight decline in purchases in the month before flooding, while insignificant, may reflect anticipatory contractions of purchases once imminent floods are forecast, as well as lags between the onset and satellite capture of flooding.

Figure 3. Impact of flooding on firm sales and purchases



(a) Log sales

(b) Log purchases

Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). The unit of observation is a firm-month-year. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Given these sizeable impacts of flooding on firm operations, Figure A.11 considers whether floods are sufficiently disruptive as to result in the exit of the worst-affected firms. The results in the pooled sample show a modest positive impact on firm exit in the direct aftermath of flooding, while strong effects are observed for some individual flood events.[16]

3.2 Direct impacts of road flooding

Flooding may disrupt firm and supply chain network activity not only via direct damage to firm buildings, equipment and stocks, but also as a result of disruptions to the road network. Such effects may be substantial: for instance, the World Bank (2010) estimates that the devastating floods of 2010 damaged 10% of Pakistan's road network. Our GPS data provides a unique opportunity to study the firm- and network-level effects of such disruptions given the fine-grained lens they provide into flood-induced road closures. Given that roads closed due to flooding are often reopened rapidly, we examine flood-induced road disruptions at the weekly level using the following specification:

$$y_{iw} = \sum_{\substack{\tau=-10 \\ \tau\neq-2}}^{20} \beta_\tau \cdot \mathbb{1}(i \text{ flooded at } w-\tau \text{ and } w-\tau \in y(w)) \cdot \text{FloodExtent}_{i,y(w)} + \alpha_i + \alpha_{dw} + \varepsilon_{iw} \quad (2)$$

where y_{iw} is an outcome for road edge i during week w; $y(w)$ is the year of week w; $\text{FloodExtent}_{i,y(w)}$ is the share of the total road length of i that is flooded in the first week of flooding during $y(w)$; α_i are road edge fixed effects; and α_{dw} are district-week fixed effects.

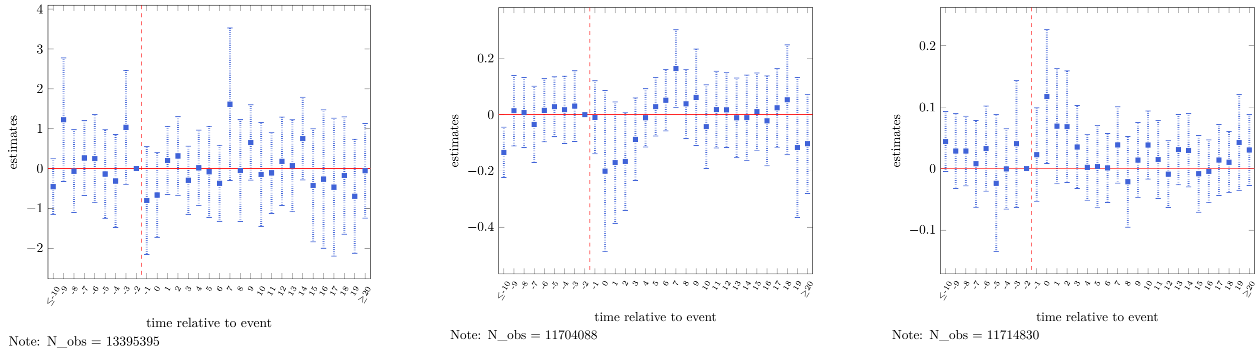
To capture alternative measures of road disruption, we consider several outcome variables. Panel (a) of Figure 4 shows the impact on the mean speed of trucks traveling on the edge; panel (b) on the log day-truck count; and panel (c) on an indicator variable denoting whether the road edge is

costs to change their supplier base adaptively following floods, see Section 4.

[16]For instance, following the severe floods in 2014, the mean firm first treated in 2014 sees a 0.40 percentage point increase in the probability of exit, as shown in the second panel of Figure A.11.

'disrupted', defined as having a day-truck count on the edge that is lower than the fifth percentile for the relevant edge across all weeks.[17]

Figure 4. Impact of flooding on road traffic



(a) Mean truck speed

(b) Day-truck count

(c) Disruption (< 5$^{\text{th}}$ percentile)

Notes: The panels plot OLS estimates of the effect of road flooding on different traffic outcomes following equation (2). The unit of observation is a road edge-week. Panel (a) excludes observations with day-truck counts < 10. Panels (b) and (c) drop edges for which the first percentile of day-truck counts is zero. The 95% confidence intervals rely on standard errors clustered at the district-time level.

The results of these specifications paint a consistent picture of sizeable but brief disruptions to traffic induced by flooding of roads. The point estimates suggest that mean truck speeds at the road edge-week level decline by 0.8km/hr in the week in which flooding is recorded, though estimates are not statistically significant at conventional levels, and return to pre-flooding levels by the following week. Day-truck counts, shown in panel (b), show a more pronounced decline in the range of 16-20%, with reversion to pre-flooding levels within a month of flooding. A disruption indicator based on a threshold of the fifth percentile of edge-level day-truck counts shows an increase of 11.7pp in the week in which flooding is recorded, with reversion within a fortnight.

The results in this section suggest that floods have sizeable disruptive impacts on firm operations and road traffic. While effects on firm exit are likely mostly permanent, the event study plots of impacts on intensive margin sales and purchases and road traffic are transient, persisting for a matter of only months or weeks respectively. This dynamic pattern is informative for our understanding of potential adaptive responses. If we see long-term firm responses to flooding of firms or roads, the results in this section suggest that these are *not* driven by long-term disruption to intensive margin firm operations or roads. In this context, we consider in the next section whether firm responses to flood events are consistent with adaptation.

4 Evidence for firm and supply chain adaptation

In this section, we turn to the key question of whether firms undertake actions following flood events that are adaptive in the sense of reducing their vulnerability to future flooding. We consider several potential margins along which firms may reduce their future flood risk in the aftermath of flood exposure. First, flooded firms may relocate towards areas that are less exposed to flood risk. Second, firms

[17]The day-truck count is the number of different trucks travelling on a given edge during a given week, counting each truck more than once if they travel on the edge on different days of the week. For the specifications examining mean speed in panel (a), we consider the set of edge-week observations for which we have at least 10 day-truck observations with valid speed since mean speed is poorly measured when trucks pass very infrequently. The regressions (b) and (c) exclude edges where the first percentile of the day-truck counts is zero; these are edges that are infrequently traversed by trucks in our dataset.

may adjust their choice of supply partners to lower indirect flood exposure, either via diversification by transacting with a larger number of supply partners, or by shifting towards less flood-prone suppliers. Finally, firms may respond to flooding of key supply routes by reducing their dependence on supply partners reached via flood-prone routes.

The adaptation margins we consider may capture both firms' forward-looking decision-making to reduce their future vulnerability to flooding, and more mechanical reductions in flood risk if, for instance, even random relocation of flooded firms (which on average have higher flood risk) should lower the flood risk of the average flooded firm. Both forward-looking and mechanical responses reduce firms' flood risk and are therefore of interest in understanding firm adaptation to flood risk. However, separating mechanical from forward-looking adaptation is important in considering policies that may help to facilitate adaptation. In Sections 4.3 and 4.4, we provide evidence that isolates forward-looking adaptive behavior in supplier and route choice adaptation, and hence suggests that adaptive responses at least in part reflect forward-looking actions to reduce future flood risk.

4.1 Location choice

We first consider the impact of flooding on firm relocation decisions for the 60% of firms for which we have a geocoded firm location in both 2011 and 2019. In these specifications, we consider whether flooding induces firms to relocate, and how far flooding prompts firms to move towards less flood-prone locations.

Firm locations are geocoded from address strings associated with each firm in 2011 and 2019. Small differences in the address strings (for instance the same street address being entered with and without a building number) may result in different geocodes being assigned in the two years even when a firm has not moved. Summary statistics in Appendix Table A.3 reveal that there is a non-zero difference between the 2011 and 2019 location of 68% of firms, an implausibly high relocation rate over an eight-year horizon which is likely predominantly accountable to these small discrepancies in address information leading to local discrepancies in geocode locations. Defining firm relocation based on a threshold of 10km gives a more plausible relocation rates of 13%, so we use this as the threshold for defining a firm 'move'.[18]

The following logit specification is used to examine the impact of flooding on the probability of firm relocation during the study period:

$$Pr\left(\text{Move}_i\right) = F\left(\beta \text{FloodExtent}_i + \alpha_{zd}\right) \tag{3}$$

where $Move_i$ is an indicator denoting whether firm i moved during the sample period; and $FloodExtent_i$ is the maximum share of firm i's 2km buffer that is flooded during the firm's first experienced flood during the study period. We consider specifications including district-level fixed effects α_d and fixed effects α_{zd} at the level of district × decile of Fathom flood risk (with a 1 in 100 year return period) in order to restrict attention to within-district variation among firms with similar levels of underlying flood risk. Standard errors are clustered at the district level.

The results, shown in columns (1) and (2) of Table 1, suggest that firm flooding increases the probability that firms relocate during the sample period. In the specification with district fixed effects (district × Fathom flood risk decile fixed effects), flooding results in a 1.79% (2.10%) increase in the odds of relocating more than 10km for the mean flooded firm, relative to 1 in 15 mean odds of

[18]Results are consistent using other thresholds, as shown in Tables A.4 to A.6.

relocating more than 10km among non-flooded firms.

Table 1. Impact of flooding on firm relocation and location flood risk

	Move Dummy		Δ Flood Risk	
	(1)	(2)	(3)	(4)
Max Share of 2km Buffer Flooded	1.583**	1.849**	-1.952*	-0.450
	(0.754)	(0.805)	(1.007)	(0.526)
District FE	Yes		Yes	
District × Fathom 1 in 100 FE		Yes		Yes
R^2	0.046	0.067	0.127	0.449
N	43,848	43,395	5,737	5,596

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on the probability of relocating by >10km following equation (3). Columns (3) and (4) report OLS estimates of the effect of flooding on the change in flood risk of firms moving by >10km as specified in equation (4). Observations are firms geocoded in 2011 and 2019. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2 for columns (1) and (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Firm relocation may help firms to adapt to flood risk if they relocate towards areas with lower underlying flood risk. We investigate this using the following specification:

$$\triangle \text{FloodRisk}_i = \beta \text{FloodExtent}_i + \alpha_{zd} + \varepsilon_i \tag{4}$$

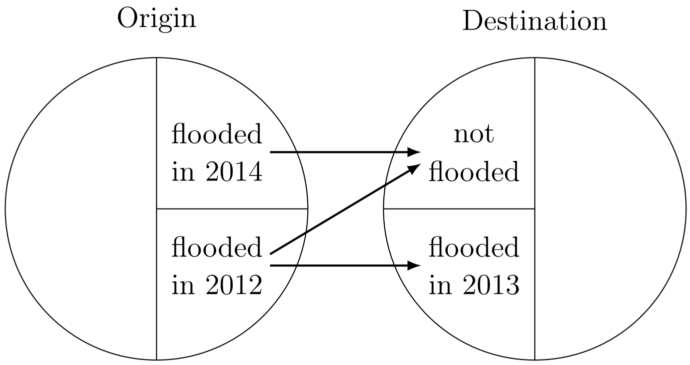
where $\triangle\text{FloodRisk}_i$ measures the change in Fathom flood risk between firm i's 2019 and 2011 addresses in units of expected flood depth under a 1 in 100 year flood; with $FloodExtent_i$ and α_{zd} as above. Standard errors are clustered at the district level.

The results, shown in columns (3) and (4) of Table 1, suggest that flooding indeed induces firms to relocate to less flood-prone locations. Using within-district variation, the mean treated firm that moved more than 10km, which has 1.94% of its buffer flooded, sees a 3.79 cm reduction in expected 1 in 100 year flood depth. Column (4) of Table 1 also displays a negative effects when restricting to within district-risk decile variation, with an intuitive reduction in magnitude and statistical significance.

In a final specification relating to relocation, we consider evidence that relocating firms take into account recent flood history in deciding on a *destination* location. Intuitively, this specification tests whether flooded firms that relocate during the sample period are more likely to move to destination areas that are flooded if, at the time when the relocating firm's area was flooded, the destination area had not yet been flooded.[19] This is illustrated in Figure 5: restricting attention to firms that relocate from the same origin district to the same destination district, do we see that firms flooded in 2014 (who were in a position to have witnessed 2013 flooding) are less likely than those flooded in 2012 (who had not witnessed 2013 flooding) to relocate to areas of the destination district flooded in 2013?

[19] Recall that firm addresses are only observed at the beginning and end of the study period, so we do not observe when a relocating firm moves. The strategy of this regression assumes that firms are more likely to move after having been flooded. If that was not the case, the coefficient in equation (5) is unlikely to be non-zero. For locations in destination districts that are not flooded during the sample period, t_d is set to a time period beyond the end of the sample. Firms whose origin address is not flooded during the study period are dropped from the estimation.

Figure 5. Illustration of differential relocation based on destination flood history



We examine this using the following gravity Poisson specification:

$$X_{ot_odt_d} = \alpha_{od} + \alpha_{ot_o} + \alpha_{t_d} + \beta \mathbb{1}\left(t_o - t_d > 12\right) + \varepsilon_{ot_odt_d} \tag{5}$$

where $X_{ot_odt_d}$ denotes the number of firms that relocate from areas of an origin district o that are flooded at time t_o to areas of a destination district d that are flooded at time t_d; α_{od} are origin district $\times$ destination district fixed effects; α_{ot_o} are fixed effects for the area of origin district o flooded at time t_o; α_{t_d} are fixed effects capturing destination areas flooded at time t_d; and $1\left(t_o - t_d > 12\right)$ is an indicator that takes the value one if the flooding of area ot_o post-dates that of area dt_d by more than 12 months. Standard errors are clustered at the level of origin-destination district pairs.

The results of this analysis in Table 2 suggest that, within origin-destination district pairs, firms relocating from origin district regions that are flooded more than 12 months after destination district regions are indeed half as likely to relocate to the latter regions as earlier-flooded firms. Firms therefore appear to take past flooding of destination locations into account when deciding where to move, systematically avoiding those destination regions that they have seen flooded.

Table 2. Impact of destination flood history on relocation flows

	Number of Firms Moved
Destination flooded 12mo prior	-0.735***
	(0.254)
Origin × Destination FE	Yes
Origin × Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10km
N	1,412

Notes: The table displays the Poisson pseudo-maximum-likelihood estimate of the effect of flood history on relocation flows following equation (5). The unit of observation is the area of an origin-district first flooded in a given year-month paired with the area in a destination district which was never flooded or first flooded in a given year-month. We only consider firms moving by >10km and location-pairs with positive flows. The standard error (in parentheses) is clustered at the origin-district-by-destination-district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Diversification of suppliers

In addition to location choice, another margin along which firms might adapt to flood risk is in their choice of supply partners. If flooding increases the risk that a firm's suppliers will be unable to meet their commitments, firms may hedge this risk by diversifying their supplier base or shifting towards less flood-prone suppliers.[20] We first consider whether firms adapt to flood risk by increasing the number of suppliers from which they source. This may help to reduce dependence on individual suppliers and spread risk across suppliers with uncorrelated shocks, in line with a literature examining diversification in other contexts (Cole et al., 2013; Meltzer et al., 2021; Boehm and Sonntag, 2022; Castro-Vincenzi, 2022; Castro-Vincenzi et al., 2024).

We test whether firms diversify their supplier base in response to flooding of their own premises using the following specification:

$$y_{it} = \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_\tau \text{FloodExtent}_{i,t-\tau} + \alpha_{im(t)} + \alpha_{iy(t)} + \alpha_t + \varepsilon_{it} \tag{6}$$

where y_{it} denotes firm i's log number of suppliers in month-year t; FloodExtent_{it} is the maximum share of firm i's 2km buffer that is flooded during month-year t; and $\alpha_{im(t)}$, $\alpha_{iy(t)}$, and α_t are firm-month, firm-year and month-year fixed effects respectively. Standard errors are clustered at the firm level.[21]

It may be more intuitive to expect firms to diversify suppliers in response to flooding of the suppliers themselves rather than their own premises. We test this using the following specification, where the coefficients of interest are the $\beta_{1,\tau}$ terms, including controls for the firm's own flood status:

$$y_{bt} = \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_{1,\tau} \text{SellerFlood}_{b,t-\tau} + \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_{2,\tau} \text{OwnFlood}_{b,t-\tau} + \alpha_{bm(t)} + \alpha_{by(t)} + \alpha_t + \varepsilon_{bt} \tag{7}$$

where y_{bt} denotes the log number of suppliers of buyer firm b during month-year t. SellerFlood_{bt} are the treatment terms, based on the firm's first observed supplier flooding event. Given that many firm-pairs transact only infrequently (see Section 2.1), a buyer may be affected by flooding of those suppliers from which it sources but with which it happens not to transact in the month under consideration. In constructing the treatment variable, we therefore define a buyer firm's suppliers as those firms from which the buyer firm has made any purchases in the prior three months.[22] $\text{SellerFlood}_{b,t-\tau}$ is the maximum share of the 2km buffer flooded across all suppliers that account for more than 10% of firm b's purchases within the three-month window. OwnFlood_{bt} are controls for the firm's own flood status during the first observed supplier flooding event, based on the maximum share of firm b's 2km buffer that is flooded during month-year t. $\alpha_{bm(t)}$, $\alpha_{by(t)}$, α_t are as previously, and standard errors are clustered at the firm level.

The results of both specifications, shown in Figure 6, do not find evidence for diversification in

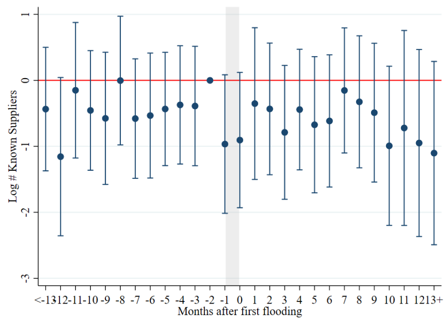
[20] All specifications investigating supplier choice restrict attention to firms that did not relocate more than 10km over the sample period, in order to remove the potential effects of relocating firms switching suppliers to those based in their new location. All results are robust to including relocating firms, as shown in Appendix C.8.1. Supplier diversification results further restrict the sample to cases where buyer and seller reports coincide exactly.

[21] The findings are robust to instead considering as an outcome variable an alternative measure of diversification given by the inverse Herfindahl index, defined by $(\sum_{i=1}^{N}(\text{Share of Purchases}_i)^2)^{-1}$ where N is the number of total suppliers, as shown in Figure A.12.

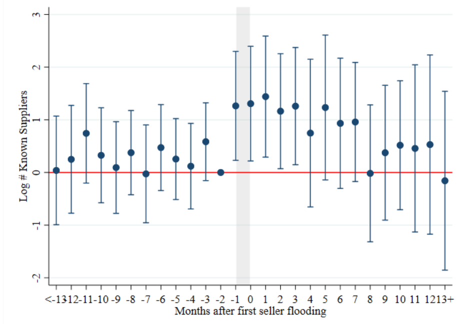
[22] All results that use this assumption are robust to alternatively defining a buyer firm's suppliers based on a six or twelve month window, see Appendix C.7.

response to flooding of a firm's own premises (panel (a)), but suggest that firms do diversify suppliers in response to supplier flooding (panel (b)). In the case of the latter, for the mean treated firm, whose maximally flooded supplier sees 1.37% of its buffer flooded, the number of suppliers increases by 1.74% by three months after supplier flooding was recorded, with no evidence of pre-trends. This response is relatively short-lived, with reversion to pre-exposure levels within a year.

Figure 6. Supplier Diversification: Impact of flooding on log number of suppliers



(a) Own flooding



(b) Supplier flooding

Notes: Panels (a) and (b) plot OLS estimates of the effect of own flooding and supplier flooding on the log number of suppliers following equations (6) and (7), respectively. Observations are firm-month-years whose 2011 and 2019 addresses are known and $\leq$ 10km apart. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

4.3 Choice of suppliers

Beyond changes in the *number* of a firm's suppliers, another potential margin of adaptation is to change the *characteristics* of their suppliers by shifting towards a portfolio of suppliers less prone to flooding. We consider two dimensions of such a decision. In this section, we examine how far flood-affected firms shift the composition of their suppliers towards suppliers located in less flood-prone regions. In the next section, we consider whether floods affecting transportation infrastructure also induce firms to reduce dependence on suppliers reached via flood-prone routes.

We study changes in the risk profile of a buyer firm's suppliers if the buyer itself, or any of their suppliers (again based on the preceding 3-month window), is flooded. This reflects the fact that firms deciding on the risk profile of their supplier base may take into account both their experience of supply chain disruptions caused by flooded suppliers, and their own direct experience of floods. The empirical specification is as follows:

$$\Delta y_{bt^*} = \beta_1 OwnFlood_{bt^*} + \beta_2 SellerFlood_{bt^*} + \alpha_{d(b)t^*} + \epsilon_{bt^*} \tag{8}$$

where t^* denotes the month-year of a flood event; $OwnFlood_{bt^*}$ is the maximum share of buyer b's 2km buffer that is flooded at t^*; $SellerFlood_{bt^*}$ is the maximum share of the 2km buffer flooded at t^* across all sellers which account for $\geq$ 10% of b's purchases over the previous three months; and $\alpha_{d(b)t^*}$ are buyer district $\times$ time fixed effects. We additionally report results using buyer district $\times$ time $\times$ buyer 1 in 100 year flood risk decile or buyer district $\times$ time $\times$ buyer industry fixed effects. The set of observations consists of all firm-by-flood-year-month pairs (b, t^*) for which the 2011 and 2019 addresses are known and less than 10km apart. The dependent variable, Δy_{bt^*}, captures the change in the sales-weighted average flood risk of all of b's suppliers in the three months before versus after flood exposure, given by:

$$\Delta y_{bt^*} = \frac{\sum_{s \in S_b(t^*,t^*+3]}, \sum_{t \in (t^*,t^*+3]} Sales_{bst} Risk_s}{\sum_{s \in S_b(t^*,t^*+3]} \sum_{t \in (t^*,t^*+3]} Sales_{bst}} - \frac{\sum_{s \in S_b(t^*-3,t^*]} \sum_{t \in (t^*-3,t^*]} Sales_{bst} Risk_s}{\sum_{s \in S_b(t^*-3,t^*]} \sum_{t \in (t^*-3,t^*]} Sales_{bst}} \quad (9)$$

where $Risk_s$ indicates seller s's expected flood depth under a 1 in 100 year flood; $Sales_{bst}$ represents the total sales from seller s to buyer b in year-month t; and $S_b(t_1, t_2]$ is the set of b's suppliers over $(t_1, t_2]$.

The results are shown in Table 3. Buyers do not appear to adjust the flood-risk composition of their suppliers in response to flooding of their own premises, but do respond to supply chain disruptions caused by flooding of their suppliers by shifting towards less flood-prone suppliers. The magnitudes are sizable and quite consistent across specifications including different fixed effects; for instance, in the central specification including district × time fixed effects, the mean treated observation (which sees a maximum flood extent among its sellers' buffers of 1.76%) experiences a 1.11cm reduction in the sales-weighted average supplier flood risk for a 1 in 100 year flood event.

Table 3. Impact of supplier flooding on supplier flood risk

	Δ Supplier Flood Risk		
	(1)	(2)	(3)
Own Max Flood Extent	-0.0648	-0.0913	-0.0908
	(0.0929)	(0.0897)	(0.118)
Suppliers' Max Flood Extent	-0.631***	-0.650***	-0.753***
	(0.165)	(0.169)	(0.190)
Time × District FE	Yes		
Time × District × Risk Dec. FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0115	0.0330	0.0610
N	144,566	143,861	139,302

Notes: The table reports OLS estimates of the effects of own and supplier flooding on the change in suppliers' sales-weighted average flood risk following equation (8). Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The shift towards less flood-prone suppliers may be driven by forward-looking adaptation, but is also consistent with the mechanical effect of being forced to source less from flood-hit suppliers while their operations are disrupted. To disentangle these effects, we consider whether flooding induces firms to shift towards less flood-prone suppliers among the subset of their suppliers that are not flooded, and therefore for which such mechanical effects are shut down. This provides the first opportunity to isolate adaptation that derives from firms' forward-looking decision-making to reduce future vulnerability to flooding, rather than also being consistent with more mechanical drivers of adaptation.

Table 4 estimates equation (8) where the dependent variable is calculated as the change in sales-weighted average flood risk of buyer b's suppliers that are not hit by a flood shock. While the coefficient on the supplier treatment is smaller than in the previous specification (meaning that some of the reduction in supplier risk is mechanically coming from reducing purchases from the flooded supplier),

Table 4. Impact of supplier flooding on flood risk of non-flooded suppliers

	Δ Risk of Non-Flooded Suppliers		
	(1)	(2)	(3)
Own Max Flood Extent	-0.115	-0.108	-0.147
	(0.0935)	(0.0895)	(0.121)
Suppliers' Max Flood Extent	-0.272***	-0.281***	-0.268**
	(0.0993)	(0.0941)	(0.108)
Time × District FE	Yes		
Time × District × Risk Dec. FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0090	0.0324	0.0586
N	144,423	143,718	139,164

Notes: The table reports OLS estimates following equation (8) of the effects of own and supplier flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as less than 5% overlap of the 2km buffer with the flood polygon). Appendix Figure A.9 shows that such firms see no reduction in sales compared to the control group. Appendix Figure A.7 shows robustness checks for varying thresholds in this definition. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart. Standard errors (in parentheses) are clustered at the time × district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

it remains large and statistically significant. This suggests that, when a buyer experiences flooding of any of their suppliers, this induces them to shift towards safer suppliers even among the subset of suppliers not disrupted by flooding at any of these levels. In terms of magnitudes, the mean treated firm sees a 0.48cm reduction in the sales-weighted average flood risk among its non-flooded suppliers.

We next consider the persistence of the shift towards less flood-prone suppliers among firms whose suppliers experience flooding, using the following specification:

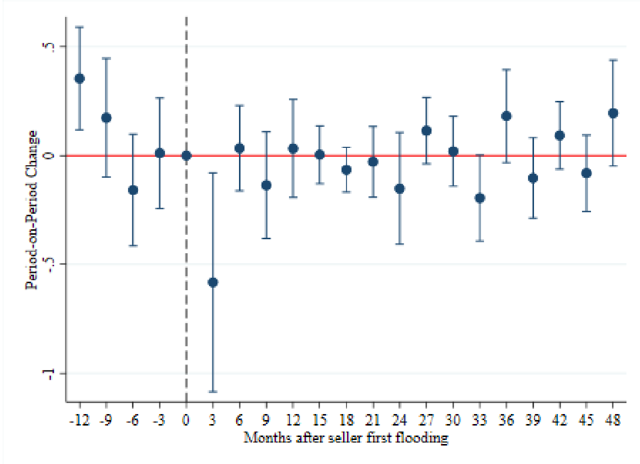
$$\Delta y_{bt} = \sum_{\substack{\tau=-12 \\ \text{s.t.} \frac{\tau}{3}\in\mathbb{N}, \tau\neq -3}}^{48} \beta_{1,\tau}\text{SellerFlood}_{b,t-\tau} + \sum_{\substack{\tau=-12 \\ \text{s.t.} \frac{\tau}{3}\in\mathbb{N}, \tau\neq -3}}^{48} \beta_{2,\tau}\text{OwnFlood}_{b,t-\tau} + \alpha_{d(b)t} + \varepsilon_{bt} \tag{10}$$

where Δy_{bt} represents the change in sales-weighted average flood risk among suppliers of firm b (defined as in equation (9)) from the previous three-month-window to that ending in the time t of the observation (b, t) (i.e., from $(t-6, t-3]$ to $(t-3, t]$); $\text{SellerFlood}_{b,t-\tau}$ indicates the maximum share of the 2km buffer flooded across b's suppliers during b's first observed supplier flooding event; $\text{OwnFlood}_{b,t-\tau}$ is the share of b's buffer flooded during that event; and $\alpha_{d(b)t}$ are buyer-district-by-time fixed effects.[23]

Given this specification, a short-lived shift towards less flood-prone suppliers would yield an initial negative coefficient of interest $\beta_{1,\tau}$, followed by positive coefficients in later time periods as the buyer reverts back towards more flood-prone suppliers. Conversely, a persistent shift would be consistent with an initial negative coefficient, without evidence of positive coefficients thereafter.

[23]We include ever treated observations only at the lags of interest $\tau_{(t)} = -12, -9, ..., 45, 48$ to prevent treated observations from confounding $\widehat{\alpha_{d(b)t}}$.

Figure 7. Dynamic impact of supplier flooding on supplier flood risk



Notes: The panel plots OLS estimates of the effect of supplier flooding on the change in suppliers' sales-weighted average flood risk following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure 7 plots the coefficients of interest $\beta_{1,\tau}$ for rolling three-month on three-month windows out to four years after the date of first observed supplier flooding. The results are consistent with buyer firms persistently shifting towards less flood-prone suppliers over this horizon. The first period coefficient is strongly negative, as firms with flooded suppliers shift their supplier mix towards less flood-prone suppliers in the subsequent three months, consistent with the results of Table 3. Importantly, there is no reversion towards higher flood risk suppliers up to four years later.[24] A persistent response is also evident when restricting attention to non-flooded suppliers, as shown in Figure A.13.

4.4 Evidence from route-level flooding

Floods may affect firm activities via transportation disruption as well as flooding of firm premises, as shown in Section 3.2. We next consider whether firms adapt to flooding of transportation routes by reducing their dependence on supply partners reached via flood-prone routes.

The route-level specifications leverage the bilateral nature of transaction-level data to fully isolate adaptive behavior from potentially confounding shocks that may affect flooded firms. In particular, using variation from pairwise route-level flooding allows us to include buyer-time and seller-time fixed effects, thereby absorbing any shocks to buyers and sellers, including those that may persist even after flooded firms' sales and purchases have recovered.[25] We estimate event study regressions of the form:

$$y_{bst} = \sum_{\substack{\tau=-12 \\ \tau\neq-1}}^{36} \beta_\tau \text{ShareRouteFlooded}_{bs,t-\tau} + \eta_{\text{age}(b,s),t} + \alpha_{bs} + \alpha_{bt} + \alpha_{st} + \varepsilon_{bst} \tag{11}$$

where y_{bst} is an outcome at the buyer-seller-time level (sales in the (b, s) relationship at time t, or an

[24]Figure C.39 presents results excluding firms which experience flooding of a supplier (accounting for at least 10% of purchases in the three months before the flood) in more than one flood event. The robustness of the results to this restriction indicates that the persistence of the effect is not driven by repeated exposures.

[25]For instance, it is possible that, even once flooded firms' sales and purchases have recovered, local labor market or correlated cost shocks (e.g. through credit markets, see Choudhary and Jain, 2022) might continue to affect their operations and contribute to persistent changes in outcomes at the firm level.

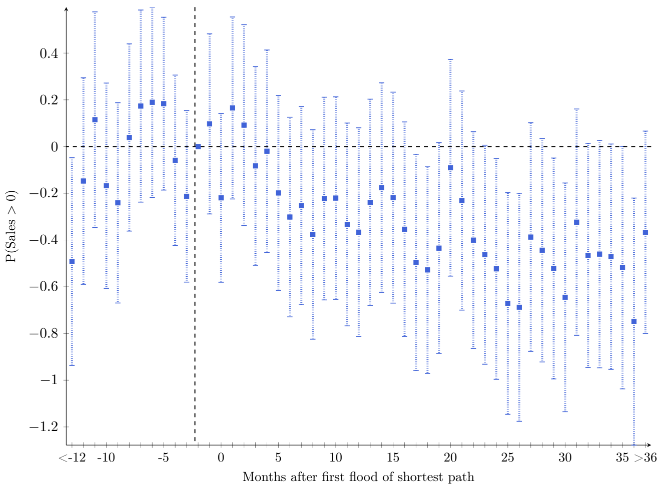
indicator variable denoting whether sales are positive); and $\text{ShareRouteFlooded}_{bst}$ is the share of the ordinary-time (i.e. during non-flooded weeks) shortest-time route between b and s flooded at time t. We consider all events where the shortest-time route between b and s is flooded for the first time after entry of b and s. $\text{ShareRouteFlooded}_{bst}$ is calculated at the weekly level and the maximum for weeks during a given month is used to generate monthly-level variables. A set of indicator variables for the age of the buyer-seller relationship, $\eta_{\text{age}(b,s),t}$, is included given evidence for strong life-cycle effects in buyer-seller relationships (see Figure A.14). α_{bs}, α_{bt}, and α_{st} are, respectively, buyer-seller, buyer-time, and seller-time fixed effects. As such, we identify outcomes from variation within buyer-seller relationships, controlling for time-varying buyer and seller characteristics. In the extensive margin specifications, the set of observations consists of all triples (b, s, t) where b and s transact at least twice, and b and s have both entered by time t. In the intensive margin specifications, the set of observations (b, s, t) is all triples where s has positive sales to b at t.

In the baseline specification, we restrict attention to manufacturing firms only. This reflects the fact that transactions between services (which account for the majority of excluded firms under this restriction) and agricultural firms are unlikely to represent shipments of physical goods between firm premises and as such disruptions to the route between firms may not be pertinent. The robustness of the results when this restriction is not imposed – as well as to alternative sample restrictions outlined in the discussion of robustness tests in Section 4.6 – is shown in Appendix Table C.27.

Figure 8 shows the baseline extensive margin results. After a flood hits the route between a buyer-seller pair, the likelihood of the relationship remaining active declines compared to non-flooded relationships. Trends are flat in the year-long window prior to flood exposure, increasing confidence that this effect is driven by the impact of flooding. To illustrate the magnitude of the estimates, a point estimate of -0.3 six months after treatment implies that the transaction probability in that period declines by 0.12 percentage points for the median flooded route (which sees 0.4% of its length being flooded).[26] The figure shows that the decline is persistent for at least three years, far beyond the duration of road disruptions, which typically last less than one month (see Section 3.2). Conditional on a transaction occurring, we do not find any adjustment in the transaction magnitude following a flood (Figure A.15). This suggests that substitution away from supply partners reached by flooded routes is driven by transactions ceasing rather than intensive margin reductions in transaction volumes.

[26] For comparison, the unconditional probability of a relationship being active in our panel—meaning not before the first transaction of each firm pair—is 18.45%.

Figure 8. Impact of road flooding on extensive margin sales in buyer-seller relationship



Notes: The graph shows the response of the probability of sales being positive in the (b, s) relationship around the first time the shortest path between b and s gets flooded (after entry of b and s) following equation (11). The sample consists of all buyer-seller-weeks such that b and s are manufacturing firms, do not relocate and transact at least twice. Regression conditions on both b and s having entered, and includes $b \times s$, $s \times t$, and $b \times t$ fixed effects and months-since-first-sale dummies. The 95% confidence intervals rely on standard errors clustered at the relationship level.

These results provide strong evidence of adaptation using clean exogenous assignment of the treatment: controlling for any direct effects of floods on buyers or sellers themselves, as well as buyer-seller fixed effects, short-lived flood disruption of transportation routes between buyer-seller pairs results in persistent cessation of transactions between them.

4.5 Mechanisms underlying adaptive responses

The results in this section suggest that firms adapt to flood risk in the aftermath of flood events via relocation towards less flood-prone locations, diversification and shifts in the supplier mix away from those in more flood-prone locations and reached via flooded routes. Distinguishing between alternative mechanisms that may underlie these adaptive responses will be informative for policy that aims to influence firm behavior in relation to climate risks: for instance, whether and for how long information treatments might be effective in inducing adaptation will depend on whether firms adapt as a result of rational learning or behavioral biases based on recent experience.

Rational learning would suggest that firms affected by floods change their beliefs over the underlying distribution of flood risk and adaptive actions reflect a rational response to this. Such channels have been studied in a recent literature examining individual decision-making in relation to climate risks (Lybbert et al., 2007; Moore, 2017; Kala, 2017; Patel, 2023), though evidence from firm behavior remains scarce (Kremer et al., 2019). A second mechanism posits that floods instead change the *importance* of flood risk in firm decision-making, for instance by increasing the salience of climate risk. Such 'availability bias' might induce flood-hit firms to infer erroneously that they are subject to higher flood risk relative to a firm with identical statistical information, simply by virtue of recent experience (Tversky and Kahneman, 1973; Kahneman, 2011; Bordalo et al., 2021), behaviors that have been documented in individuals' decisions to purchase weather insurance and responses to surveys about climate change (Gallagher, 2014; Turner et al., 2014; Karlan et al., 2014; Deryugina, 2013).[27]

While mechanisms predicated on experience-based updating should imply persistent responses, availability heuristics would predict larger impacts from more recent floods, with 'forgetting' as flood events recede into the more distant past. We observe firm and network behavior over eight years, a relatively long timespan relative to the frequency of flooding. The evidence in Section 4.1 suggesting that firms undertake adaptive relocation is consistent with a permanent response following a temporary shock. Flood-induced adaptive shifts in supplier mix persist for at least four years (Figure 7), and shifts away from suppliers reached via flooded routes for at least three years (Figure 4), without evidence of attenuation in either case. While it is possible that behavior may revert over longer timescales, the fact that these adaptive responses persist for as long as is measurable in our data is inconsistent with salience effects being first-order in the medium-run.

4.6 Robustness

Appendix C considers the robustness of the reduced form evidence on adaptive behaviors to using alternative estimators that aim to overcome potential challenges with the use of two-way fixed effects regressions including treatment leads and lags (Appendix C.1); excluding industries for which supply disruptions of the nature considered in the analysis may not be pertinent (Appendix C.2-C.4); considering only transaction observations where buyer and seller reports coincide exactly (Appendix C.5); and considering floods with return periods of 1 in 10 or 1 in 50 rather than 1 in 100 years (Appendix C.6). The central results are all qualitatively robust to these alternative specifications.

5 Quantifying the aggregate impacts of adaptation

The evidence in the previous section suggests that flooding induces firms to undertake adaptive adjustments that reduce their exposure to flood risk. In this section, we quantify the importance of these adaptive responses for the aggregate vulnerability of the production network to future flooding.

While the reduced form results in Section 4 are informative in identifying evidence for adaptation, a simple aggregation of these estimates is unlikely to yield an accurate estimate of their economy-wide impacts. This results from the fact that aggregate effects will reflect firm connections via multi-step linkages and general equilibrium forces, as well as direct impacts on affected firms.[28] We therefore estimate the aggregate impacts of adaptation by constructing a quantitative spatial model of production network formation and adaptation which models general equilibrium and indirect effects explicitly.

Section 5.1 outlines the theoretical model. Section 5.2 describes how we bring the model to the data in our empirical setting, and Section 5.3 estimates the model to quantify the implications of post-flood adaptation observed in our sample for the damages imposed by subsequent floods.

[27] A third possible alternative is that floods lower the fixed cost of making changes that the firm may already have wished to make. Such a mechanism is potentially consistent with the adaptive relocation results in Section 4.1: firms that wished to relocate to safer areas but previously found the fixed cost of doing so too high may use the 'opportunity' afforded by the need to rebuild to do so in a less flood-prone location. It is possible, though arguably less intuitive, to apply a similar logic to the shift towards safer suppliers described in Table 3 if there are large human capital or systems costs to switching suppliers. Such a mechanism cannot, however, account for flood-induced supplier diversification (Section 4.2) and the finding in Table 4 that supplier flooding induces buyers to shift their *non-flooded* supplier mix towards less flood-prone firms.

[28] For example, a firm may substitute towards suppliers which are less likely to be directly flooded, but which may nevertheless be subject to flood shocks because it purchases from flood-prone regions.

5.1 Theoretical model

The model builds on recent models of production network formation under uncertainty (Kopytov et al., 2022) but allows for imperfectly informed firms that learn about underlying flood risk from flood shock realizations. Firms are subject to idiosyncratic and aggregate flood risk, about which they update their beliefs in response to floods. Before flood shocks are realized, firms search for suppliers taking into account their beliefs over the flood risk of potential partner firms. Once floods have occurred, firms then choose suppliers to minimize costs conditional on the outcomes of their search. We incorporate extreme value distribution assumptions in this framework (following Oberfield, 2018 and Boehm and Oberfield, 2020, 2022) in order to yield tractable empirical estimates of sourcing shares which can be inverted to yield adaptive changes in supplier search decisions.[29] Despite the model's rich microfoundations, this allows us to estimate the aggregate benefits of adaptation without imposing assumptions about the nature of the belief updating process.

5.1.1 Model setup

The economy consists of N locations indexed by n. Location n contains an exogenous number of firms J_n. Each firm sells a good which is considered differentiated by the representative household, but which is perfectly substitutable with goods produced by other firms when used as an intermediate input in production.

5.1.2 Households

Households have constant relative risk aversion preferences over consumption of a bundle of goods comprising individual varieties produced by firms in different locations. Households' expenditure shares on goods from different locations are assumed to be constant and given by β_n:

$$u(q) = \frac{1}{1-\rho} q^{1-\rho}, \qquad \rho > 0, \qquad q = \prod_{n=1}^{N} \left(\frac{q_n}{\beta_n} \right)^{\beta_n}, \qquad q_n = \left(\int_{J_n} q_n(j)^{\frac{\varepsilon - 1}{\varepsilon}} dj \right)^{\frac{\varepsilon}{\varepsilon - 1}}$$

Utility maximization yields demand $q_n(j)$ for each variety and the ideal price index p_n in each location:

$$q_n(j) = \beta_n p_n^{\varepsilon - 1} (p_n(j))^{-\varepsilon}, \qquad p_n = \left(\int_{J_n} p_n(j)^{1-\varepsilon} dj \right)^{1/(1-\varepsilon)}, \qquad p = \prod_{n=1}^{N} p_n^{\beta_n}$$

Isoelastic demand means that firms choose a constant markup over marginal cost, $p_n(j) = \varepsilon/(\varepsilon - 1)c_n(j)$, where $c_n(j)$ denotes the marginal cost of production of firm j in location n. The Lagrange multiplier on the household's budget constraint is $\lambda = u'(q)/p = q^{-\rho}/p$.

5.1.3 Production

Production takes place in two stages. In the first, firms search optimally for suppliers in different locations given their beliefs over flood risk. This yields combinations of suppliers and idiosyncratic productivity realizations ('techniques') that firms can use to produce. In the second stage, shocks are realized and firms choose the technique with which they will produce to maximize profits. We start by describing the second stage, where technique draws and shock realizations are taken as given.

[29] See also Eaton et al. (2022) for a related model with matching intensities.

Second stage: Sourcing and production

Search results in the arrival of techniques ϕ, consisting of a supplier s and a match-specific factor-augmenting productivity z. Each technique describes a production function:

$$y_j(\phi) = a_{n(j)} b_{n(j)} \xi_j l_j^{1-\alpha} (z(\phi) x_j)^{\alpha} \tag{12}$$

where l_j and x_j are the quantity of equipped labor and intermediate inputs respectively; z is the match-specific productivity draw; $a_{n(j)}$ is a deterministic time-invariant productivity level associated with the location n of firm j; $b_{n(j)}$ is a location-specific productivity shock common to all firms in n, interpreted as coming from floods; and ξ_j is a firm-specific idiosyncratic flood shock.

Suppliers set prices at their marginal cost c_s when they sell to downstream firms, i.e. buyers have full bargaining power. Trade is subject to location-specific iceberg costs such that, for each unit to be used as an input in production, $\tau_{n(j)n(s)} \geq 1$ units must be shipped. Denoting the cost of one unit of equipped labor by w, the marginal cost of production using technique ϕ is:

$$c_j(\phi) = \frac{1}{a_{n(j)} b_{n(j)} \xi_j} w^{1-\alpha} \left(\tau_{n(j)n(s)} \frac{c_s(\phi)}{z(\phi)} \right)^{\alpha} \tag{13}$$

In this setup, sourcing decisions depend on suppliers' production costs c_s, which in turn depend on their own sourcing decisions, and so on. In order to characterize the aggregate equilibrium, we impose two key functional form assumptions. Following Kortum (1997) and Oberfield (2018), we assume that the distribution of match-specific productivity draws z is such that the number of technique draws where the supplier is in location n' and that yield a match-specific productivity z greater than a threshold $\bar{z}$ is Poisson distribution with mean $m_{nn'}\bar{z}^{-\zeta}$, where $m_{nn'}$ describe search effort in the first stage. The parameter ζ governs the tail of the distribution of match-specific productivity draws: higher ζ implies on average more similar draws, such that a buyer will be more willing to substitute to a different supplier when a supplier experiences an idiosyncratic cost shock. Second, we place a functional form assumption on the distribution of the idiosyncratic flood shock by assuming that $\xi_j^{\zeta/\alpha}$ follows a positive one-sided stable distribution characterized by its Laplace transform:

$$\mathbb{E}\left(e^{-u\xi_j^{\zeta/\alpha}}\right) = e^{u^{\beta}}$$

These assumptions allow us to characterize the distribution of firm production costs in each location:

Lemma 1. *Conditional on the realization of the aggregate flood shocks b, the cost distribution of firms in location n is Weibull:*

$$P(c_j > c | b) = \exp\left[- \left[\left(a_{n(j)} b_{n(j)}\right)^{\zeta\beta/\alpha} \left(w^{1-\alpha}\right)^{-\zeta\beta/\alpha} \left[\sum_{n'} m_{nn'} \tau_{nn'}^{-\zeta} \bar{c}_{n'}^{-\zeta} \right]^{\beta} \right] c^{\zeta\beta/\alpha} \right]$$

where:

$$\bar{c}_n^{-\zeta} = \left(a_{n(j)} b_{n(j)}\right)^{\zeta} \left(w^{1-\alpha}\right)^{-\zeta} \left(\sum_{n'} m_{nn'} \tau_{nn'}^{-\zeta} \bar{c}_{n'}^{-\zeta} \right)^{\alpha} \Gamma\left(1 - \frac{\alpha}{\beta}\right) \tag{14}$$

Sourcing shares follow the gravity form, with search efforts $m_{nn'}$ as bilateral trade flows shifters:

Corollary 1. *The expenditure share of location n on inputs from n' is:*

$$\frac{X_{nn'}}{X_n} = \frac{m_{nn'}\tau_{nn'}^{-\zeta}\bar{c}_{n'}^{-\zeta}}{\sum_{\tilde{n}} m_{n\tilde{n}}\tau_{n\tilde{n}}^{-\zeta}\bar{c}_{\tilde{n}}^{-\zeta}} \tag{15}$$

The first stage of the firms' production problem endogenizes search efforts $m_{nn'}$ as the optimal ex-ante investments in the face of uncertainty over flood outcomes, given beliefs over flood risk.

First stage: Search

Before location-specific flood shocks b_n have been realized, firms in location n have beliefs over the distribution of these shocks described by the information set $\mathcal{I}_n$. Firms are owned by the representative household and maximize profits π discounted by the households' stochastic discount factor λ, subject to a resource constraint. In the first stage, a firm j in location n chooses search efforts $m_{nn'}$ to solve:

$$\begin{aligned} &\max_{m_{nn'}} \mathbb{E}\left(\lambda\pi_j(m_{n1},\ldots,m_{nN})|\mathcal{I}_n\right) \qquad (16)\\ \text{s.t.}\quad & g(m_{n1},\ldots,m_{nN}) = \bar{m} \\ & m_{nn'} \geq 0 \quad \text{for all } n' \end{aligned}$$

We assume that g is such that the solution matrix $\mathbf{m}(\mathcal{I}) = \left(m_{nn'}(\mathcal{I}_n)\right)_{nn'}$ to this problem is unique.

5.1.4 Equilibrium

An equilibrium of the economy is a matrix of search efforts $\mathbf{m}(\mathcal{I})$ and cost indices $\bar{c}_n$ such that (i) $\mathbf{m}(\mathcal{I})$ solves the firms' optimal search problem (16); (ii) conditional on the realization of shocks, firms choose techniques to minimize costs and markups to maximize profits; (iii) conditional on the realization of shocks, the representative household maximizes utility; and (iv) goods and labor markets clear.

Lemma 2. *Let $\alpha > 0$. Then for each realization of the aggregate shocks b_n an equilibrium exists and is unique.*

Changes in the household price index p in response to flood shocks or changes in search efforts m can be characterized as a function of shocks, elasticities, and pre-shock equilibrium outcomes following Dekle et al. (2007). Denoting ratios of a variable in one equilibrium to another $\hat{x} = x'/x$ yields:

$$\hat{p}\left(\mathbf{X},\hat{\mathbf{b}},\hat{\mathbf{m}}\right) = \boldsymbol{\beta}\cdot\hat{\bar{\mathbf{c}}}\left(\mathbf{X},\hat{\mathbf{b}},\hat{\mathbf{m}}\right) \tag{17}$$

where $\mathbf{X} \equiv \left(X_{ni}/X_n\right)_{n,i}$ and $\hat{\bar{\mathbf{c}}}\left(\mathbf{X},\hat{\mathbf{b}},\hat{\mathbf{m}}\right)$ satisfies:

$$\hat{\bar{c}}_n\left(\mathbf{X},\hat{\mathbf{b}},\hat{\mathbf{m}}\right) = \hat{b}_n^{-\zeta}\left[\sum_{n'}\frac{X_{nn'}}{X_n}\hat{m}_{nn'}\hat{\bar{c}}_{n'}\left(\mathbf{X},\hat{\mathbf{b}},\hat{\mathbf{m}}\right)^{-\zeta}\right]^{-\alpha/\zeta} \tag{18}$$

5.1.5 Dynamics

The static economy described above is played out in each time period, which are linked by the dynamics of firms beliefs $\mathcal{I}$ over the distribution of floods. Changes in beliefs alter ex-ante search decisions for suppliers, $\mathbf{m}(\mathcal{I})$, which in turn shift sourcing shares according to the gravity equation (15).

5.2 Quantitative implementation

This section describes how we take the model in Section 5.1 to the data in our empirical setting. Our aim is to use the model-implied gravity equation (15) to identify adaptation as enduring changes in sourcing shares, consistent with the evidence in Section 4 that firms persistently shift sourcing shares towards less flood-prone suppliers following flood events. We then estimate the consequences of this adaptation for the network's aggregate vulnerability to future flooding in Section 5.3.

To estimate the model, we need to specify empirical counterparts for locations and time periods in the model. Locations comprise groups of firms and are defined for each flood event by two firm characteristics, chosen to reflect the model's key assumption that all firms in a location n have the same beliefs. First, location definitions reflect whether or not any of a firm's suppliers experience flooding of more than 10% of their buffer in the flood event under consideration.[30] This reflects the evidence in Table 4 that firms whose suppliers are flooded update their beliefs differentially.[31] Second, the definition of locations accounts for the district in which the firm is located, to permit heterogeneity in adaptation according to the proximity of flooding. Sales transactions between firms in each location are aggregated in order to interpret them through the lens of the model.

Estimation of the model is based on three time periods around each flood event. The flooded period is defined as the six month period starting when flooding is first recorded (consistent with the dynamics of direct flood impacts in Section 3), during which the flood reduces TFP in affected locations. The six months prior to this are defined as the pre-flood period, when no flood is present and $b_n = 1$ for all locations n. The six months subsequent to the flooded period are defined as the post-flood period, when the temporary disruptive effects of the flood have subsided and all observed changes in sourcing shares are interpreted as being driven by changes in beliefs.[32] Technological productivity levels a_n, elasticity parameters and trade costs $\tau_{nn'}$ are assumed constant over the three periods of each flood event.[33] Flood shocks b and ξ are realized independently across flood events.

Based on this specification of locations and time periods, the next section describes how we parameterize flood-induced productivity shocks. Section 5.2.2 then uses the model to identify adaptive changes in firms' search decisions over potential suppliers in response to each flood in our sample.

5.2.1 Estimating flood-induced productivity shocks

To quantify the consequences of adaptive changes in search decisions, we require a parameterization of location-level productivity shocks induced by flooding. We assume that productivity shocks b_n in each location n are related in a log-linear way to $\overline{\text{ShareFlooded}}_n$, the share of firms in n experiencing flooding of more than 10% of their 2-kilometer buffer:

$$\log b_n = \eta \log(1 + \overline{\text{ShareFlooded}}_n) \tag{19}$$

[30] A threshold of 10% is chosen to define flood status given non-linearities in the impact of flooding according to the share of the firm's buffer flooded, see Figures A.9 and A.10.

[31] Here a firm's suppliers are defined as those that account for more than 10% of the firm's expenditures in the three months prior to flooding. We restrict attention to firms that report at least ten times in the 13 months of the panel that precede the first flood event in 2012 to ensure that changes in sourcing shares over the six-month periods considered in the estimation are likely to capture true changes in sourcing behavior rather than noise resulting from sporadic reporting.

[32] This definition of time periods ensures that, for each flood event, the pre- and post-flood periods span the same six months of the calendar year, ameliorating concerns that differences in sourcing behavior may reflect seasonal effects.

[33] Trade costs could be made stochastic akin to ξ, but as long as they are i.i.d across buyer-supplier pairs, it would not change the identification and counterfactual.

We estimate η by substituting this expression into the gravity equation (15) for sourcing shares expressed in changes from the pre-flood period to the flooded period, during which time search decisions $m_{nn'}$ are assumed unchanged:

$$\widehat{\left(\frac{X_{nn't}}{X_{nt}}\right)} = \exp\left(-\zeta \log \hat{c}_{n'} + \frac{\zeta}{\alpha} \log \hat{\hat{c}}_n + \frac{\zeta}{\alpha} \log \hat{b}_n\right) \tag{20}$$

where $\hat{x} = x_{during}/x_{pre}$ and:

$$\hat{\hat{c}}_n = \hat{b}_n^{-1} \left[\sum_{n'} \frac{X_{nn'}}{X_n} \hat{\hat{c}}_{n'}^{-\zeta}\right]^{-\alpha/\zeta} \tag{21}$$

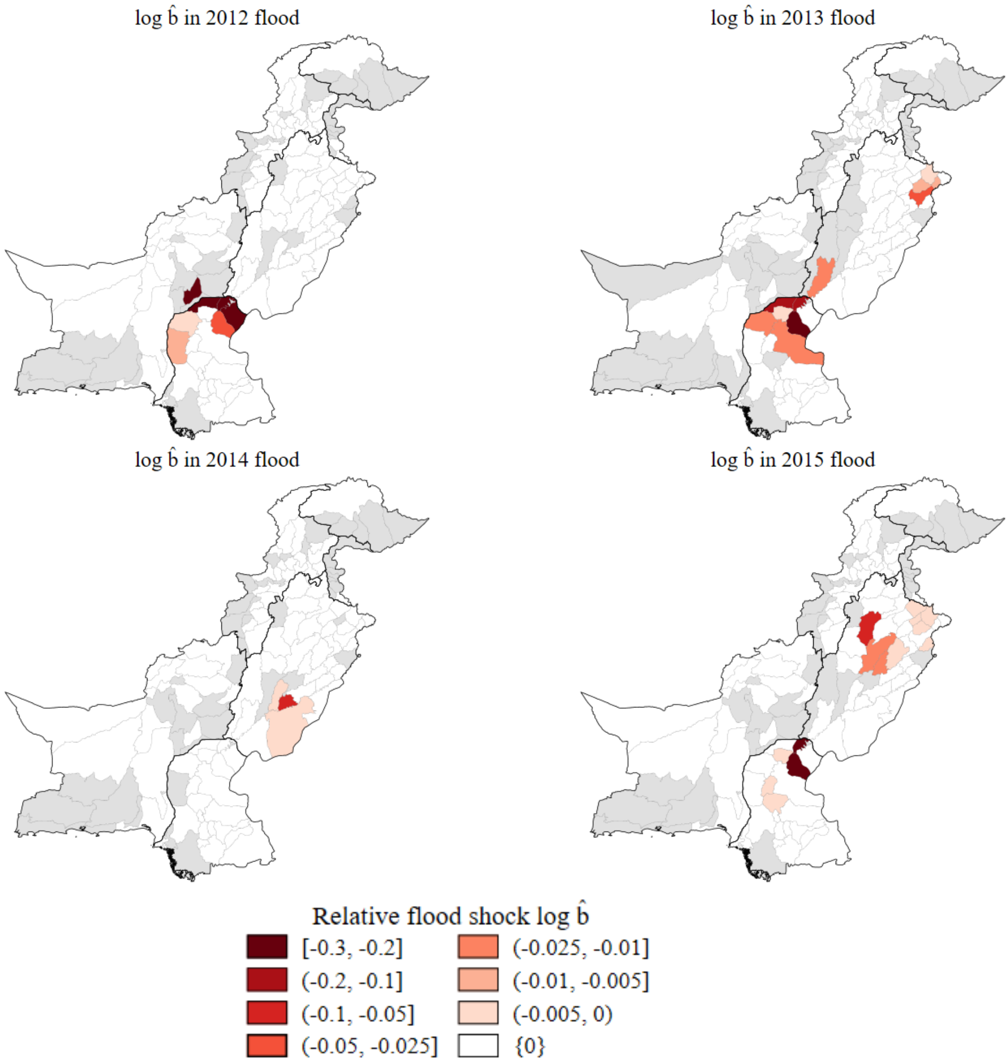
Estimation of equation (20) using observed sourcing shares, together with values for the parameters α and ζ, can be used to obtain an estimate of η. We set the input share α equal to the average annual share of reported purchases to sales, which is 0.77.[34] The trade elasticity ζ is calibrated to be 4 following Simonovska and Waugh (2014).

This estimation yields an estimate of $\eta = -0.42$, which implies that a location where all firms saw flooding of more than 10% of their 2-kilometer buffer would experience a 30% reduction in TFP.[35] This estimate of η, together with the observed share of firms in each location n experiencing flooding of more than 10% of their 2-kilometer buffer, yields the productivity cost of flooding b_n in each location from equation (19). These values are mapped for each flood event in Figure 9. While the majority of locations do not experience direct reductions in TFP in a given flood event, the maximum decrease across locations ranges from 20% to 29%.

[34]In this calculation we ignore firms that report fewer than three times in a year, and firms that have purchase-to-sales ratios exceeding 3. This value is larger than most materials shares reported in the literature because purchases from firms can also include capital.

[35]We ensure that all observations of shares are finite and reduce the influence of outliers by estimating Equation (20) on the set of cell pair $\times$ events (n, i, t^*) where, prior to the flood, the purchases of n from i account for at least half a percent of n's purchases, and winsorizing the change in purchase shares at the 99th percentile.

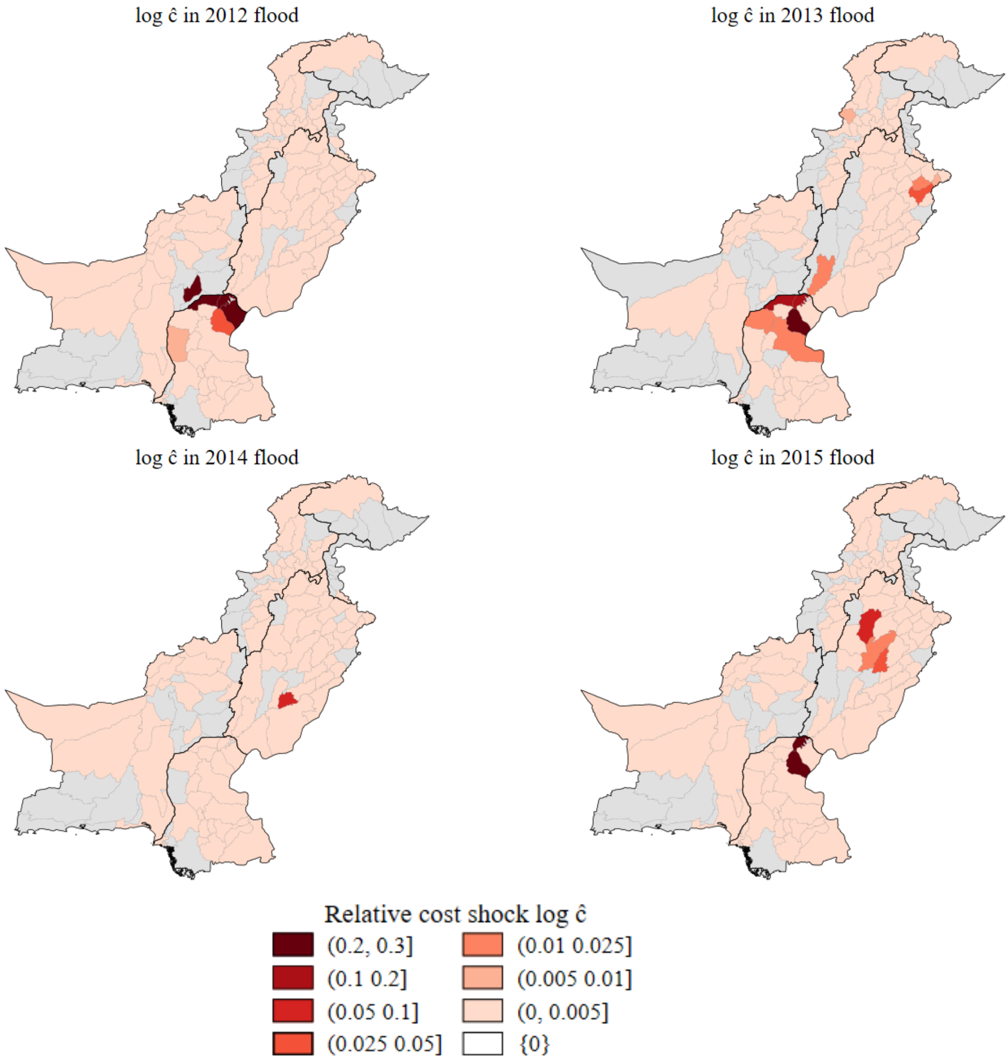
Figure 9. Estimated productivity shocks from floods in sample



Notes: The figure maps the productivity shocks $\log \hat{b}$ estimated from equation (19) as described in this section. We obtain $\log \hat{b}$ at the district level by taking the average across both locations in the district weighted by pre-flood period sales to households.

The impact of flooding on firm costs is likely to extend beyond direct location-level TFP reductions via the general equilibrium effects of flood exposure of firms' suppliers (as well as that of their suppliers' suppliers, and so on). The total increase in firm costs in each location accounting for such effects is calculated from Equation (21) and plotted for the flood events in our sample in Figure 10. While cost increases are more widespread than the direct productivity impacts in Figure 9, the latter can be seen to dominate the general equilibrium impact of suppliers' exposures.

Figure 10. Estimated increases in firm costs across locations from floods in sample



Notes: The figure displays the increases in firm costs $\log \hat{c}$ estimated from equation (21) as described in this section. We obtain $\log \hat{c}$ at the district level by taking the average across both locations within the district weighted by pre-flood period sales to households.

The economy-wide impact of each flood event can be estimated as the increase in the households' cost index p. This is calculated by aggregating location-level cost increases using Equation (17), where the final demand shares β_n are calibrated to the share of each location's sales to out-of-network buyers. The results yield estimated increases in the households' cost index as a result of the 2012, 2013, 2014 and 2015 floods of 0.05%, 0.30%, 0.06% and 0.16% respectively.[36]

5.2.2 Recovering adaptation

Adaptation is captured in the model by changes in sourcing behavior resulting from changes in firm beliefs once the direct disruptive impacts of flooding have passed. We identify changes in search decisions $\hat{m}_{nn'}$ of firms in location n over potential suppliers in location n' using the gravity equation

[36]To benchmark the magnitude of these estimates, estimated total annual direct economic losses from all categories of natural disasters in Pakistan between 2000 and 2013 averaged 1.16% of national GDP, including substantial losses from the severe 2010 floods and 2005 earthquake (ADB, 2021).

(15) expressed in changes between the pre- and post-flood periods:

$$\widehat{\left(\frac{X_{nn't}}{X_{nt}}\right)} = \exp\left(\log \hat{m}_{nn'} - \zeta \log \hat{\tilde{c}}_{n'} + \frac{\zeta}{\alpha} \log \hat{\tilde{c}}_n\right) \tag{22}$$

where $\hat{x} = x_{post}/x_{pre}$ and $\hat{\tilde{\mathbf{c}}} = \hat{\tilde{\mathbf{c}}}\left(\mathbf{X}, \mathbf{1}, \mathbf{m}\right)$ following Equation (18). Consistent with the empirical result in Section 4.2 that flood-induced diversification of suppliers is not persistent, we impose the restriction that, for all n, the sum of each firm's log search efforts across upstream locations remains constant between pre- and post-flood periods, i.e. $\sum_{n'} \log \hat{m}_{nn'} = 0$.[37]

This system of equations can be solved directly for changes in search decisions $\hat{m}_{nn'}$ from the period before to after each flood event, which characterize adaptation. These adaptive sourcing decisions reflect the aggregate effect of firms' changing exposure due to upstream firms exiting or moving away from affected areas, and buyers choosing to purchase from less risk-prone areas, thereby capturing all relevant adaptation margins highlighted in Section 4.[38] Furthermore, this approach to identifying adaptation is based on the central intuition that changes in beliefs over flood risk can drive changes in sourcing behavior, but does not require us to take a stance on how floods reveal information about flood risk or how firms update their beliefs. The first stage problem in Equation (16) could be replaced by many alternative formulations to accommodate, for instance, forward-looking expectations, adjustment costs, or behavioral biases, without affecting the estimation of $\hat{m}_{nn'}$ and consequently the quantification of the impacts of adaptation.

5.3 Estimating the implications of adaptation for the damages from subsequent floods

The central aim of the model is to estimate the aggregate implications of adaptation undertaken by firms in the aftermath of floods for the vulnerability of the production network to future flooding. In this section, we use the estimates of flood-induced productivity shocks and post-flood changes in search decisions from Section 5.2 to quantify the impacts of observed post-flood adaptation for the response of the economy to subsequent floods.

We consider the example of adaptive changes in sourcing shares undertaken following the observed flood in 2012, and estimate the impacts of this adaptation for the damages imposed by subsequent floods in the sample. We use the model to quantify this by estimating the change in the household price index resulting from a subsequent flood (for example, the flood in 2013) in two scenarios: one in which the sourcing shares are those that prevailed in the period before the 2012 flood, and one in which the sourcing shares correspond to those in the period after the 2012 flood.

We recover adaptative changes in sourcing behavior following the 2012 flood as described in Section 5.2.2. Estimation of Equation (22) reveals that the 2013 flood would have resulted in a 5% higher increase in the household price index in the absence of adaptation following the 2012 flood, as captured by changes in the pre- to post-2012 flood sourcing shares.[39] Similarly, damages from the 2015 flood would have been 1% higher. While this suggests that adaptation in the aftermath of the 2012 flood helped in ameliorating damages from the subsequent floods in 2013 and 2015, this need not be the case for all future flood shocks. In contrast, adaptation following the 2012 floods relocated sourcing

[37] This assumption corresponds to a constraint of $g(m_{n1}, \ldots, m_{nN}) = \sum_{n'} \log m_{nn'} = \log \bar{m}$ in the firm's search problem described in Equation (16). A microfoundation for this constraint could be that the manager needs to spend $\log m$ units of time to search for a mass m of potential suppliers in a location, and the total time available to the manager in which to search for suppliers is constant.

[38] The model holds fixed household sourcing shares across locations $\boldsymbol{\beta}$ given our focus on firms' adaptive decisions.

[39] Aggregation weights locations by their share of out-of-network sales in the period preceding the adaptation year.

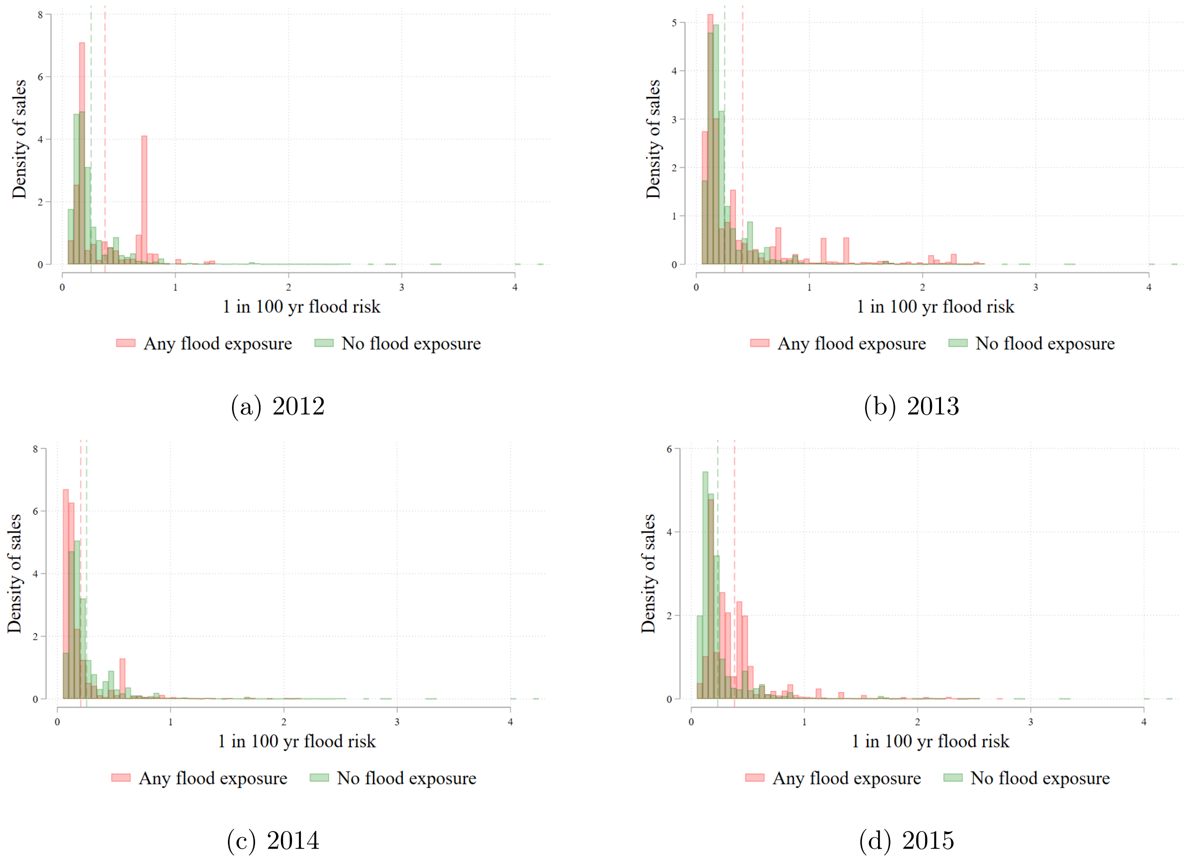
activity *towards* areas that would subsequently be affected by the 2014 floods, and as a result damages from the 2014 floods would have been 4% *lower* without adaptation following the 2012 flood.

To understand these patterns, consider the spatial distribution of flood impacts shown in Figures 9 and 10. The 2012 and 2013 floods can be seen to affect very similar areas. Consistent with this, sourcing share changes undertaken following the 2012 floods shift activity away from regions that will face flood exposure in 2013, and as such attenuate damages from a 2013 flood scenario. Conversely, the 2014 floods afflict quite different regions, such that adaptive changes in sourcing shares following the 2012 floods are associated with *higher* damages in this case. The 2015 flood is intermediate between these two cases, affecting both areas that were and were not flooded in 2012, so that adaptation following the 2012 floods had more muted protective impacts with respect to the damages imposed by a 2015 flood scenario.

The economy-wide aggregate figures mask substantial heterogeneity in the effects of adaptation across regions. While overall damages in a 2013 flood scenario would have been 5% higher in the absence of adaptation following the 2012 floods, flood damages would have been at least twice as large in four regions. The benefits of adaptation are also widely felt in this case, with 94% of locations seeing higher estimated damages in the absence of adaptation. Conversely, aggregate damages in a 2015 flood scenario would have been 1% higher without adaptation following the 2012 floods, but with a smaller interquartile range of location-specific changes from -1% to 7%, and only 66% of locations seeing benefits from adaptation.

The heterogeneous impacts of adaptation following the 2012 flood across subsequent floods in the sample raises a question as to the conditions under which post-flood adaptation may be expected to help or hurt in the face of future disasters. Some guidance on this question may be derived from considering how far the locations flooded in each of the floods in our sample coincide with regions of high flood risk in the Fathom data. Intuitively, for the majority of floods, the flood risk distribution among flooded firms is rightward shifted relative to that of their non-flooded counterparts, as shown in panels (a), (b) and (d) of Figure 11. Flood events are, however, stochastic, and may also hit lower flood risk areas. Indeed, panel (c) of Figure 11 suggests that firms affected by the 2014 flood are on average *less* flood-prone than those that are not. This is exactly the flood for which adaptation following the 2012 flood worsened outcomes – and is the outlier in other pairwise comparisons of the impact of post-flood adaptation on the damages from subsequent flood events (see Appendix Table A.8). This suggests that post-flood adaptation may be more likely to reduce damages from future floods on average where floods affect flood-prone regions, but that the converse may be more likely for idiosyncratic events that affect areas that are not especially flood prone.

Figure 11. Density of sales across 1 in 100 year flood risk by flood exposure



(a) 2012

(b) 2013

(c) 2014

(d) 2015

Notes: The figure plots the density of sales by flood exposure in different flood events. Dashed lines indicate sales-weighted average flood risk. Sales refer to total declared sales between July 2011 and August 2012. Flood risk is defined as the expected flood depth in meters for a 1 in 100 year return period. Flood exposure indicates whether the firm had a positive share of its buffer flooded during the flood event.

This examination of the implications of adaptation following a given flood for the impact of subsequent flood events highlights that adaptation can result in quantitatively important reductions in the damages from future flooding that afflicts similar locations. Importantly, however, such adaptation does not always help to reduce the damages from future floods, and indeed may worsen the impacts of some future flood shocks, especially those affecting spatially disjoint regions. The pattern of gains and losses from post-flood adaptation for future vulnerability will depend intuitively on the spatial correlation between areas that firms shift their sourcing towards or away from following one flood event, and areas adversely affected by a subsequent event.

6 Conclusion

The results of this paper suggest a consequential role for natural disaster events — a key manifestation of climate change — in influencing its impacts by inducing firm-level adaptation. We find that, while even major floods result in only temporary disruption to production and transportation links, these prompt persistent shifts in firm location, supplier and route choice that reduce firms' vulnerability to the recurrence of such events in the future. These responses are enduring, consistent with flood events causing firms to update their beliefs about underlying flood risk.

The interdependent nature of firm supply chains and the central role of vertical linkages in adaptation suggest that firm adjustments may have important general equilibrium implications for other firms and the resilience of the aggregate firm network. We estimate a spatial equilibrium model of firm production and sourcing decisions to capture such spillovers and estimate general equilibrium effects. This exercise reveals that firms' adaptive behavior following floods observed in our sample has quantitatively meaningful implications for the damages imposed by future flood events.

The fact that firms learn from flood experience, and respond by undertaking adaptive actions to reduce their vulnerability, raises the optimistic prospect that private adaptation may go some way to mitigating the projected impacts of a rapidly changing climate. But recent experience and significant remaining uncertainty about future climate impacts are cause to sound a note of caution. In the last 15 years, Pakistan has experienced two '1 in 100 year' floods, and average annual flood losses continue to reach catastrophic levels. Importantly, the structural estimation reveals that post-flood adaptation does not always reduce aggregate damages from future floods, and may exacerbate costs imposed by floods affecting low flood risk areas. Such considerations will be especially important as climate change alters the distribution and severity of flooding across regions in uncertain ways.

The paper's findings raise important policy questions about whether complementary approaches might effectively induce adaptation – for instance, could providing accurate information to firms on flood risk be sufficient to induce meaningful adaptation, or do firms only respond to costly flood experience? The finding that firms anticipate and adapt to flood risk also opens up an exciting research agenda on firm expectations about long-range climate change trajectories. Dynamic effects may be especially interesting if, for instance, belief updating and adaptive behaviors attenuate over time as major flood events become more common, consistent with evidence for shorter-lived employment impacts of natural disasters in contexts where they are experienced more often (Belasen and Polachek, 2008). Given sharply deteriorating projections of natural disaster incidence as climate change proceeds, understanding such dynamics will be crucial in anticipating future adaptation and damages.

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A Supplementary Tables and Figures

Table A.1. Firm-level summary statistics

Buyers = Sellers	73,336			
Share of firms with 2011 and 2019 geocodes	60%			
Share of firms ever flooded	28%			
Share of firms flooded > once	4%			
Share of firms ever had important recent supplier flooded	19%			
Share of firms had important recent supplier flooded > once	2%			
Median firm age at end of sample period (years)	32			
Average probability of firm exit in given month	0.25%			
	Monthly		Annual	
	Mean	SD	Mean	SD
Log total declared sales	14.74	2.07	16.73	2.15
Share of months with positive declared sales	49%	34pp		
Log self-reported sales	14.84	2.08	17.01	2.10
Share of months with positive self-reported sales	50%	33pp		
Log all aggregated sales	14.78	2.14	16.86	2.20
Share of months with positive aggregated sales	51%	33pp		
Log total declared purchases	14.45	2.15	16.35	2.20
Share of months with positive declared purchases	45%	34pp		
Log self-reported purchases	14.46	2.22	16.42	2.25
Share of months with positive self-reported purchases	47%	34pp		
Log all aggregated purchases	14.27	2.38	16.28	2.39
Share of months with positive aggregated purchases	52%	34pp		

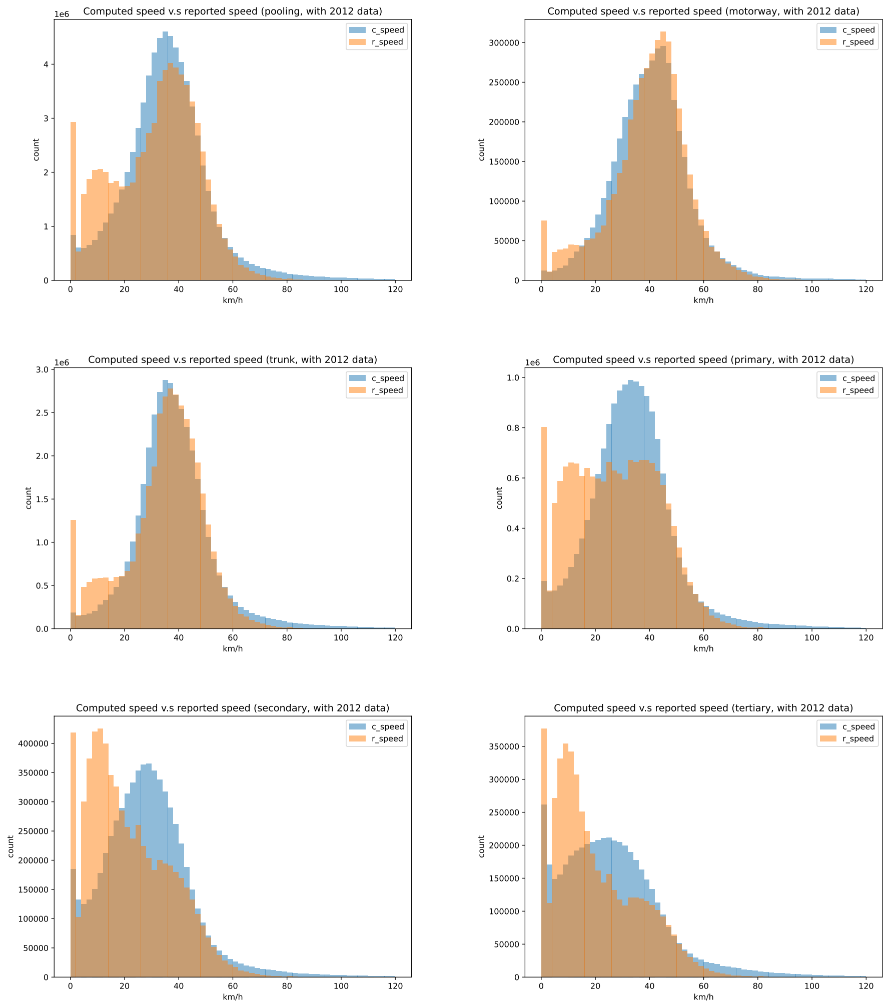
The table reports descriptive statistics on the firm level. We impose standard restrictions on firms and transaction partners. For the self-reported and all aggregated transaction variables, we do not restrict transaction partners to the standard sample. This is because these variables are only used to compute reporting frequencies for sample restrictions. All firms are considered both buyers and sellers because the sample is restricted to firms that report at least three nonzero values for each transaction measure. Sales and purchases may be measured in one of three ways: (1) declared as aggregate by a firm, (2) aggregated based on self-reported transaction values, or (3) aggregated based on self-reported and reverse-reported transaction values. All sales and purchases are denominated in Pakistani Rupee (PKR) before logging. The flooding of an important recent supplier follows the definition in sections (4.2) and (4.3). It is a buyer-year-month observation in which a seller accounting for $\geq 10\%$ of buyer purchases over the preceding three months was flooded. Standard deviations for shares of year-months in which a variable is positive are computed as the standard deviation across firms of the corresponding within-firm share. Other standard deviations are computed across all observations. Years refer to fiscal years, which last July through June.

Table A.2. Transaction-level summary statistics

Transaction panel observations (transaction $>$ 0)	15,473,279	
Buyer-seller pairs ever reported	1,657,933	
Share active pairs among possible combinations	0.031%	
	Mean	SD
Log transaction value	12.43	2.27
Transactions per pair in years with ≥ 1	4.30	3.81
Transactions per pair per year over sample period if ≥ 1	1.33	2.27
Months between transactions of pair if ≥ 2	2.13	4.10
Distinct suppliers per buyer over sample period if ≥ 1	25.35	81.41
Distinct quarterly suppliers per buyer if ≥ 1	7.77	24.15
Share of quarterly buyer purchases from average supplier	52%	37pp
Share of sellers supplying $\geq$ 10% of buyer's quarterly purchases	72%	34pp
Distinct buyers per seller over sample period if ≥ 1	29.23	111.81
Distinct quarterly buyers per seller if ≥ 1	10.57	54.97
Share of quarterly seller sales to average buyer	46%	38pp
Share of buyers purchasing $\geq$ 10% of seller's quarterly sales	65%	36pp

Transactions refer to buyer-seller-year-month observations with a positive transaction value. All sales and purchases are denominated in Pakistani Rupee (PKR) before logging. Both the number of distinct active buyer-seller-pairs and the number of possible buyer-seller-pairs are defined as permutations. That is, we count firm A selling to firm B and firm B selling to firm A as two distinct buyer-seller pairs. In defining quarterly partner variables, a firm's buyers (suppliers) refer to companies purchasing (selling) a positive amount to the firm in a given quarter. Years refer to fiscal years, which last July through June.

Figure A.1. Histograms of calculated speed and reported speed using 2012 data



Notes: The histograms plot the count of computed speeds in the full sample (blue) and of speeds reported by the trackers (orange) for different road types in 2012.

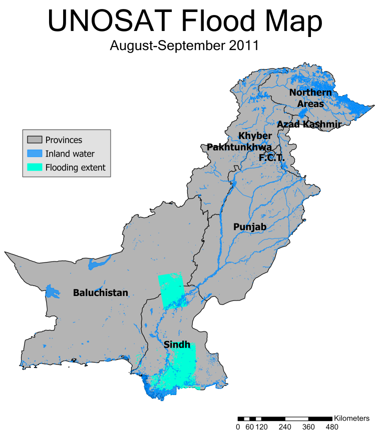
Figure A.2. Comparison of calculated and reported truck speeds in Lahore

(a) Calculated speeds, 2015

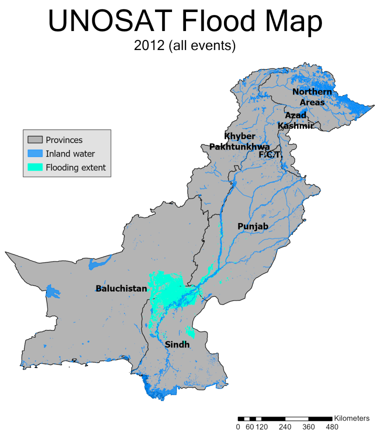
(b) Reported speeds, 2010

Notes: Panel (a) maps computed 2015 speeds and panel (b) maps 2010 speeds reported in Japan International Cooperation Agency (2012) for the same area in Lahore.

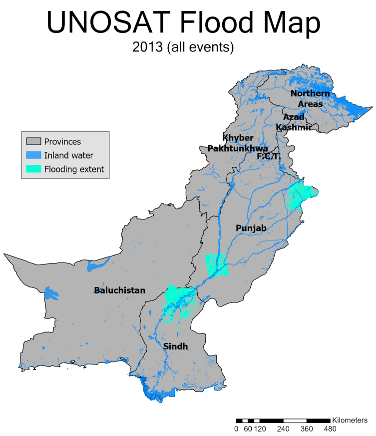
Figure A.3. Flood extent maps during sample period



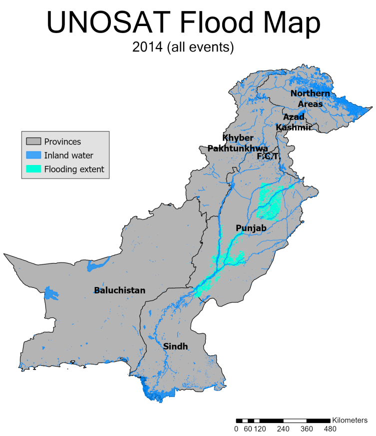
(a) 2011: Aug.-Sep.



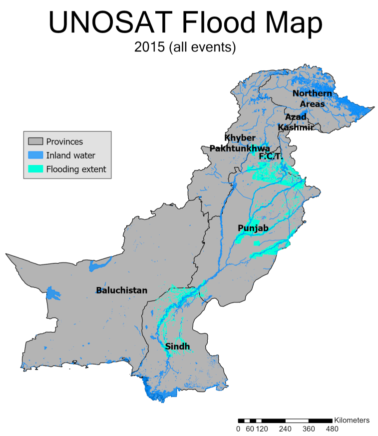
(b) 2012



(c) 2013



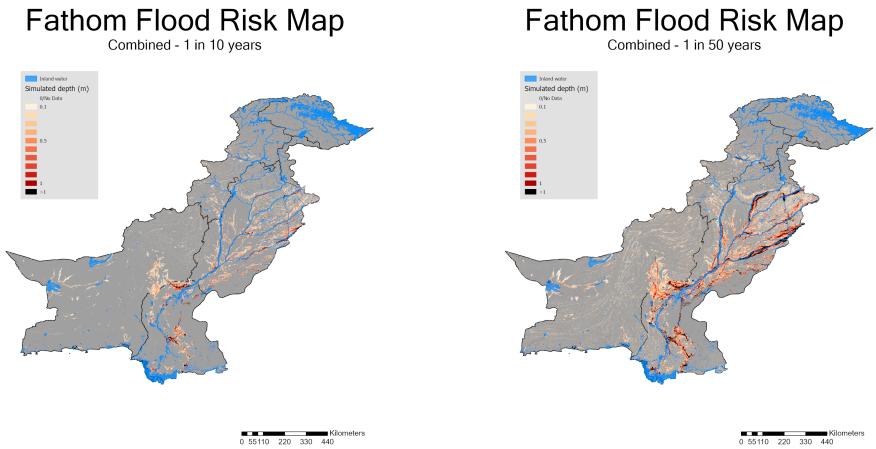
(d) 2014



(e) 2015

Notes: The figure maps the aggregate extent of flooding in the sample period in different years in which we observe flood events. Panel a) omits the January 2011 flood since it lies outside the sample period.

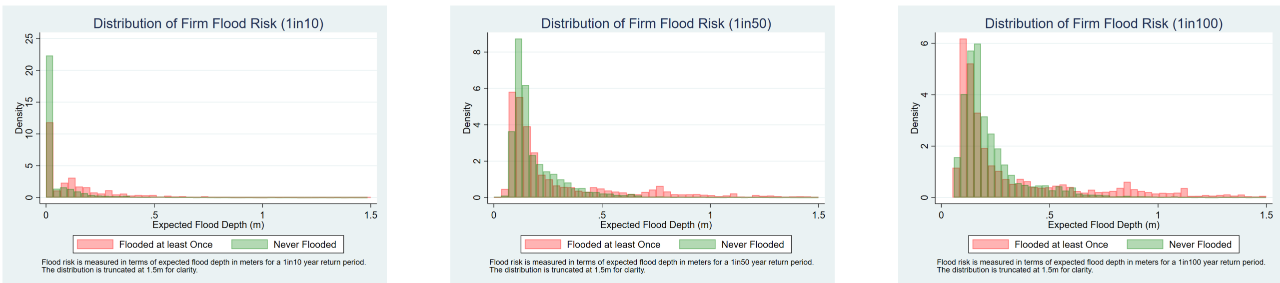
Figure A.4. Fathom flood risk maps of Pakistan for return periods of 10 and 50 years



(a) 1 in 10 years (b) 1 in 50 years

Notes: The maps display flood risk across Pakistan for a 1 in 10 and a 1 in 50 year return period. Flood risk is defined as the maximum across pluvial and fluvial flood risk, measured as expected flood depth in meters.

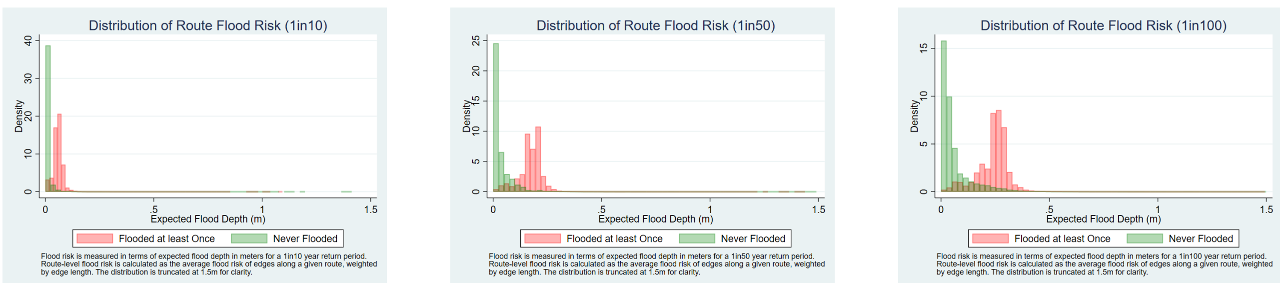
Figure A.5. Distribution of firms by Fathom flood risk



(a) 1 in 10 years return period (b) 1 in 50 years return period (c) 1 in 100 years return period

Notes: The histograms display the density of firms' flood risk by whether a firm's buffer was flooded at least once over the sample period. Flood risk is measured as expected flood depth in meters. The histograms are truncated at 1.5m.

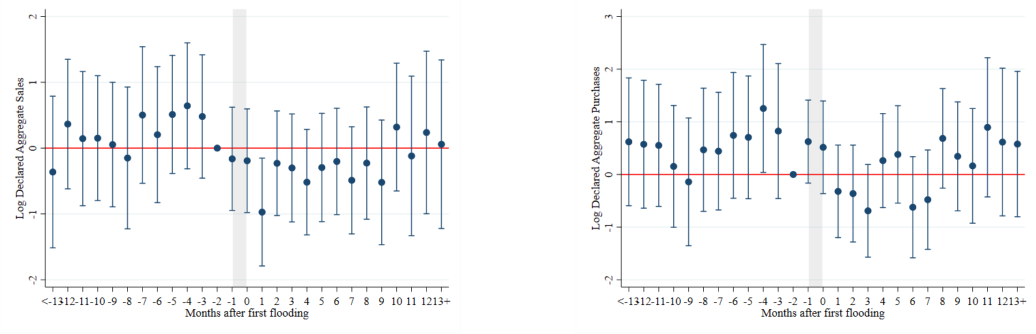
Figure A.6. Distribution of firm-pair routes by Fathom flood risk



(a) 1 in 10 years return period (b) 1 in 50 years return period (c) 1 in 100 years return period

Notes: The histograms display the density of firm-pair-route flood risk by whether the route was flooded at least once over the sample period. Flood risk is measured as the length weighted average expected flood depth in meters of edges along a give route. The histograms are truncated at 1.5m.

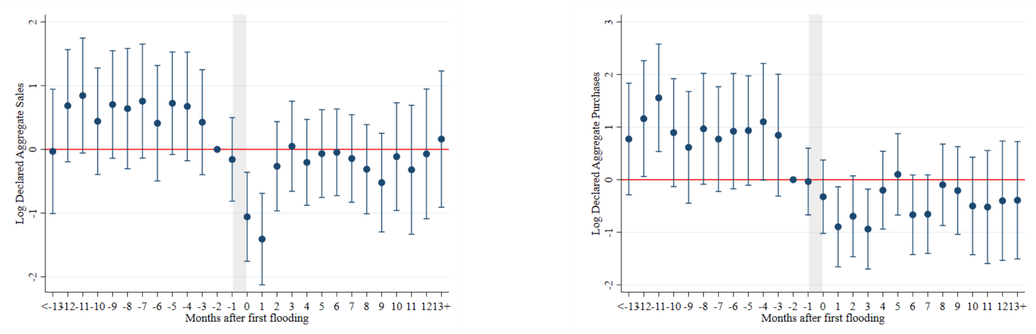
Figure A.7. Impact of flooding on firm sales and purchases using district × time FEs



(a) Log sales (b) Log purchases

Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases following equation (1). Here, we use district × time FEs instead of time FEs. The unit of observation is a firm-month-year. The 95% confidence intervals rely on standard errors clustered at the firm-level.

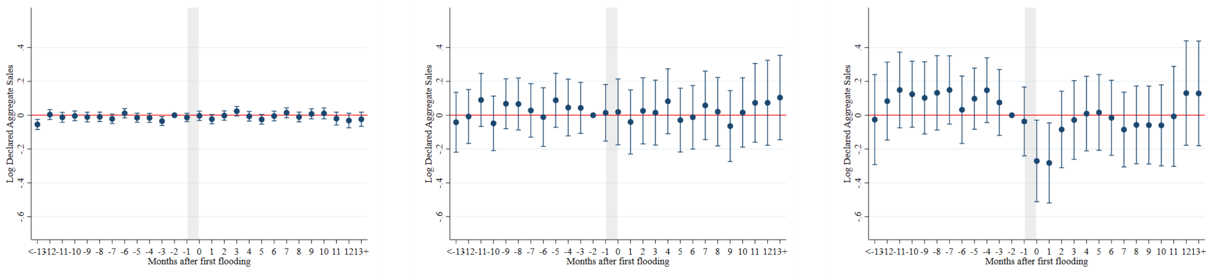
Figure A.8. Impact of flooding on firm sales and purchases using flood-risk-decile × time FEs



(a) Log sales (b) Log purchases

Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases following equation (1). Here, we use flood-risk-decile × time FEs instead of time FEs. The flood risk decile is defined as the decile of a firm's expected flood depth in meters for a 1 in 100 year return period. The unit of observation is a firm-month-year. The 95% confidence intervals rely on standard errors clustered at the firm-level.

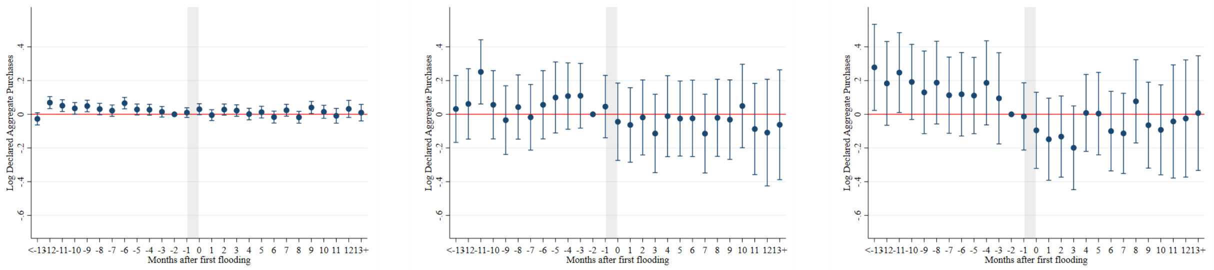
Figure A.9. Impact of binned own flooding on firm sales



(a) 0-5% (b) 5-10% (c) >10%

Notes: The panels plot the estimated effect of flooding on log declared sales from a single OLS regression specified analogously to equation (1). Here, we include dummy treatment variables $D^I_{i,t-\tau} := 1\{\text{FloodExtent}_{i,t-\tau} \in I\}$ for each flood extent bin $I \in \{(0\%, 5\%], (5\%, 10\%], (10\%, 100\%]\}$ instead of the buffer share flooded. The unit of observation is a firm-month-year. The 95% confidence intervals rely on standard errors clustered at the firm-level.

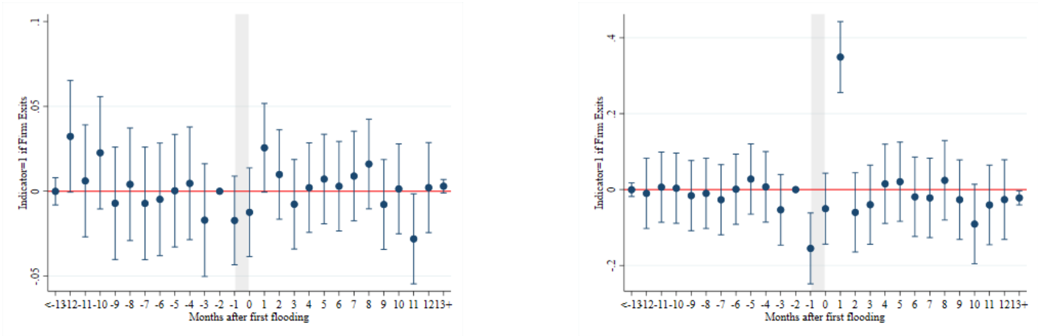
Figure A.10. Impact of binned own flooding on firm purchases



(a) 0-5% (b) 5-10% (c) >10%

Notes: The panels plot the estimated effect of flooding on log declared purchases from a single OLS regression specified analogously to equation (1). Here, we include treatment dummies $D^I_{i,t-\tau} := 1\{\text{FloodExtent}_{i,t-\tau} \in I\}$ for each flood extent bin $I \in \{(0\%, 5\%], (5\%, 10\%], (10\%, 100\%]\}$ instead of the buffer share flooded. The unit of observation is a firm-month-year. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure A.11. Impact of flooding on firm exit



(a) All floods (b) September 2014 flood

The figure displays the estimated impact of firm flooding on firm exit, specified as follows:

$$y_{it} = \sum_{\substack{\tau=-12 \\ \tau \neq -2}}^{12} \beta_\tau \text{FloodExtent}_{i,t-\tau} + \alpha_{dt} + \varepsilon_{it} \tag{23}$$

where the unit of observation, (i, t), is a firm-month-year; y_{it} is an indicator variable equal to one if firm i exits in month-year t; $\text{FloodExtent}_{i,t-\tau}$ is the share of firm i's buffer flooded in its first flood month; and α_{dt} are district-month-year fixed effects. As in section (2.1), we define a firm's exit date as the year-month of its last report if this is more than a year from the end of the panel. Panel (b) only includes firms which are either never flooded or first flooded in September 2014. We display 95% confidence intervals.

Table A.3. Share and number of firms by distance moved

	Share of Firms Moved	# of Firms Moved
Moved >0km	0.68	29,699
Moved >1km	0.47	20,474
Moved >2km	0.39	17,004
Moved >5km	0.24	10,638
Moved >10km	0.13	5,755
Moved >15km	0.09	3,795
Moved >20km	0.07	2,928
Observations	43877	

Notes: The sample is restricted to firms with 2011 and 2019 geocodes.

Table A.4. Impact of flooding on firm relocation (0, 5, 15km move thresholds)

	Move Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Max Share of 2km Buffer Flooded	-0.222	1.685**	0.783	-0.432	1.534*	1.426*
	(0.739)	(0.702)	(0.830)	(0.754)	(0.906)	(0.862)
District FE	Yes	Yes	Yes			
District × Fathom 1 in 100 FE				Yes	Yes	Yes
Move Dummy Threshold	0km	5km	15km	0km	5km	15km
McFadden's Pseudo R^2	0.005	0.021	0.061	0.017	0.041	0.088
N	43,831	43,841	43,845	43,515	43,487	43,152

Notes: The columns display logit estimates of the effect of flooding on the probability of relocating by >0km, >5km, or >15km following equation (3). Observations are firms geocoded in 2011 and 2019. Standard errors (in parentheses) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5. Impact of flooding on flood risk of firm's location (no, 0, 5, 15km move restrictions)

	Δ Flood Risk							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max Share of 2km Buffer Flooded	-1.370*	-1.906*	-2.331*	-1.969**	-0.543*	-0.752*	-0.598	-0.458
	(0.779)	(1.110)	(1.351)	(0.822)	(0.285)	(0.424)	(0.581)	(0.392)
District FE	Yes	Yes	Yes	Yes				
District × Fathom 1 in 100 FE					Yes	Yes	Yes	Yes
Move Distance Restriction	None	>0km	>5km	>15km	None	>0km	>5km	>15km
R^2	0.029	0.039	0.086	0.161	0.190	0.268	0.424	0.479
N	43,866	29,684	10,623	3,780	43,754	29,569	10,481	3,652

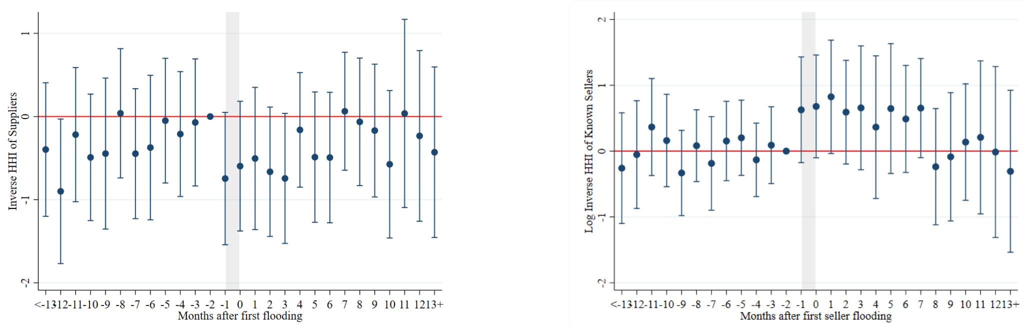
Notes: The table reports OLS estimates of the effect of flooding on firms' change in flood risk as specified in equation (4). Observations are firms geocoded in 2011 and 2019 or those which additionally moved by >0km, >5km, or >15km. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6. Impact of destination flood history on relocation flows (0, 5, 15km move restrictions)

	Number of Firms Moved		
	(1)	(2)	(3)
Dest. flooded 12mo prior	-1.766***	-0.803***	-0.827***
	(0.281)	(0.225)	(0.293)
Origin × Destination FE	Yes	Yes	Yes
Origin × Flood Event (month) FE	Yes	Yes	Yes
Flood Event of Destination FE	Yes	Yes	Yes
Move Distance Restriction	>0km	>5km	>15km
N	1,626	1,469	1,304

Notes: The table displays Poisson pseudo-maximum-likelihood estimates of the effect of flood history on relocation flows following equation (5). The unit of observation is the area of an origin-district first flooded in a given year-month paired with the area in a destination district which was never flooded or first flooded in a given year-month. We only consider firms moving by >0km, >5km, or >15km and location-pairs with positive flows. The standard errors (in parentheses) are clustered at the origin-district-by-destination-district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.12. Supplier Diversification: Impact of flooding on suppliers' log inverse HHI



(a) Own flooding

(b) Supplier flooding

Notes: Panels (a) and (b) plot OLS estimates of the effect of own flooding and supplier flooding on the log inverse Herfindahl index of a buyer's suppliers in a given month following equations (6) and (7), respectively. Observations are firm-month-years whose 2011 and 2019 addresses are known and $\leq$ 10km apart. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Table A.7. Impact of flooding on supplier flood risk

	Δ Flood Risk of Suppliers Flooded by					
	$\leq 5\%$			$\leq 10\%$		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Max Flood Extent	-0.115	-0.108	-0.147	-0.0860	-0.0835	-0.120
	(0.0935)	(0.0895)	(0.121)	(0.0956)	(0.0890)	(0.125)
Suppliers' Max Flood Extent	-0.272***	-0.281***	-0.268**	-0.483**	-0.504**	-0.508**
	(0.0993)	(0.0941)	(0.108)	(0.200)	(0.205)	(0.225)
Time × District FE	Yes			Yes		
Time × District × Risk Dec. FE		Yes			Yes	
Time × District × Industry FE			Yes			Yes
R^2	0.0090	0.0324	0.0586	0.0098	0.0323	0.0586
N	144,423	143,718	139,164	144,494	143,789	139,235

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ or $\leq 10\%$ during the flood risk windows. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.13. Dynamic impact of supplier flooding on flood risk of $\leq 5\%$ flooded suppliers

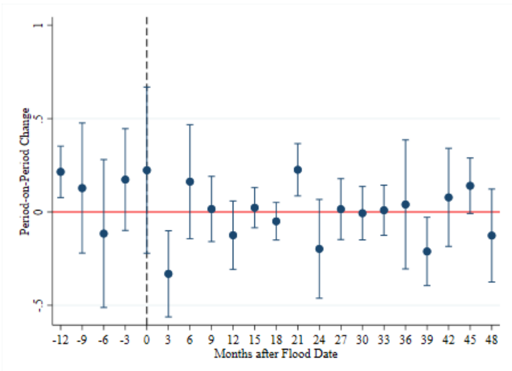
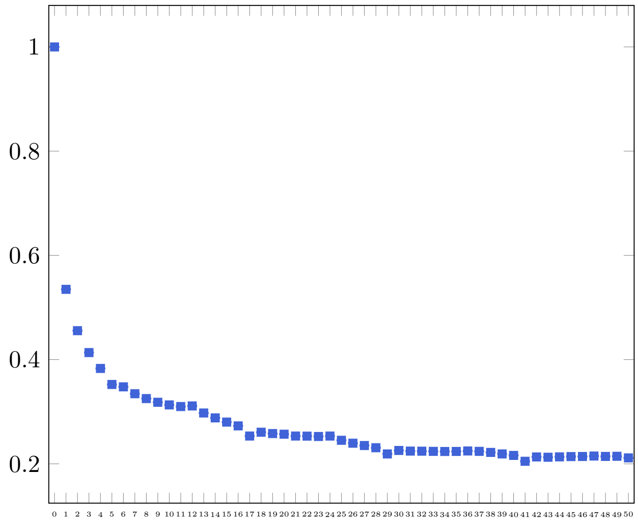


Figure A.13 plots OLS estimates of a sequence of separate regressions examining the impact of supplier flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$. The specification for the estimate at lag $l \in \{-12, -9, -6, ..., 48\}$ is defined analogously to equation (8), but with the dependent variable lagged by l months:

$$\Delta y_{b(t^*+l)} = \beta_1 OwnFlood_{bt*} + \beta_2 SellerFlood_{bt*} + \alpha_{d(b)t*} + \epsilon_{bt*} \tag{24}$$

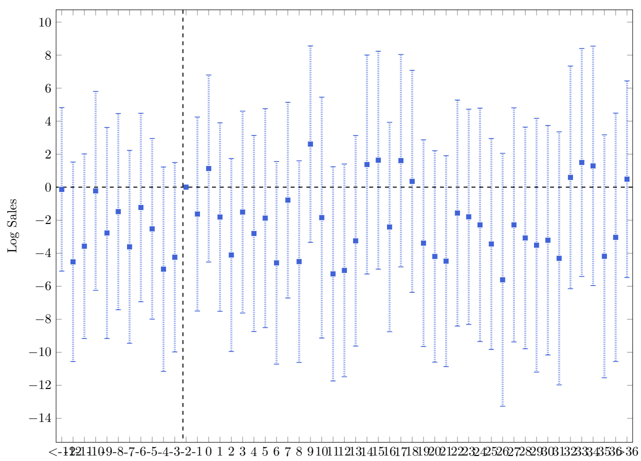
where t^* denotes the month-year of a flood event; $OwnFlood_{bt^*}$ is the maximum share of buyer b's 2km buffer that is flooded at t^*; $SellerFlood_{bt^*}$ is the maximal maximum share of the 2km buffer flooded at t^* across all sellers which account for $\geq 10\%$ of b's purchases over the previous three months; and $\alpha_{d(b)t^*}$ are buyer district × time fixed effects. $\Delta y_{b(t^*+l)}$, denotes the change in the sales-weighted average flood risk of b's suppliers from $(t^* + l - 6, t^* + l - 3]$ to $(t^* + l - 3, t^* + l]$ which were not flooded by >5% before or at $t^* + l$. Otherwise, flood risk is defined analogously to equation (9). The set of observations consists of all firm-by-flood-year-month pairs (b, t^*) for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. To ensure later lags capture long term effects, we exclude all buyers which are flooded themselves or experience supplier flooding (defined like the treatment) in the period before or at $t^* + l$ but excluding the flood event around t^*. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure A.14. Probability of having positive sales in the relationship, by month after first sale



The graph shows the unconditional probability of the buyer-seller relationship having positive sales (vertical axis), n months after the first sale in the relationship (horizontal axis).

Figure A.15. No impact of road flooding on intensive margin sales in buyer-seller relationship



The graph shows the response of log sales in the (b, s) relationship around the first time the shortest path between b and s gets flooded (after entry of b and s) following equation (11). Observations are buyer-seller-weeks in the manufacturing sector. Regression conditions on b and s having positive sales, and includes $b \times s$, $s \times t$, and $b \times t$ fixed effects and months-since-first-sale dummies. The 95% confidence intervals are clustered at the relationship level.

Table A.8. Percentage difference in household price index in flood year in absence of adaptation following adaptation year flood

Adaptation year	Flood year		
	2013	2014	2015
2012	5%	-4%	1%
2013		-14%	-1%
2014			3%

The table displays counterfactual changes in the household price index estimated as described in section 5.2

B Proofs

Lemma 3 (Shanbhag and Sreehari, 1977)**.** *If Z is a standard exponential random variable and X is a positive α-stable random variable defined by*

$$E\left(e^{-uX}\right) = e^{-u^{\alpha}}$$

and independent from Z, then $\left(\frac{Z}{X}\right)^{\alpha}$ is also a standard exponential random variable.

Proof.

$$P\left(\left(\frac{Z}{X}\right)^{\alpha} > u\right) = P\left(Z > u^{1/\alpha}X\right) = \int e^{-u^{1/\alpha}x}dF(x) = E\left[e^{-u^{1/\alpha}X}\right] = e^{-\left(u^{1/\alpha}\right)^{\alpha}} = e^{-u}$$

□

Lemma 4. *Let X be Fréchet distributed with*

$$P\left(X > x\right) = e^{-Tx^{\theta}}$$

and Y independent from X such that $E\left[e^{-uY}\right] = e^{-u^{\beta}}$. Then $\left(X/Y^{1/\theta}\right)^{\alpha}$ is Fréchet distributed with

$$P\left(\left(\frac{X}{Y^{1/\theta}}\right)^{\alpha} > x\right) = \exp\left[-T^{\beta}x^{\frac{\theta\beta}{\alpha}}\right]$$

Proof. We have that $T\left(X\right)^{\theta}$ is standard exponential:

$$P\left(T\left(X\right)^{\theta} > x\right) = P\left(X > \left(\frac{x}{T}\right)^{1/\theta}\right) = e^{-x}$$

From the Shabhag-Sreehari lemma above we know that

$$P\left(\left(\frac{T\left(X\right)^{\theta}}{Y}\right)^{\beta} > x\right) = e^{-x}.$$

Rearrange to get □

$$\begin{aligned}
P\left(\left(\frac{X}{Y^{1/\theta}}\right)^{\alpha\frac{\theta\beta}{\alpha}} > \left(T^{-\beta}x\right)\right) &= e^{-x} \\
P\left(\left(\frac{X}{Y^{1/\theta}}\right)^{\alpha} > \left(T^{-\beta}x\right)^{\frac{\alpha}{\theta\beta}}\right) &= e^{-x} \\
P\left(\left(\frac{X}{Y^{1/\theta}}\right)^{\alpha} > u\right) &= \exp\left[-T^{\beta}u^{\frac{\theta\beta}{\alpha}}\right]
\end{aligned}$$

Lemma 5. *Let X be Frechet with*

$$P(X < x) = e^{-ax^{-\zeta}}.$$

Then $\log X$ *has the characteristic function*

$$\chi\left(\log X\right)(t) = E\left[e^{it\log X}\right] = a^{\frac{it}{\zeta}}\Gamma\left(1-\frac{it}{\zeta}\right).$$

Proof.

$$\begin{aligned}
\chi\left(\log X\right)(t) &= E\left[e^{it\log X}\right] = \int_0^\infty e^{it\log x} a\zeta x^{-\zeta-1}e^{-ax^{-\zeta}}dx \\
&= \int_0^\infty a\zeta x^{-\zeta-1+it}e^{-ax^{-\zeta}}dx \\
&= \int_0^\infty x^{it}e^{-u}du = \int_0^\infty \left(\frac{u}{a}\right)^{-\frac{it}{\zeta}} e^{-u}du \\
&= a^{\frac{it}{\zeta}}\int_0^\infty (u)^{-\frac{it}{\zeta}} e^{-u}du \\
&= a^{\frac{it}{\zeta}}\Gamma\left(1-\frac{it}{\zeta}\right)
\end{aligned}$$

$$f(x) = a\zeta x^{-\zeta-1}e^{-ax^{-\zeta}}$$

where we've used the substitution

$$\begin{aligned}
u &= ax^{-\zeta} \\
\left(\frac{u}{a}\right)^{-1/\zeta} &= x \\
-\frac{1}{a}\frac{1}{\zeta}\left(\frac{u}{a}\right)^{-1/\zeta-1} &= \frac{dx}{du} \\
\frac{du}{dx} &= -a\zeta x^{-\zeta-1} \\
-\frac{1}{\zeta a}x^{\zeta+1}du &= dx
\end{aligned}$$

□

Lemma 6 (Lemma 1 in the main text)**.** *Conditional on the realization of the aggregate flood shocks* b*, the cost distribution of firms in* n *is Weibull:*

$$P\left(c_j > c|b\right) = \exp\left[-\left[\left(a_{n(j)}b_{n(j)}\right)^{\zeta\beta/\alpha}\left(w^{1-\alpha}\right)^{-\zeta\beta/\alpha}\left[\sum_{n'} m_{nn'}\tau_{nn'}^{-\zeta}\bar{c}_{sn'}^{-\zeta}\right]^{\beta}\right]c^{\zeta\beta/\alpha}\right]$$

where:

$$\bar{c}_n^{-\zeta} = \left(a_n b_n\right)^{\zeta}\left(w^{1-\alpha}\right)^{-\zeta}\left(\sum_{n'} m_{nn'}\tau_{nn'}^{-\zeta}\bar{c}_{n'}^{-\zeta}\right)^{\alpha}\Gamma\left(1-\frac{\alpha}{\beta}\right)$$

Proof. Let $F_i(c)$ be the CDF of firm's costs in a location i. We have

$$c_j\left(\phi\right) = \frac{1}{a_{n(j)}b_{n(j)t}\xi_{jt}}w^{1-\alpha}\left(\tau_{n(j)n(s)}\frac{c_s(\phi)}{z\left(\phi\right)}\right)^{\alpha}$$

$$\begin{aligned}
P\left(c_j\left(\phi\right) > c | b, \xi\right) &= P\left(\frac{1}{a_{n(j)} b_{n(j)t} \xi_{jt}} w^{1-\alpha} \left(\tau_{n(j)n(s)} \frac{c_s(\phi)}{z\left(\phi\right)}\right)^{\alpha} > c\right) \\
&= P\left(\frac{c_s(\phi)}{z\left(\phi\right)} > \tau_{n(j)n(s)}^{-1} \left(w^{1-\alpha}\right)^{-1/\alpha} \left[a_{n(j)} b_{n(j)t} \xi_{jt}\right]^{1/\alpha} c^{1/\alpha}\right)
\end{aligned}$$

The distribution of effective cost from techniques with a supplier in n' follows

$$\begin{aligned}
P\left(\frac{c_s}{z} > c\right) &= \exp\left[-m_{nn'} \int \int 1\left\{\frac{c_s}{z} < c\right\} dF_{n'}(c_s) \zeta z^{-\zeta-1} dz\right] \\
&= \exp\left[-m_{nn'} \int \int 1\left\{\frac{c_s}{u} < 1\right\} dF_{n'}(c_s) \zeta u^{-\zeta-1} c^{\zeta} du\right] \\
&= \exp\left[-m_{nn'} c^{\zeta} \int \int 1\left\{\frac{c_s}{u} < 1\right\} dF_{n'}(c_s) \zeta u^{-\zeta-1} du\right] \\
&= \exp\left[-m_{nn'} \bar{c}_s^{-\zeta} c^{\zeta}\right]
\end{aligned}$$

where we have used the substitutions

$$\begin{aligned}
u &= cz \\
du/dz &= c \\
z^{-\zeta-1} dz &= u^{-\zeta-1} c^{\zeta} du
\end{aligned}$$

and where we have used the notation

$$\begin{aligned}
\bar{c}_s^{-\zeta} &= \int \int 1\left\{\frac{c_s}{u} < 1\right\} dF_{n'}(c_s) \zeta u^{-\zeta-1} du \\
&= -\int \int 1\left\{t > 1\right\} \left(c_s\right)^{-\zeta} dF_{n'}(c_s) \zeta t^{\zeta-1} dt \\
&= \int \left(c_s\right)^{-\zeta} dF_{n'}(c_s)
\end{aligned}$$

Let $c_{\min}(j)$ be the lowest cost that j can achieve, and $c_{\min,n'}$ the lowest cost it can achieve by sourcing from n', then

$$\begin{aligned}
P\left(c_{\min,n'} > c | b, \xi\right) &= P\left(\left(\frac{c_s(\phi)}{z\left(\phi\right)}\right)_{\min,n'} > \tau_{n(j)n'}^{-1} \left(w^{1-\alpha}\right)^{-1/\alpha} \left[a_{n(j)} b_{n(j)} \xi_j\right]^{1/\alpha} c^{1/\alpha}\right) \\
&= \exp\left[-m_{nn'} \bar{c}_{n'}^{-\zeta} \left(\tau_{n(j)n'}^{-1} \left(w^{1-\alpha}\right)^{-1/\alpha} \left[a_{n(j)} b_{n(j)} \xi_j\right]^{1/\alpha}\right)^{\zeta} c^{\zeta/\alpha}\right]
\end{aligned}$$

is Weibull distributed. Hence

$$\begin{aligned}
P\left(c_{\min} > c | b, \xi\right) &= \prod_{n'} P\left(c_{\min,n'} > c | b, \xi\right) \\
&= \exp\left[-\left(\left(w^{1-\alpha}\right)^{-1/\alpha} \left[a_n b_n \xi_j\right]^{1/\alpha}\right)^{\zeta} \left(\sum_{n'} m_{nn'} \tau_{nn'}^{-\zeta} \bar{c}_{n'}^{-\zeta}\right) c^{\zeta/\alpha}\right]
\end{aligned}$$

where we write shorthand n for $n(j)$. Conditional on b an ξ, the minimum cost is Weibull distributed.

Apply now Lemma 4,

$$P\left(\left(\frac{X}{Y^{1/\theta}}\right) > x^{1/\alpha}\right) = \exp\left[-T^{\beta} x^{\frac{\theta\beta}{\alpha}}\right]$$

with

$$\begin{aligned} X &= (c_j|b)\,\xi_{jt} \\ T &= \left(\left(w^{1-\alpha}\right)^{-1/\alpha}[a_n b_n \xi_j]^{1/\alpha}\right)^{\zeta}\left(\sum_{n'} m_{nn'}\tau_{nn'}^{-\zeta}\bar{c}_{n'}^{-\zeta}\right) \\ \theta &= \zeta/\alpha \\ Y &= \xi^{\zeta/\alpha} \end{aligned}$$

to get

$$\begin{aligned} P\left((c_j) > x|b\right) &= \exp\left[-\left[\left(\left(w^{1-\alpha}\right)^{-1/\alpha}[a_n b_n]^{1/\alpha}\right)^{\zeta}\left(\sum_{n'} m_{nn'}\tau_{nn'}^{-\zeta}\bar{c}_{n'}^{-\zeta}\right)\right]^{\beta} x^{\zeta\beta/\alpha}\right] \\ &= \exp\left[-\left(\left(w^{1-\alpha}\right)^{-\zeta\beta/\alpha}[a_n b_n]^{\zeta\beta/\alpha}\right)\left(\sum_{n'} m_{nn'}\tau_{nn'}^{-\zeta}\bar{c}_{n'}^{-\zeta}\right)^{\beta} x^{\zeta\beta/\alpha}\right] \end{aligned}$$

which is the first part of the statement of the Lemma. For the second part, use the definition of $\bar{c}$ and Lemma 5:

$$\bar{c}_n^{-\zeta} = E\left[c^{-\zeta}\right] = E\left[X^{\zeta}\right] = [a_n b_n]^{\zeta}\left(w^{1-\alpha}\right)^{-\zeta}\left(\sum_{n'} m_{nn'}\tau_{nn'}^{-\zeta}\bar{c}_{n'}^{-\zeta}\right)^{\alpha}\Gamma\left(1-\frac{\alpha}{\beta}\right)$$

□

Lemma 7 (Lemma 2 in the main text)**.** *Let $\alpha > 0$. Then for each realization of the aggregate shocks b_n an equilibrium exists and is unique.*

Proof. The proof of Lemma 2 follows directly from Theorem 1 in Alvarez and Lucas (2007) with $\beta := 1-\alpha$ and $\theta := \alpha/\zeta$. □

C Robustness Specifications

C.1 Results using Sun and Abraham (2021) estimator and event-by event regressions

A recent literature has highlighted potential challenges with the use of two-way fixed effects regressions including treatment leads and lags, since variation in treatment timing may give rise to contamination of coefficients on lead or lag terms by effects from other periods (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). While the major floods in our sample are generally close to a year apart so that such effects may not be first order, we re-run all key results using the estimator proposed in Sun and Abraham (2021). This estimator aims to overcome the challenges that may be associated with two-way fixed effects event study regressions by using never-treated (or, if these are not available, last-treated) firms to form the control group. It relies on a binary treatment variable. Since Figure A.9 suggests that the impact of flooding is concentrated among firms which have more than 10% of their buffer flooded, we consider a firm treated only if the treatment variable is greater than 10%. We drop all firms with a treatment variable ϵ $(0\%, 10\%]$. Further, we use never treated firms as the control cohort. All key results are robust to using this estimator.

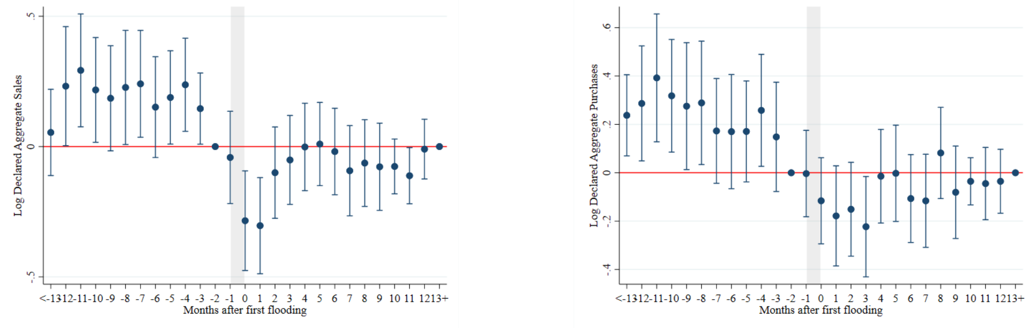
We further present results separately by flood event. Specifically, we restrict the sample to firms which are either never treated or treated only in a given flood event. The flood events in our sample period are Aug-Sep 2011, Sep 2012, Aug 2013, Sep 2014, and Jul-Aug 2015. For the two-month flood events (Aug-Sep 2011 and Jul-Aug 2015), we define event time relative to the first month of the event. This applies even where firms are only treated in the second month. This specification shuts down variation in treatment timing while using the standard quantitative treatment variable. Note that since the panel begins in July 2011 and ends in June 2018, coefficients for earlier and later periods are omitted. Furthermore, we have to omit one coefficient in each fiscal year in the sales, purchases, and log number of supplier regressions. This is because the full set of treatment variables, the firm-fiscal-year FEs and the firm-month-of-the-year FEs are perfectly collinear within each fiscal year when restricting to a single flood event. Finally, substantially fewer firms are either treated by >10%, or in the 2011 or 2012 events than in our standard specification. Therefore, we include the number of treated firms, $N_{treated}$, with each regressions below.

We omit the following analyses as they are not estimated with two-way fixed effect models:

- Impact of flooding on firm relocation and flood risk of firm location
- Impact of destination flood history on relocation flows
- Impact of supplier flooding on on flood risk of all suppliers suppliers flooded by $\leq 5\%$
- Dynamic impact of supplier flooding on flood risk of suppliers flooded by $\leq 5\%$ (the coefficients are estimated not as an event study, but as a series of separate regressions with different lags between windows over which flood risk is calculated).

C.1.1 Intensive Margin

Figure C.1. Impact of flooding on firm sales and purchases (Sun & Abraham)



(a) Log sales

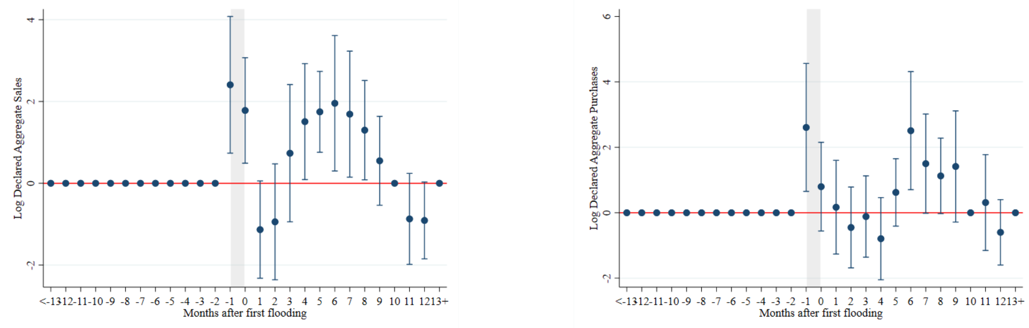
$N_{treated} = 681$

(b) Log purchases

$N_{treated} = 681$

Notes: The panels plot the effect of flooding on log declared sales and purchases. We use the method by Sun and Abraham (2021) to estimate equation (1) but with a binary treatment variable based on a 10% cutoff. Observations are firm-month-years which are never flooded or flooded by > 10% in their first flood month. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure C.2. Impact of flooding on firm sales and purchases (Aug-Sep 2011)



(a) Log sales

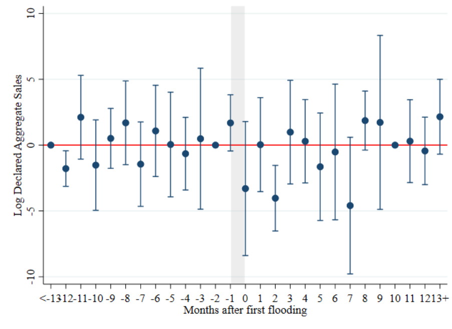
$N_{treated} = 990$

(b) Log purchases

$N_{treated} = 990$

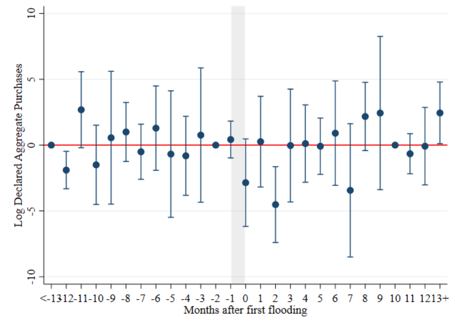
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Aug-Sep 2011 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure C.3. Impact of flooding on firm sales and purchases (Sep 2012)



(a) Log sales

$N_{treated} = 37$

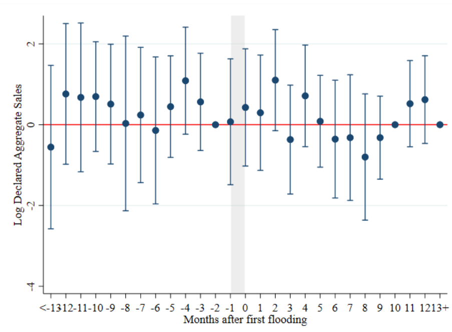


(b) Log purchases

$N_{treated} = 37$

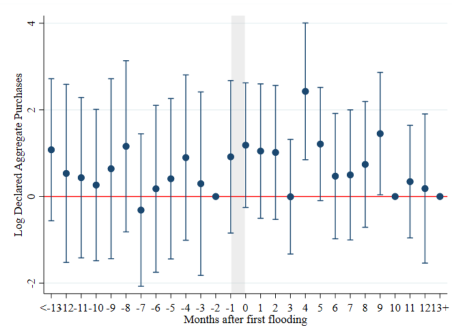
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Sep 2012 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure C.4. Impact of flooding on firm sales and purchases (Aug 2013)



(a) Log sales

$N_{treated} = 3602$

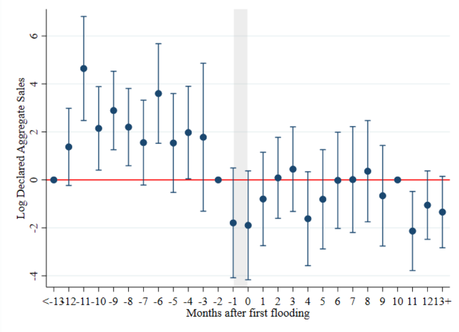


(b) Log purchases

$N_{treated} = 3602$

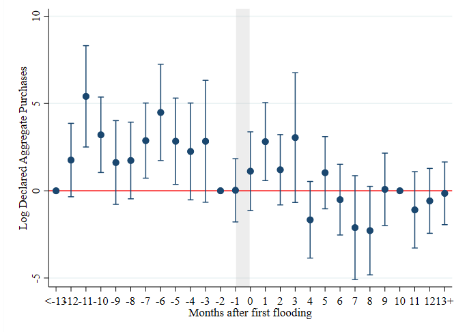
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Aug 2013 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure C.5. Impact of flooding on firm sales and purchases (Sep 2014)



(a) Log sales

$N_{treated} = 7870$

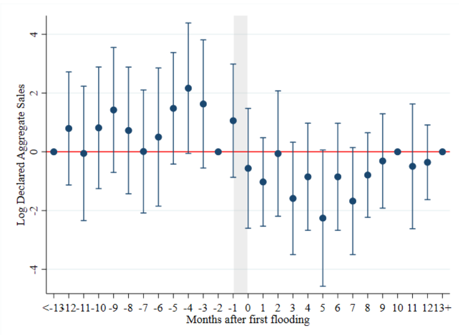


(b) Log purchases

$N_{treated} = 7870$

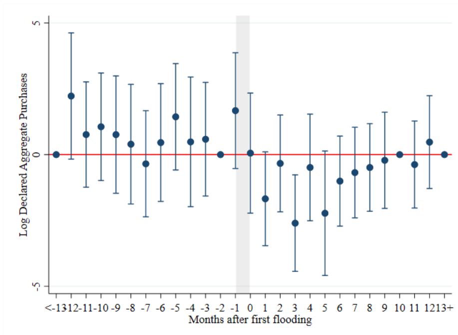
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Sep 2014 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure C.6. Impact of flooding on firm sales and purchases (Jul-Aug 2015)



(a) Log sales

$N_{treated} = 9507$



(b) Log purchases

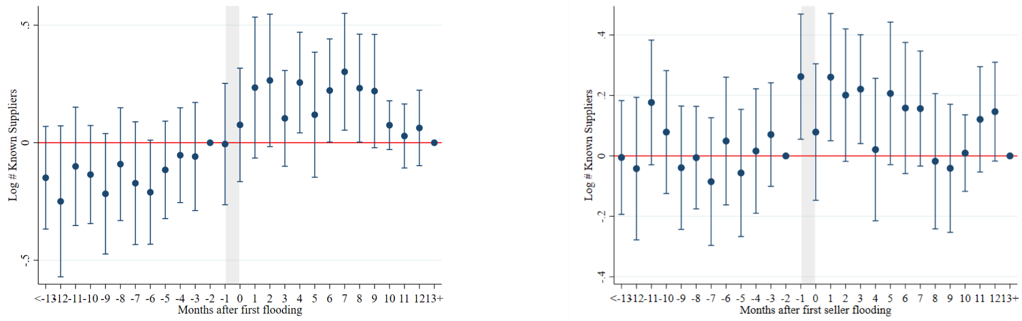
$N_{treated} = 9507$

Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Jul-Aug 2015 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.1.2 Supplier Diversification

We omit regressions for the September 2012 flood since only five firms with a nonmissing dependent variable saw a buffer that was more than 10% flooded during this episode.

Figure C.7. Impact of flooding on log number of suppliers (Sun and Abraham estimator)



(a) Own flooding

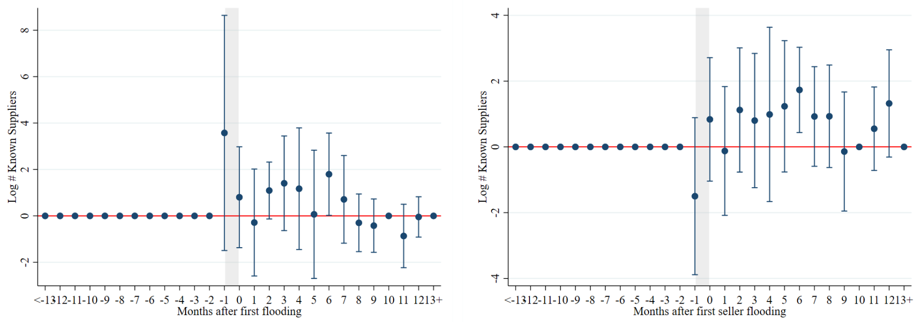
$N_{treated} = 216$

(b) Supplier flooding

$N_{treated} = 125$

Notes: The panels plot the effect of own flooding or supplier flooding on log number of suppliers. We use the method by Sun and Abraham (2021) to estimate equations (6) and (7), but with a binary treatment variable based on a 10% threshold. Observations are firm-month-years whose 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or treated by $>$ 10% in their first treatment month. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure C.8. Impact of flooding on log number of suppliers (Aug-Sep 2011)



(a) Own flooding

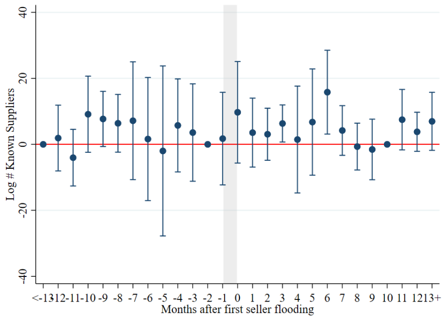
$N_{treated} = 442$

(b) Supplier flooding

$N_{treated} = 281$

Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on log number of suppliers following equations (6) and (7). Observations are firm-month-years whose 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Aug-Sep 2011 event. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

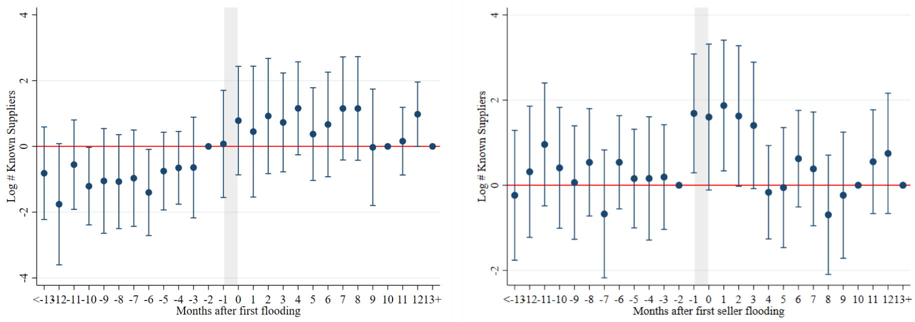
Figure C.9. Impact of supplier flooding on log number of suppliers (Sep 2012)



$N_{treated} = 38$

Notes: The panel plots OLS estimates of the effect of supplier flooding on log number of suppliers following equation (7). Observations are firm-month-years whose 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Sep 2012 event. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure C.10. Impact of flooding on log number of suppliers (Aug 2013)



(a) Own flooding

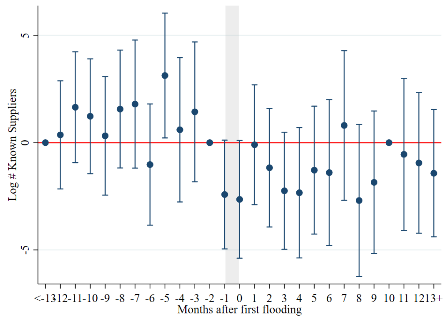
$N_{treated} = 1651$

(b) Supplier flooding

$N_{treated} = 1108$

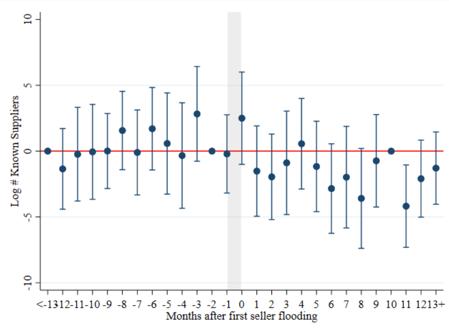
Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on log number of suppliers following equations (6) and (7). Observations are firm-month-years whose 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Aug 2013 event. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure C.11. Impact of flooding on log number of suppliers (Sep 2014)



(a) Own flooding

$N_{treated} = 3994$

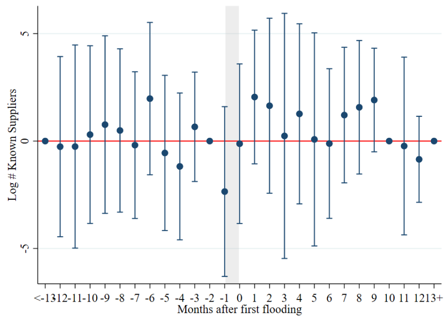


(b) Supplier flooding

$N_{treated} = 1854$

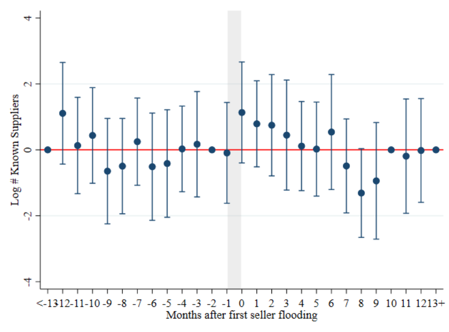
Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on log number of suppliers following equations (6) and (7). Observations are firm-month-years whose 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Sep 2014 event. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure C.12. Impact of flooding on log number of suppliers (Jul-Aug 2015)



(a) Own flooding

$N_{treated} = 4730$



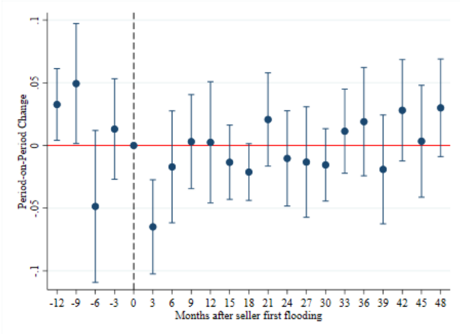
(b) Supplier flooding

$N_{treated} = 1772$

Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on log number of suppliers following equations (6) and (7). Observations are firm-month-years whose 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Jul-Aug 2015 event. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.1.3 Supplier choice

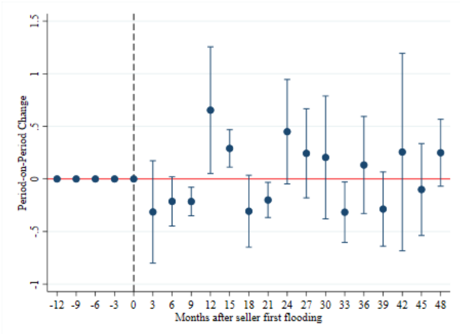
Figure C.13. Dynamic impact of supplier flooding on flood risk of all suppliers (Sun and Abraham)



$N_{treated} = 198$

Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers. We use the method by Sun and Abraham (2021) to estimate equation (10) with a binary treatment variable based on a 10% threshold. Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq$ 10km apart and which are either never treated or treated by >10% in their first treatment month. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

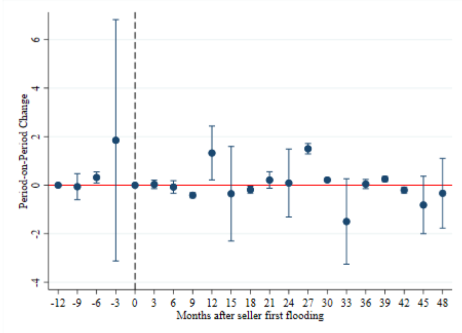
Figure C.14. Dynamic impact of supplier flooding on flood risk of all suppliers (Aug-Sep 2011)



$N_{treated} = 481$

Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Aug-Sep 2011 event. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

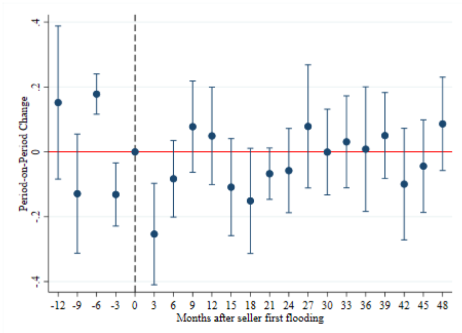
Figure C.15. Dynamic impact of supplier flooding on flood risk of all suppliers (Sep 2012)



$N_{treated} = 52$

Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Sep 2012 event. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

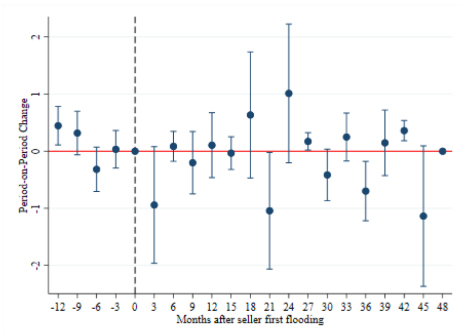
Figure C.16. Dynamic impact of supplier flooding on flood risk of all suppliers (Aug 2013)



$N_{treated} = 1360$

Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Aug 2013 event. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

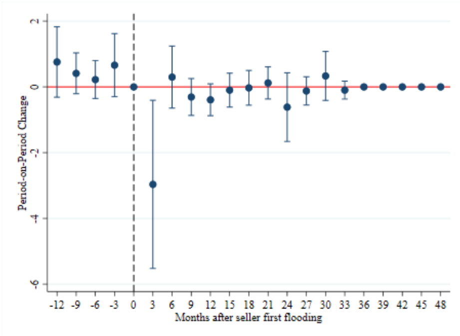
Figure C.17. Dynamic impact of supplier flooding on flood risk of all suppliers (Sep 2014)



$N_{treated} = 2595$

Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Sep 2014 event. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure C.18. Dynamic impact of supplier flooding on flood risk of all suppliers (Jul-Aug 2015)



$N_{treated} = 2829$

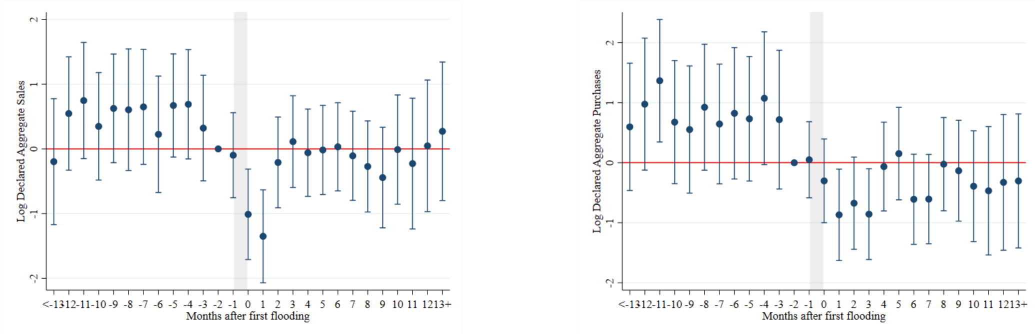
Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Jul-Aug 2015 event. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

C.2 Results excluding electricity and gas producers

We examine how far the results are affected by industries for which supply disruptions of the nature considered in the analysis may not be pertinent. The first of these robustness checks excludes from the sample the 1% of firms, accounting for 14% of aggregate sales, with two-digit industry identifiers corresponding to electricity, gas and extraction of crude petroleum.[40] This accounts for the fact that, while firms purchase these inputs regularly, these are monopolies that firms are unable to substitute away from. The results in this case are very similar to the baseline results.

C.2.1 Intensive Margin

Figure C.19. Impact of flooding on firm sales and purchases (excl. electricity and gas)



(a) Log Sales

(b) Log Purchases

Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observations are firm-month-years excluding electricity and gas producers. The 95% confidence intervals rely on standard errors clustered at the firm-level.

[40]The two-digit industry code corresponding to electricity, gas and extraction of crude petroleum also includes steam and air conditioning suppliers.

C.2.2 Firm Location

Table C.1. Impact of flooding on firm relocation and location flood risk (excl. electricity and gas)

	Move Dummy		Δ Flood Risk	
	(1)	(2)	(3)	(4)
Max Share of 2km Buffer Flooded	1.569**	1.912**	-1.954*	-0.451
	(0.758)	(0.800)	(1.009)	(0.537)
District FE	Yes		Yes	
District × Fathom 1 in 100 FE		Yes		Yes
R^2	0.045	0.068	0.127	0.449
N	43,525	43,074	5,663	5,525

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on the probability of relocating by >10km following equation (3). Columns (3) and (4) report OLS estimates of the effect of flooding on moving firms' change in flood risk as specified in equation (4). Observations are firms fully geocoded in 2011 and 2019 excluding electricity and gas producers. The flood risk regressions only include firms which moved by >10km. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2 for columns (1) and (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

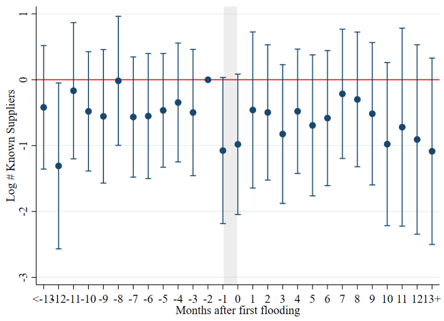
Table C.2. Impact of destination flood history on relocation flows (excl. electricity and gas)

	Number of Firms Moved
Dest. flooded 12mo prior	-0.718***
	(0.250)
Origin × Destination FE	Yes
Origin × Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10km
N	1,392

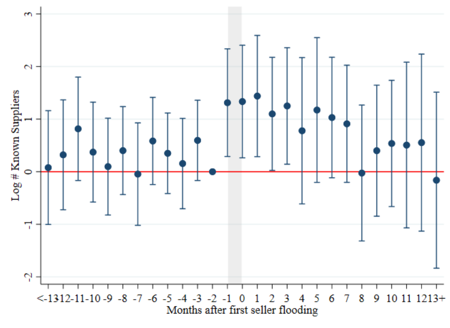
Notes: The table displays the Poisson pseudo-maximum-likelihood estimate of the effect of flood history on relocation flows following equation (5). The unit of observation is the area of an origin-district first flooded in a given year-month paired with the area in a destination district which was never flooded or first flooded in a given year-month. We only consider firms moving by >10km which are not electricity or gas producers and location-pairs with positive flows. The standard error (in parentheses) is clustered at the origin-district-by-destination-district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.2.3 Supplier Diversification

Figure C.20. Impact of flooding on log number of suppliers (excl. electricity and gas)



(a) Own flooding



(b) Supplier flooding

Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on log number of suppliers following equations (6) and (7), respectively. Observations are firm-month-years whose 2011 and 2019 addresses are known, ≤ 10km apart and not electricity or gas producers. We restrict attention to transactions for which buyer and seller reports coincide precisely and which do not involve electricity or gas producers. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.2.4 Supplier Choice

Table C.3. Impact of supplier flooding on supplier flood risk (excl. electricity and gas)

	Δ Supplier Flood Risk		
	(1)	(2)	(3)
Own Max Flood Extent	0.0277	-0.0160	0.0637
	(0.0401)	(0.0373)	(0.0450)
Suppliers' Max Flood Extent	-0.630***	-0.662***	-0.768***
	(0.156)	(0.163)	(0.183)
Time × District FE	Yes		
Time × District × Risk Dec. FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0088	0.0253	0.0542
N	138,885	138,174	133,913

Notes: The table reports OLS estimates of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers following equation (8). Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10km apart. We exclude electricity and gas producers from buyers and sellers. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4. Impact of supplier flooding on supplier flood risk (excl. electricity and gas)

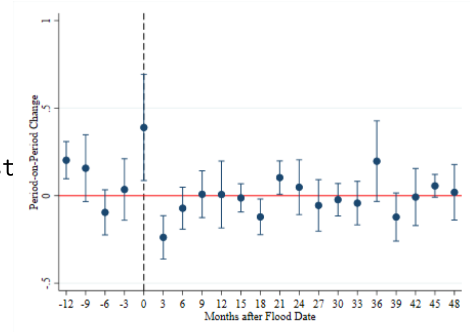
	Dependent Variable: Δ Flood Risk of Suppliers Flooded by								
	$\leq 1\%$			$\leq 5\%$			$\leq 10\%$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own Max Flood Extent	0.0134	0.0163	0.0288	0.0112	0.00536	0.0278	0.0307	0.0116	0.0530
	(0.0209)	(0.0209)	(0.0264)	(0.0236)	(0.0257)	(0.0295)	(0.0298)	(0.0258)	(0.0377)
Suppliers' Max Flood Extent	-0.0633*	-0.0782*	-0.0462	-0.202***	-0.222***	-0.209***	-0.421**	-0.449**	-0.455**
	(0.0383)	(0.0411)	(0.0403)	(0.0638)	(0.0663)	(0.0678)	(0.187)	(0.197)	(0.214)
Time × District FE	Yes			Yes			Yes		
Time × District × Risk Dec. FE		Yes			Yes			Yes	
Time × District × Industry FE			Yes			Yes			Yes
R^2	0.0056	0.0221	0.0508	0.0058	0.0219	0.0505	0.0066	0.0226	0.0509
N	138,283	137,571	133,334	138,715	138,001	133,757	138,792	138,079	133,834

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers flooded by $\leq 1\%$, $\leq 5\%$, or $\leq 10\%$ during the flood risk windows. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. We exclude electricity and gas producers from buyers and sellers. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.21. Dynamic impact of supplier flooding on supplier flood risk (excl. electricity and gas)

Images/SupplierRiskiness/long_event_st

(a) All Suppliers



_Mon_on_3m_s_tr_max

(b) Suppliers flooded by $\leq 5\%$

Notes: Panels (a) and (b) plot OLS estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers and suppliers flooded by $\leq 5\%$ following equations (10) and (24), respectively. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. We exclude electricity and gas producers from buyers and sellers. Panel (b) excludes buyers which experience own or supplier flooding before the lag. The 95% confidence intervals rely on standard errors clustered at the time × district level.

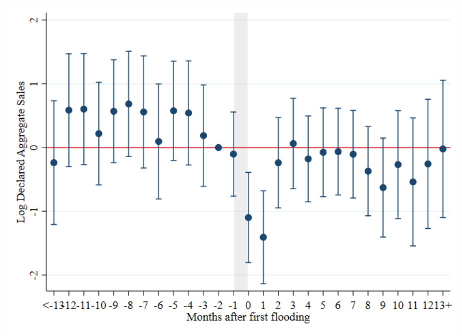
C.3 Results excluding capital purchases

We next consider the robustness of results to excluding transactions involving capital goods, given that lumpy capital purchases are likely to be infrequent and may be less prone to flood-induced supply disruptions. To do so, we remove all transactions in which either the buyer or the seller has a primary product code which maps to a capital good, identified using Part I of the Fifth Schedule of the Customs Act.[41] The central results showing evidence for firm-level adaptation are robust to this restriction.

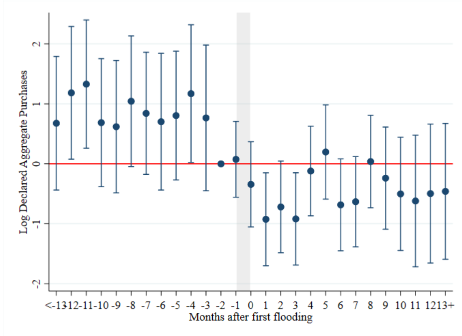
[41] https://www.fbr.gov.pk/categ/customs-tariff/51149/70853/131188

C.3.1 Intensive Margin

Figure C.22. Impact of flooding on firm sales and purchases (excl. capital purchases)



(a) Log Sales



(b) Log Purchases

Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observations are firm-month-years excluding firms transacting primarily in capital goods. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.3.2 Firm location

Table C.5. Impact of flooding on firm relocation and location flood risk (excl. capital purchases)

	Move Dummy		Δ Flood Risk	
	(1)	(2)	(3)	(4)
Max Share of 2km Buffer Flooded	1.583**	1.849**	-1.952*	-0.450
	(0.754)	(0.805)	(1.007)	(0.526)
District FE	Yes		Yes	
District $\times$ Fathom 1 in 100 FE		Yes		Yes
R^2	0.046	0.067	0.127	0.449
N	43,848	43,395	5,737	5,596

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on the probability of relocating by >10km following equation (3). Columns (3) and (4) report OLS estimates of the effect of flooding on moving firms' change in flood risk as specified in equation (4). Observations are firms geocoded in 2011 and 2019 which do not primarily transact in capital goods. The flood risk regressions only include firms which moved by >10km. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2 for columns (1) and (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6. Impact of destination flood history on relocation flows (excl. capital purchases)

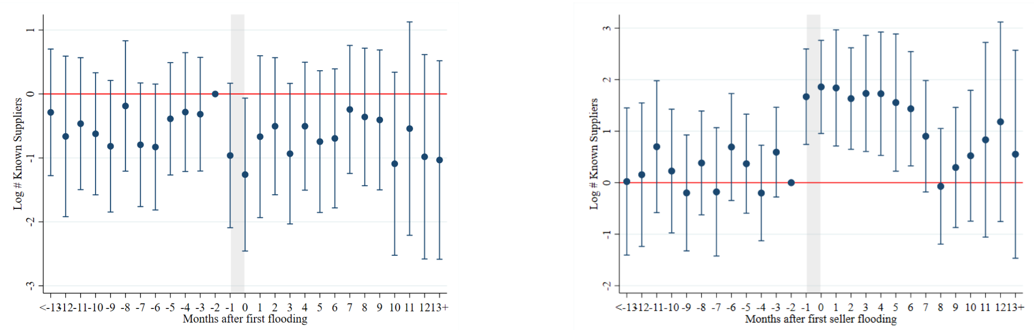
	Number of Firms Moved
Dest. flooded 12mo prior	-0.735***
	(0.254)
Origin × Destination FE	Yes
Origin × Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10km
N	1,412

Notes: The table displays the Poisson pseudo-maximum-likelihood estimate of the effect of flood history on relocation flows following equation (5). The unit of observation is the area of an origin-district first flooded in a given year-month paired with the area in a destination district which was never flooded or first flooded in a given year-month. We only consider firms moving by >10km which do not primarily transact in capital goods and location-pairs with positive relocation flows. The standard error (in parentheses) is clustered at the origin-district-by-destination-district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.3.3 Supplier Diversification

Figure C.23. Impact of flooding on log number of suppliers (excl. capital purchases)



(a) Own flooding (b) Supplier flooding

Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on log number of suppliers following equations (6) and (7), respectively. Observations are firm-month-years whose 2011 and 2019 addresses are known, ≤ 10km apart and do not primarily transact in capital goods. We restrict attention to transactions for which buyer and seller reports coincide precisely and which do not involve firms primarily transacting in capital goods. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.3.4 Supplier Choice

Table C.7. Impact of supplier flooding on supplier flood risk (excl. capital purchases)

	Δ Supplier Flood Risk		
	(1)	(2)	(3)
Own Max Flood Extent	-0.0734	-0.0462	-0.119
	(0.106)	(0.0919)	(0.133)
Suppliers' Max Flood Extent	-0.514***	-0.527***	-0.604***
	(0.144)	(0.150)	(0.166)
Time × District FE	Yes		
Time × District × Risk Dec. FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0111	0.0355	0.0671
N	125,091	124,384	120,023

Notes: The table reports OLS estimates of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers following equation (8). Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10km apart. We exclude firms primarily transacting in capital goods from buyers and sellers. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.8. Impact of supplier flooding on supplier flood risk (excl. capital purchases)

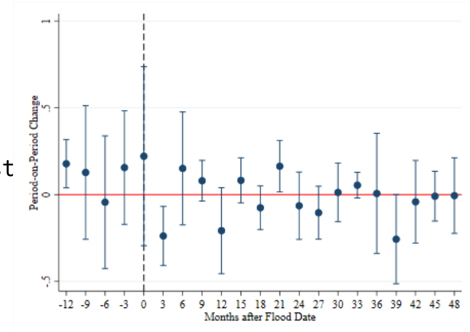
	Dependent Variable: Δ Flood Risk of Suppliers Flooded by								
	≤ 1%			≤ 5%			≤ 10%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own Max Flood Extent	-0.126	-0.0982	-0.173	-0.118	-0.0777	-0.165	-0.0971	-0.0496	-0.146
	(0.108)	(0.0911)	(0.138)	(0.110)	(0.0951)	(0.139)	(0.111)	(0.0921)	(0.141)
Suppliers' Max Flood Extent	-0.138*	-0.0951	-0.103	-0.198**	-0.169**	-0.177*	-0.345**	-0.332*	-0.352*
	(0.0702)	(0.0782)	(0.0932)	(0.0770)	(0.0836)	(0.0979)	(0.161)	(0.171)	(0.190)
Time × District FE	Yes			Yes			Yes		
Time × District × Risk Dec. FE		Yes			Yes			Yes	
Time × District × Industry FE			Yes			Yes			Yes
R^2	0.0102	0.0385	0.0669	0.0098	0.0364	0.0663	0.0100	0.0355	0.0652
N	124,576	123,859	119,528	124,953	124,246	119,893	125,022	124,315	119,960

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers flooded by ≤ 1%, ≤ 5%, or ≤ 10% during the flood risk windows. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart. We exclude firms primarily transacting in capital goods from buyers and sellers. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.24. Dynamic impact of supplier flooding on supplier flood risk (excl. capital purchases)

Images/SupplierRiskiness/long_event_st ı100_3m_s_CG_on_3m_

(a) All Suppliers



(b) Suppliers flooded by $\leq 5\%$

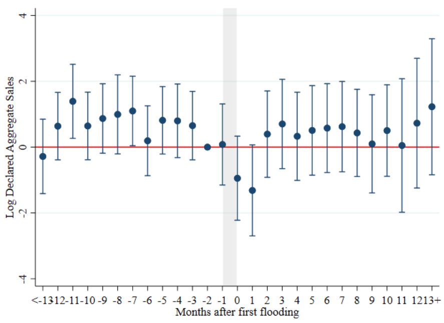
Notes: Panels (a) and (b) plot OLS estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers and suppliers flooded by $\leq 5\%$ following equations (10) and (24), respectively. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. We exclude firms primarily transacting in capital goods from buyers and sellers. Panel (b) excludes buyers which experience own or supplier flooding before the lag. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

C.4 Results using manufacturing firms

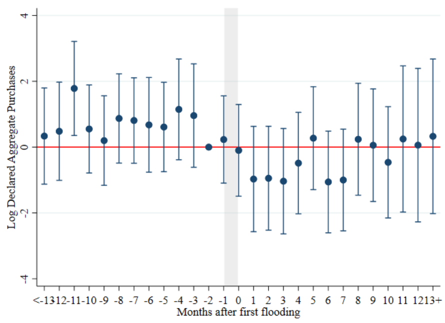
We restrict attention to the 37% of firms, accounting for 53% of sales, with industry codes corresponding to manufacturing sectors. The majority of firms excluded under this restriction are services firms, with a smaller number of firms in the agricultural sector. Services and agricultural firms may be expected to face distinct flood-related disruptions relative to the production network effects that are the focus of the current analysis. The central results are robust to this sample restriction.

C.4.1 Intensive Margin

Figure C.25. Impact of flooding on firm sales and purchases (manufacturing sample)



(a) Log Sales



(b) Log Purchases

Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observations are firm-month-years in the manufacturing sector. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.4.2 Firm location

Table C.9. Impact of flooding on firm relocation and location flood risk

	Move Dummy		Δ Flood Risk	
	(1)	(2)	(3)	(4)
Max Share of 2km Buffer Flooded	1.026	1.046	-1.292	-0.0300
	(0.958)	(0.931)	(0.987)	(0.552)
District FE	Yes		Yes	
District × Fathom 1 in 100 FE		Yes		Yes
R^2	0.052	0.072	0.146	0.459
N	17,422	17,070	2,752	2,660

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on the probability of relocating by >10km following equation (3). Columns (3) and (4) report OLS estimates of the effect of flooding on moving firms' change in flood risk as specified in equation (4). Observations are firms geocoded in 2011 and 2019. The flood risk regressions only include manufacturing firms which moved by >10km. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2 for columns (1) and (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

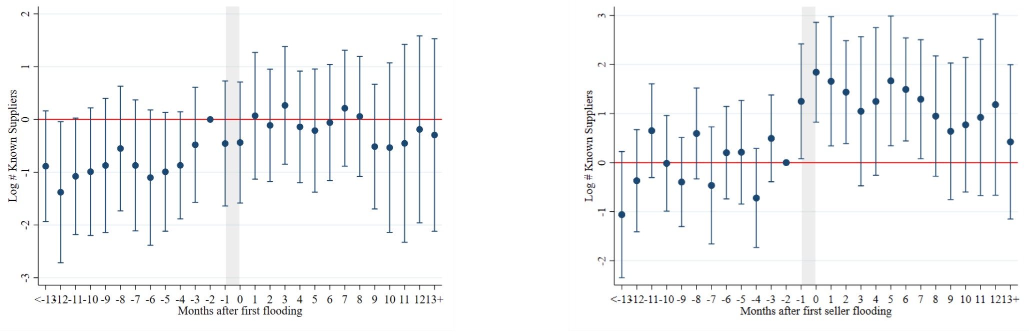
Table C.10. Impact of destination flood history on relocation flows

	Number of Firms Moved
Dest. flooded 12mo prior	-0.846***
	(0.284)
Origin × Destination FE	Yes
Origin × Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10km
N	784

Notes: The table displays the Poisson pseudo-maximum-likelihood estimate of the effect of flood history on relocation flows following equation (5). The unit of observation is the area of an origin-district first flooded in a given year-month paired with the area in a destination district which was never flooded or first flooded in a given year-month. We only consider manufacturing firms moving by >10km and location-pairs with positive relocation flows. The standard error (in parentheses) is clustered at the origin-district-by-destination-district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.4.3 Supplier Diversification

Figure C.26. Impact of flooding on log number of suppliers (manufacturing sample)



(a) Own flooding

(b) Supplier flooding

Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on the log number of suppliers following equations (6) and (7), respectively. Observations are firm-month-years in the manufacturing sector whose 2011 and 2019 addresses are known and $\leq$ 10km apart. We restrict attention to transactions for which buyer and seller reports coincide precisely and which only involve manufacturers. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.4.4 Supplier Choice

Table C.11. Impact of supplier flooding on supplier flood risk (manufacturing)

	Δ Supplier Flood Risk		
	(1)	(2)	(3)
Own Max Flood Extent	0.174***	0.177***	0.203***
	(0.0385)	(0.0416)	(0.0648)
Suppliers' Max Flood Extent	-0.670***	-0.667***	-0.674***
	(0.122)	(0.126)	(0.126)
Time × District FE	Yes		
Time × District × Risk Dec. FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0195	0.0472	0.0670
N	52,769	52,238	51,413

Notes: The table reports OLS estimates of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers following equation (8). Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. We restrict buyers and sellers to manufacturing firms. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.12. Impact of supplier flooding on supplier flood risk (manufacturing)

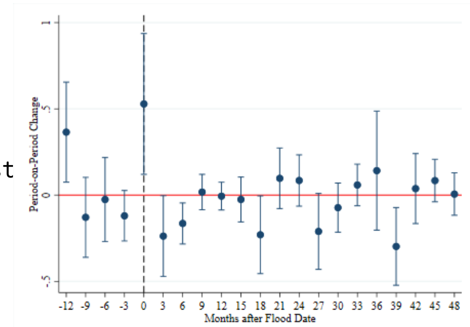
	Dependent Variable: Δ Flood Risk of Suppliers Flooded by								
	≤ 1%			≤ 5%			≤ 10%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own Max Flood Extent	0.0522	0.0533	0.0832	0.124**	0.126**	0.150**	0.143***	0.155***	0.176**
	(0.0509)	(0.0557)	(0.0558)	(0.0529)	(0.0565)	(0.0718)	(0.0469)	(0.0482)	(0.0685)
Suppliers' Max Flood Extent	-0.0678	-0.0549	-0.0588	-0.221**	-0.216**	-0.214**	-0.365**	-0.360**	-0.362**
	(0.0832)	(0.0808)	(0.0757)	(0.108)	(0.107)	(0.108)	(0.150)	(0.150)	(0.152)
Time × District FE	Yes			Yes			Yes		
Time × District × Risk Dec. FE		Yes			Yes			Yes	
Time × District × Industry FE			Yes			Yes			Yes
R^2	0.0167	0.0438	0.0633	0.0155	0.0420	0.0622	0.0156	0.0426	0.0628
N	52,049	51,518	50,703	52,655	52,123	51,299	52,712	52,183	51,356

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers flooded by ≤ 1%, ≤ 5%, or ≤ 10% during the flood risk windows. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart. We restrict buyers and sellers to manufacturing firms. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.27. Dynamic impact of supplier flooding on supplier flood risk (manufacturing)

Images/SupplierRiskiness/long_event_st _3m_s_Man_on_3m_s_t

(a) All Suppliers



(b) Suppliers flooded by ≤ 5%

Notes: Panels (a) and (b) plot OLS estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers and suppliers flooded by ≤ 5% following equations (10) and (24), respectively. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10km apart. We restrict buyers and sellers to manufacturing firms. Panel (b) excludes buyers which experience own or supplier flooding before the lag. The 95% confidence intervals rely on standard errors clustered at the time × district level.

C.5 Results using precisely coinciding buyer and seller reports only

While the firm transactions data described in Section 2.1 offers a unique lens into supply chain relationships in Pakistan, these data may be subject to misreporting by firms in order to reduce their tax liability (Waseem, 2019). We exclude 'invoice mills' from our estimation sample in order to overcome an especially pernicious documented source of such behavior. In order to rule out other potential sources of misreporting, we consider the robustness of our results to considering only those 42% of monthly transaction observations (representing 22% of total sales) where buyer and seller reports coincide exactly.

To the extent that buyer and seller reports of the same monthly-level transactions reflect strategic misreporting rather than random error, we expect the two parties to have conflicting incentives to misreport: while sellers will wish to understate their sales to reduce their VAT liability, the converse is true for buyers who will wish to overstate their purchases. Using the fact that we observe independent reports of pair-level monthly transactions from the buyer and seller, we can investigate the potential importance of such biases. In this robustness specification, we take an extremely stringent approach to ruling this out by restricting attention to cases where buyer and seller reports match exactly and as such where misreporting is highly unlikely. The results of this robustness test for those specifications that draw on transaction-level reports are included below. While results become noisier in light of the significant reduction in the sample size, our key results are generally robust to this sample restriction.

We omit the following regressions as they do not rely on transaction-level data and, thus, are not affected by restricting to precisely coinciding reports.

- Impact of flooding on firm sales and purchases
- Impact of flooding on firm relocation and location flood risk
- Impact of destination flood history on relocation flows

We further omit the regressions examining the impact of flooding on the log number of suppliers as these use precisely coinciding reports by default.

C.5.1 Supplier choice

Table C.13. Impact of supplier flooding on supplier flood risk (coinciding reports)

	Δ Supplier Flood Risk		
	(1)	(2)	(3)
Own Max Flood Extent	0.0451	-0.0347	0.0624
	(0.0925)	(0.123)	(0.0942)
Suppliers' Max Flood Extent	-0.984***	-0.965***	-0.956***
	(0.216)	(0.222)	(0.229)
Time × District FE	Yes		
Time × District × Risk Dec. FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0111	0.0301	0.0601
N	86,786	86,184	83,675

Notes: The table reports OLS estimates of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers following equation (8). Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10km apart. We restrict attention to transactions for which buyer and seller reports coincide precisely. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.14. Impact of supplier flooding on supplier flood risk (coinciding reports)

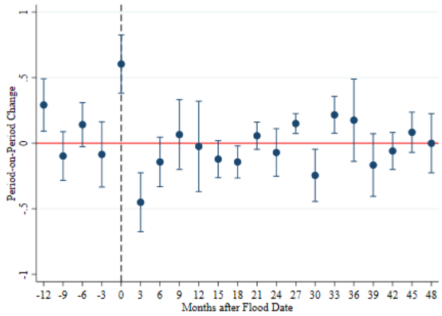
	Dependent Variable: Δ Flood Risk of Suppliers Flooded by								
	$\leq$ 1%			$\leq$ 5%			$\leq$ 10%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own Max Flood Extent	0.0777	0.0661	0.0943	0.0411	-0.00569	0.0497	0.0600	0.00608	0.0671
	(0.0599)	(0.0712)	(0.0643)	(0.0724)	(0.101)	(0.0809)	(0.0821)	(0.106)	(0.0932)
Suppliers' Max Flood Extent	-0.100	-0.0763	-0.0769	-0.451***	-0.428***	-0.410***	-0.765***	-0.745***	-0.728**
	(0.119)	(0.121)	(0.126)	(0.118)	(0.119)	(0.121)	(0.276)	(0.281)	(0.289)
Time $\times$ District FE	Yes			Yes			Yes		
Time $\times$ District $\times$ Risk Dec. FE		Yes			Yes			Yes	
Time $\times$ District $\times$ Industry FE			Yes			Yes			Yes
R^2	0.0073	0.0252	0.0591	0.0081	0.0274	0.0578	0.0093	0.0283	0.0578
N	85,941	85,330	82,838	86,654	86,054	83,550	86,728	86,128	83,621

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers flooded by $\leq$ 1%, $\leq$ 5%, or $\leq$ 10% during the flood risk windows. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. We restrict attention to transactions for which buyer and seller reports coincide precisely. Standard errors (in parentheses) are clustered at the time $\times$ district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.28. Dynamic impact of supplier flooding on supplier flood risk (coinciding reports)

Images/SupplierRiskiness/long_event_st

(a) All Suppliers



ɔng_d1in100_3m_s_CV

(b) Suppliers flooded by $\leq$ 5%

Notes: Panels (a) and (b) plot OLS estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers and suppliers flooded by $\leq$ 5% following equations (10) and (24), respectively. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. Panel (b) excludes buyers which experience own or supplier flooding before the lag. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

C.6 Floods with return periods of 1 in 10 years and 1 in 50 years

Our central results relating to flood risk consider the combined fluvial and pluvial flood risk, measured as the expected flood depth in each location associated with a 1 in 100 year flood. This represents the most expansive definition of flood risk captured by the Fathom flood risk data, as can be seen by comparing Panel (c) of Figure 1 with both panels in Figure A.4. All key results are robust to measuring flood risk in relation to 1 in 10 year floods or 1 in 50 year floods. We omit the following regressions since they do not use the flood risk variable:

- Impact of flooding on firm sales and purchases
- Impact of destination flood history on relocation flows
- Impact of flooding on log number of suppliers

C.6.1 Firm location

Table C.15. Impact of flooding on firm relocation and location flood risk (1 in 10 year return period)

	Move Dummy		Δ Flood Risk	
	(1)	(2)	(3)	(4)
Max Share of 2km Buffer Flooded	1.583**	1.509**	-1.245	-0.0891
	(0.754)	(0.745)	(0.871)	(0.530)
District FE	Yes		Yes	
District × Fathom 1 in 10 FE		Yes		Yes
R^2	0.046	0.066	0.072	0.380
N	43,848	43,665	5,737	5,689

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on the probability of relocating by >10km following equation (3). Columns (3) and (4) report OLS estimates of the effect of flooding on moving firms' change in flood risk as specified in equation (4). Here, flood risk is measured for a 1 in 10 instead of a 1 in 100 year return period (for both the dependent variables in columns (3) and (4) and the FEs in columns (2) and (4)). Observations are firms geocoded in 2011 and 2019. The flood risk regressions only include firms which moved by >10km. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2 for columns (1) and (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.16. Impact of flooding on firm relocation and location flood risk (1 in 50 year return period)

	Move Dummy		Δ Flood Risk	
	(1)	(2)	(3)	(4)
Max Share of 2km Buffer Flooded	1.583**	1.950**	-1.791*	-0.317
	(0.754)	(0.947)	(0.997)	(0.529)
District FE	Yes		Yes	
District × Fathom 1 in 50 FE		Yes		Yes
R^2	0.046	0.068	0.111	0.447
N	43,848	43,522	5,737	5,588

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on the probability of relocating by >10km following equation (3). Columns (3) and (4) report OLS estimates of the effect of flooding on moving firms' change in flood risk as specified in equation (4). Here, flood risk is measured for a 1 in 50 instead of a 1 in 100 year return period (for both the dependent variables in columns (3) and (4) and the FEs in columns (2) and (4)). Observations are firms geocoded in 2011 and 2019. The flood risk regressions only include firms which moved by >10km. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2 for columns (1) and (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.6.2 Supplier choice

Table C.17. Impact of supplier flooding on supplier flood risk (1 in 10 year return period)

	Δ Supplier Flood Risk		
	(1)	(2)	(3)
Own Max Flood Extent	-0.0513	-0.0562	-0.0537
	(0.0596)	(0.0608)	(0.0763)
Suppliers' Max Flood Extent	-0.409***	-0.431***	-0.492***
	(0.155)	(0.160)	(0.185)
Time × District FE	Yes		
Time × District × Risk Dec. FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0073	0.0192	0.0551
N	144,566	144,230	139,302

Notes: The table reports OLS estimates of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers following equation (8). Here, flood risk is measured for a 1 in 10 instead of a 1 in 100 year return period. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.18. Impact of supplier flooding on supplier flood risk (1 in 10 year return period)

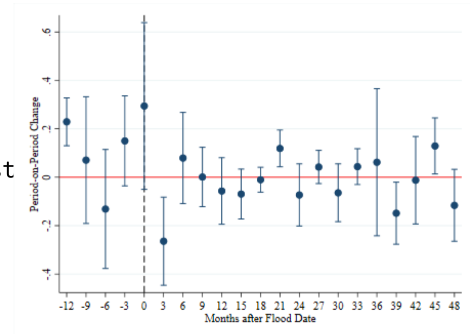
	Dependent Variable: Δ Flood Risk of Suppliers Flooded by								
	$\leq$ 1%			$\leq$ 5%			$\leq$ 10%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own Max Flood Extent	-0.0799	-0.0879	-0.0979	-0.0854	-0.0810	-0.0958	-0.0624	-0.0530	-0.0709
	(0.0558)	(0.0575)	(0.0729)	(0.0566)	(0.0584)	(0.0736)	(0.0598)	(0.0592)	(0.0779)
Suppliers' Max Flood Extent	-0.0853	-0.0898	-0.0835	-0.233***	-0.242***	-0.249***	-0.414**	-0.431**	-0.456**
	(0.0703)	(0.0672)	(0.0770)	(0.0777)	(0.0753)	(0.0845)	(0.175)	(0.179)	(0.198)
Time × District FE	Yes			Yes			Yes		
Time × District × Risk Dec. FE		Yes			Yes			Yes	
Time × District × Industry FE			Yes			Yes			Yes
R^2	0.0058	0.0191	0.0551	0.0060	0.0187	0.0544	0.0069	0.0189	0.0543
N	144,007	143,668	138,752	144,423	144,086	139,164	144,494	144,157	139,235

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers flooded by $\leq$ 1%, $\leq$ 5%, or $\leq$ 10% during the flood risk windows. Here, flood risk is measured for a 1 in 10 instead of a 1 in 100 year return period. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.29. Dynamic impact of supplier flooding on supplier flood risk (1 in 10 year return period)

Images/SupplierRiskiness/long_event_st

(a) All Suppliers



chases/long_d1in10_

(b) Suppliers flooded by $\leq$ 5%

Notes: Panels (a) and (b) plot OLS estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers and suppliers flooded by $\leq$ 5% following equations (10) and (24), respectively. Here, flood risk is measured for a 1 in 10 instead of a 1 in 100 year return period. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. Panel (b) excludes buyers which experience own or supplier flooding before the lag. The 95% confidence intervals rely on standard errors clustered at the time × district level.

Table C.19. Impact of supplier flooding on supplier flood risk (1 in 50 year return period)

	Δ Supplier Flood Risk		
	(1)	(2)	(3)
Own Max Flood Extent	-0.0636	-0.0827	-0.0846
	(0.0862)	(0.0786)	(0.109)
Suppliers' Max Flood Extent	-0.558***	-0.593***	-0.667***
	(0.167)	(0.174)	(0.194)
Time × District FE	Yes		
Time × District × Risk Dec. FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0100	0.0300	0.0582
N	144,566	143,843	139,302

Notes: The table reports OLS estimates of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers following equation (8). Here, flood risk is measured for a 1 in 50 instead of a 1 in 100 year return period. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.20. Impact of supplier flooding on supplier flood risk (1 in 50 year return period)

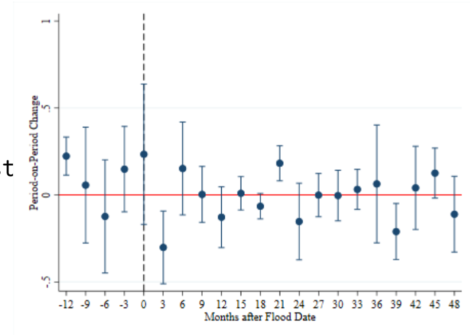
	Dependent Variable: Δ Flood Risk of Suppliers Flooded by								
	≤ 1%			≤ 5%			≤ 10%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own Max Flood Extent	-0.109	-0.0999	-0.146	-0.109	-0.0991	-0.141	-0.0823	-0.0719	-0.115
	(0.0874)	(0.0795)	(0.114)	(0.0877)	(0.0791)	(0.113)	(0.0899)	(0.0799)	(0.117)
Suppliers' Max Flood Extent	-0.120	-0.128	-0.101	-0.259***	-0.270***	-0.256**	-0.468**	-0.492**	-0.494**
	(0.0846)	(0.0797)	(0.0942)	(0.0934)	(0.0896)	(0.102)	(0.200)	(0.207)	(0.227)
Time × District FE	Yes			Yes			Yes		
Time × District × Risk Dec. FE		Yes			Yes			Yes	
Time × District × Industry FE			Yes			Yes			Yes
R^2	0.0078	0.0303	0.0560	0.0078	0.0289	0.0561	0.0088	0.0294	0.0562
N	144,007	143,282	138,752	144,423	143,703	139,164	144,494	143,774	139,235

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers flooded by ≤ 1%, ≤ 5%, or ≤ 10% during the flood risk windows. Here, flood risk is measured for a 1 in 50 instead of a 1 in 100 year return period. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.30. Dynamic impact of supplier flooding on supplier flood risk (1 in 50 year return period)

Images/SupplierRiskiness/long_event_st

(a) All Suppliers



chases/long_d1in50_

(b) Suppliers flooded by $\leq 5\%$

Notes: Panels (a) and (b) plot OLS estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers and suppliers flooded by $\leq 5\%$ following equations (10) and (24), respectively. Here, flood risk is measured for a 1 in 50 instead of a 1 in 100 year return period. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. Panel (b) excludes buyers which experience own or supplier flooding before the lag. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

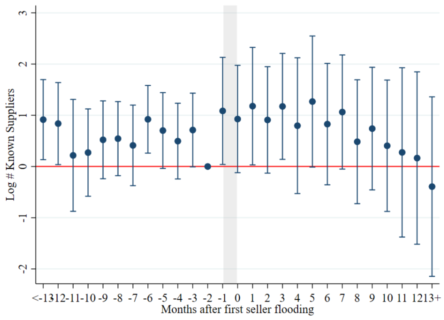
C.7 6-month or 12-month partner window for indirect treatment specifications

We omit the following regressions as they do not rely on partner level variables, which are affected by the duration of the partner window.

- Impact of flooding on firm sales and purchases
- Impact of own flooding on log number of suppliers
- Impact of flooding on firm relocation and location flood risk
- Impact of destination flood history on relocation flows
- Impact of own flooding on log number of suppliers (for any given year-month and buyer firm, the number of suppliers is defined as the number of firms selling a positive amount to the buyer firm in that year-month)

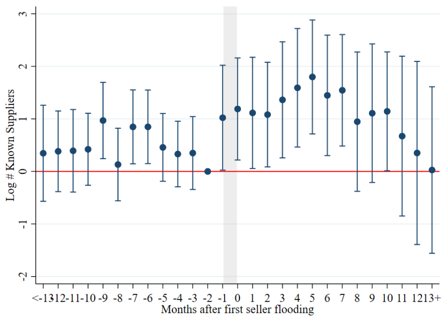
C.7.1 Supplier diversification

Figure C.31. Impact of supplier flooding on log number of suppliers (6 month window)



Notes: The panel plots OLS estimates of the effect of supplier flooding on the log number of suppliers following equation (7). Here, we define the treatment variable based on a six instead of a three month supplier window. Observations are firm-month-years whose 2011 and 2019 addresses are known and $\leq$ 10km apart. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure C.32. Impact of supplier flooding on log number of suppliers (12 month window)



Notes: The panel plots OLS estimates of the effect of supplier flooding on the log number of suppliers following equation (7). Here, we define the treatment variable based on a twelve instead of a three month supplier window. Observations are firm-month-years whose 2011 and 2019 addresses are known and $\leq$ 10km apart. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.7.2 Supplier choice

Table C.21. Impact of supplier flooding on supplier flood risk (6 month window)

	Δ Supplier Flood Risk		
	(1)	(2)	(3)
Own Max Flood Extent	-0.00582	-0.103	-0.0141
	(0.0799)	(0.0845)	(0.0965)
Suppliers' Max Flood Extent	-0.633***	-0.659***	-0.729***
	(0.135)	(0.138)	(0.151)
Time × District FE	Yes		
Time × District × Risk Dec. FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0107	0.0312	0.0553
N	155,182	154,474	149,598

Notes: The table reports OLS estimates of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers following equation (8). Here, we use a 6 instead of a 3 month window to define suppliers. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.22. Impact of supplier flooding on supplier flood risk (6 month window)

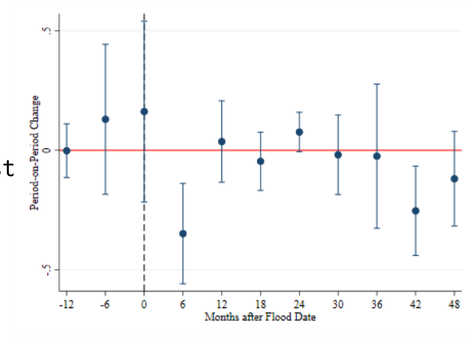
	Dependent Variable: Δ Flood Risk of Suppliers Flooded by								
	≤ 1%			≤ 5%			≤ 10%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own Max Flood Extent	-0.0621	-0.0934	-0.0718	-0.0656	-0.0992	-0.0684	-0.0319	-0.0892	-0.0398
	(0.0830)	(0.103)	(0.104)	(0.0844)	(0.101)	(0.106)	(0.0884)	(0.101)	(0.111)
Suppliers' Max Flood Extent	-0.129	-0.123	-0.125	-0.298***	-0.304***	-0.311***	-0.482***	-0.496***	-0.518***
	(0.0855)	(0.0836)	(0.0878)	(0.0936)	(0.0909)	(0.0971)	(0.163)	(0.167)	(0.180)
Time × District FE	Yes			Yes			Yes		
Time × District × Risk Dec. FE		Yes			Yes			Yes	
Time × District × Industry FE			Yes			Yes			Yes
R^2	0.0083	0.0319	0.0542	0.0084	0.0307	0.0535	0.0090	0.0305	0.0534
N	154,643	153,929	149,070	155,051	154,344	149,473	155,116	154,409	149,538

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers flooded by ≤ 1%, ≤ 5%, or ≤ 10% during the flood risk windows. Here, we use a 6 instead of a 3 month window to define suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.33. Dynamic impact of supplier flooding on supplier flood risk (6 month window)

Images/SupplierRiskiness/long_event_st

(a) All Suppliers



chases/long_d1in100

(b) Suppliers flooded by $\leq 5\%$

Notes: Panels (a) and (b) plot OLS estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers and suppliers flooded by $\leq 5\%$ following equations (10) and (24), respectively. Here, we use a 6 instead of a 3 month window to define suppliers. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. Panel (b) excludes buyers which experience own or supplier flooding before the lag. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Table C.23. Impact of supplier flooding on supplier flood risk (12 month window)

	Δ Supplier Flood Risk		
	(1)	(2)	(3)
Own Max Flood Extent	-0.00923	-0.123*	0.0112
	(0.0676)	(0.0651)	(0.0759)
Suppliers' Max Flood Extent	-0.622***	-0.650***	-0.733***
	(0.120)	(0.123)	(0.136)
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk Dec. FE		Yes	
Time $\times$ District $\times$ Industry FE			Yes
R^2	0.0107	0.0294	0.0548
N	164,681	163,976	158,820

Notes: The table reports OLS estimates of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers following equation (8). Here, we use a 12 instead of a 3 month window to define suppliers. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.24. Impact of supplier flooding on supplier flood risk (12 month window)

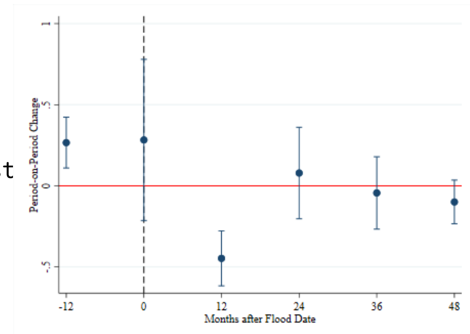
	Dependent Variable: Δ Flood Risk of Suppliers Flooded by								
	$\leq$ 1%			$\leq$ 5%			$\leq$ 10%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own Max Flood Extent	-0.169*	-0.249*	-0.177*	-0.193**	-0.315***	-0.182*	-0.143	-0.328***	-0.129
	(0.0913)	(0.136)	(0.106)	(0.0840)	(0.110)	(0.0996)	(0.103)	(0.107)	(0.119)
Suppliers' Max Flood Extent	-0.128*	-0.130	-0.131	-0.434***	-0.449***	-0.456***	-0.659***	-0.683***	-0.703***
	(0.0770)	(0.0807)	(0.0808)	(0.0846)	(0.0858)	(0.0872)	(0.188)	(0.197)	(0.206)
Time × District FE	Yes			Yes			Yes		
Time × District × Risk Dec. FE		Yes			Yes			Yes	
Time × District × Industry FE			Yes			Yes			Yes
R^2	0.0075	0.0297	0.0560	0.0084	0.0293	0.0550	0.0096	0.0301	0.0564
N	131,808	131,088	126,563	132,180	131,469	126,923	132,236	131,525	126,978

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers flooded by $\leq$ 1%, $\leq$ 5%, or $\leq$ 10% during the flood risk windows. Here, we use a 12 instead of a 3 month window to define suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.34. Dynamic impact of supplier flooding on supplier flood risk (12 month window)

Images/SupplierRiskiness/long_event_st

(a) All Suppliers



chases/long_d1in100

(b) Suppliers flooded by $\leq$ 5%

Notes: Panels (a) and (b) plot OLS estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers and suppliers flooded by $\leq$ 5% following equations (10) and (24), respectively. Here, we use a 12 instead of a 3 month window to define suppliers. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. Panel (b) excludes buyers which experience own or supplier flooding before the lag. The 95% confidence intervals rely on standard errors clustered at the time × district level.

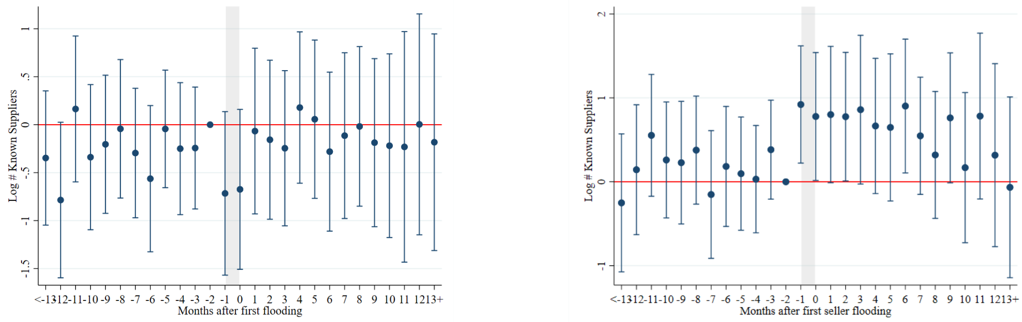
C.8 Results including moving firms

We omit the following regressions since they include moving firms by default:

- Impact of flooding on firm sales and purchases
- Impact of flooding on firm relocation and location flood risk (We present results with alternative move distance thresholds in Tables A.4 and A.5.)
- Impact of destination flood history on relocation flows (We present results with alternative move distance thresholds in Table A.6.)

C.8.1 Supplier Diversification

Figure C.35. Supplier Diversification: Impact of flooding on log number of suppliers (incl. movers)



(a) Own flooding (b) Supplier flooding

Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on the log number of suppliers following equations (6) and (7), respectively. The unit of observation is a firm-month-year. Here, we do not drop relocating firms. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.8.2 Supplier Choice

Table C.25. Impact of supplier flooding on supplier flood risk (incl. movers)

	Δ Supplier Flood Risk		
	(1)	(2)	(3)
Own Max Flood Extent	-0.0502	-0.0775*	-0.0477
	(0.0438)	(0.0418)	(0.0468)
Suppliers' Max Flood Extent	-0.495***	-0.506***	-0.623***
	(0.144)	(0.146)	(0.157)
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk Dec. FE		Yes	
Time $\times$ District $\times$ Industry FE			Yes
R^2	0.0095	0.0275	0.0545
N	217,289	216,535	208,992

Notes: The table reports OLS estimates of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers following equation (8). Observations are all firm-by-flood-year-month pairs. Here, this includes relocating firms. Standard errors (in parentheses) are clustered at the time $\times$ district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.26. Impact of supplier flooding on supplier flood risk (incl. movers)

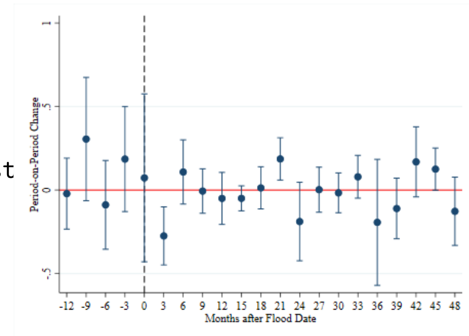
	Dependent Variable: Δ Flood Risk of Suppliers Flooded by								
	$\leq 1\%$			$\leq 5\%$			$\leq 10\%$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own Max Flood Extent	-0.0504	-0.0641	-0.0558	-0.0592	-0.0803*	-0.0632	-0.0558	-0.0813*	-0.0568
	(0.0461)	(0.0420)	(0.0496)	(0.0463)	(0.0440)	(0.0498)	(0.0454)	(0.0429)	(0.0481)
Suppliers' Max Flood Extent	-0.112*	-0.107*	-0.120*	-0.213***	-0.212***	-0.239***	-0.406**	-0.410**	-0.454**
	(0.0656)	(0.0619)	(0.0693)	(0.0773)	(0.0743)	(0.0780)	(0.168)	(0.171)	(0.182)
Time $\times$ District FE	Yes			Yes			Yes		
Time $\times$ District $\times$ Risk Dec. FE		Yes			Yes			Yes	
Time $\times$ District $\times$ Industry FE			Yes			Yes			Yes
R^2	0.0082	0.0293	0.0557	0.0079	0.0277	0.0537	0.0085	0.0272	0.0527
N	216,282	215,536	208,010	217,018	216,271	208,726	217,139	216,391	208,845

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers flooded by $\leq 1\%$, $\leq 5\%$, or $\leq 10\%$ during the flood risk windows. Observations are all firm-by-flood-year-month pairs. Here, this includes relocating firms. Standard errors (in parentheses) are clustered at the time $\times$ district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.36. Dynamic impact of supplier flooding on supplier flood risk (incl. movers)

Images/SupplierRiskiness/long_event_st

(a) All Suppliers



chases/long_d1in100

(b) Suppliers flooded by $\leq 5\%$

Notes: Panels (a) and (b) plot OLS estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers and suppliers flooded by $\leq 5\%$ following equations (10) and (24), respectively. Observations are firm-by-flood-year-month pairs. Here, this includes relocating firms. Panel (b) excludes buyers which experience own or supplier flooding before the lag. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

C.9 Results excluding repeated exposures

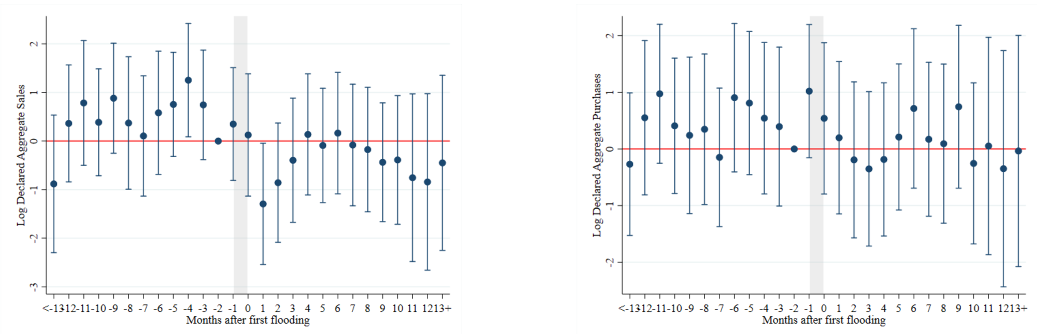
In the standard event studies, we consider a firm treated at the intensity of its first treatment in all periods following this first treatment. Treatment in a subsequent flood event could affect estimates for later treatment lags. As the flood events under investigation are at least ten months apart, this issue should mainly affect coefficients ten months after treatment and later lags. Below, we present event study results restricting attention to firms which are either never treated or treated only in one flood event. For the two-month flood events (Aug-Sep 2011 and Jul-Aug 2015), we define event time relative to the first month of the event (even where firms are only treated in the second month). We continue to define treatment intensity as the treatment intensity experienced in the first year-month in which a firm is treated. This specification rules out the possibility that effects at specific event times are driven by later flood events. We omit the following regressions since they do not estimate coefficients associated with specific relative times:

- Impact of flooding on flood risk of firm's location
- Impact of destination flood history on relocation flows
- Impact of supplier flooding on flood risk of all suppliers/suppliers flooded by $\leq 5\%$

We further omit the regressions estimating the impact of supplier flooding on the flood risk of suppliers flooded by $\leq 5\%$. For any given lag of this specification, we by default omit all buyer firms which are either flooded or have an important supplier flooded (at any level) between or during the windows over which flood risk is calculated.

C.9.1 Intensive Margin

Figure C.37. Impact of flooding on firm sales and purchases (excl. repeated exposures)

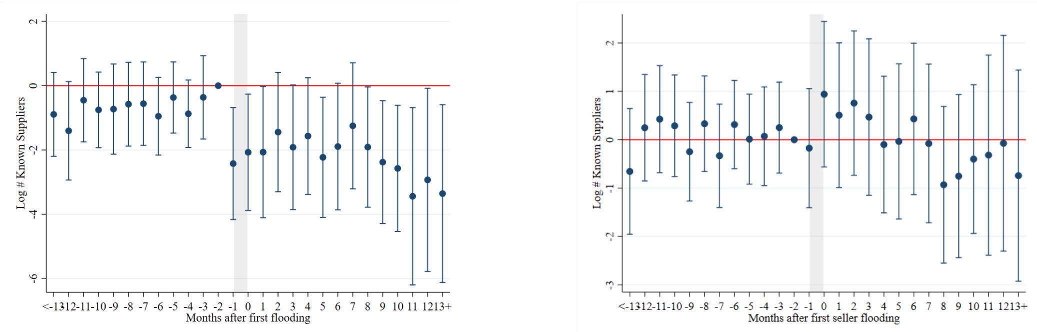


(a) Log sales (b) Log purchases

Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observations are firm-month-years which are flooded in no or one flood event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.9.2 Supplier diversification

Figure C.38. Supplier Diversification: Impact of flooding on log number of suppliers (excl. repeated exposures)



(a) Own flooding (b) Supplier flooding

Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on the log number of suppliers following equations (6) and (7), respectively. Observations are firm-month-years whose 2011 and 2019 addresses are known, $\leq$ 10km apart, and which are flooded in no or one flood event. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C.9.3 Supplier Choice

Figure C.39. Dynamic impact of supplier flooding on flood risk of all suppliers (excl. repeated exposures)

Images/SupplierRiskiness/long_event_study/restrict_all_min_sales_pur

Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are firm-year-months for which the 2011 and 2019 addresses are known, $\leq$ 10km apart and which are treated in no or one flood event. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

C.10 Robustness of route-level flooding impacts

Table C.27. Impact of route-level flooding on probability of relationship being active

	Dependent variable: $\mathbf{1}(\text{Sales}_{bst} > 0)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Shortest Path Flooded$_{bst^*}$) $\times$ Post$_t$	-0.009***	-0.010***	-0.002***	-0.005***	-0.006***	-0.010***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Years since first sale FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seller $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer $\times$ Seller FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Baseline	NonMan	Cap	CV only	Mov	2015 only	1 Exposure
N	11,193,406	33,856,461	9,471,209	10,288,183	26,884,973	11,193,406	8,021,948
R^2	0.546	0.558	0.585	0.505	0.536	0.546	0.562

The table reports the response of the probability of sales being positive in the (b, s) relationship around the first time the shortest path between b and s gets flooded following equation (11) but with a static treatment. Observations are buyer-seller-weeks for which b and s are both active. Robust standard errors in parentheses, clustered at the relationship level. Sample abbreviations are as follows. Baseline: both buyer and seller are manufacturing firms; at least two months of transactions, excluding relationships where at least one firm moves between 2011 and 2019. NonMan: like baseline, but includes non-manufacturing firms. Cap: like baseline, but excluding firms that are capital goods suppliers. CV: like baseline, but including only transactions that are reported by both buyer and seller and that are in agreement. Mov: like baseline, but includes also firms that move. 2015 only: consider only floods from 2015. 1 Exposure: only relationships where the shortest path gets flooded at most once after the first transaction in the relationship.