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

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November 12, 2025

Abstract

This paper considers how far private adaptation may reduce future vulnerability to climate risks. Using data on monthly firm-to-firm transactions from Pakistan, we find that flood-affected firms are more likely to relocate to safer ground, and shift purchases towards suppliers in less flood-prone regions and reached via less flood-prone roads. The results indicate that firms are imperfectly informed about flood risk, and update their beliefs following floods. We quantify aggregate impacts using a spatial model of endogenous production network formation. The findings suggest that firms' learning will shape the economic impact of increasingly frequent climate-related 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—the primary sites of economic activity, and central to population welfare—anticipate and adapt to climate-related shocks.

Estimating firm adaptation to climate change 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., 2025). Firm responses to such disasters can therefore reduce their risk exposure 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.[1] 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 leverages detailed data on transactions between firms, as well as measures of both firm- and supply route-level exposure to natural disasters, to provide evidence that firms undertake adaptive production and sourcing decisions in the aftermath of major floods. 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 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. The transaction records are complemented with 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 severely flooded firms (defined as those for which more than 10% of land within a 2km radius is flooded) decline by 9.6% and 3.7% respectively in the month of recorded flooding, though both recover within six months. Following severe flood events, the

[1] IPCC (2001) define adaptation as "adjustment... in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities". As discussed in more detail below, this may include both forward-looking decisions intended to reduce future vulnerability, and reductions in risk that result from the direct impacts of disasters. Both may be 'adaptive' by this definition, but given their potentially divergent policy implications, we present evidence that aims to distinguish the two channels in our analysis.

probability of firm exit increases. Flooding of roads also leads to large but brief disruptions to traffic flows: mean truck speeds decline by 1km/hr and truck-day counts by 14-17% 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 that reduce their vulnerability to future flooding. We consider evidence for adaptive adjustments along the margins of firm relocation, supplier choice and supply route choice.

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 severely flooded firms see a 2.42 percentage point increase in the probability of relocating more than 10km away over the study period relative to those that are not flooded, a large increase relative to the 12.94% probability of moving by more than 10km among non-flooded firms. Importantly, this relocation is adaptive in the sense that flooding induces firms to relocate systematically towards less flood-prone locations: severely flooded firms that relocate more than 10km see an 18cm reduction in the expected flood depth that they 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., 2019; 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 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.[2] These results highlight 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-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

[2]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).

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 demonstrate that firms respond adaptively to climate shocks and may therefore play an important role alongside governments and households in adaptation to climate risks (Grover and Kahn, 2024; Goicoechea and Lang, 2025). As discussed in Carleton et al. (2024), climate adaptation may occur both ex-ante ('anticipatory') and ex-post ('reactive'); our evidence is consistent with a key role for reactive adaptation in response to flood events in this context. This may encompass both forward-looking actions intended to reduce future vulnerability and more 'mechanical' effects of destruction: for instance, a firm that exits following a flood may do so in expectation of lower profitability in the future, but this may also simply reflect capital destruction experienced during the flood. Given that both sources of adjustments will alter future vulnerability of the production network, we aim to capture both in our analysis of adaptation. While several of the adaptation margins we identify might plausibly reflect a combination of both effects, the finding that firms shift towards suppliers that are less flood-prone even among their non-flooded suppliers highlights an important role for forward-looking adjustments. This 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). 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 range of economic and policy questions.

While a worsening trajectory of natural disaster risk will have damaging impacts for firms, our results suggest that these may be moderated by firms responding adaptively as more information becomes available. 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 effects 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 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., 2024) 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 estimate flood-induced productivity shocks and identify the role that adaptive changes in firms' supplier search decisions play in shaping the economy's exposure to floods.

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 assess how flood damages differ if we shut down 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 adaptive post-flood responses, while reducing firm exposure to flood *risk*, need not always ameliorate damages from individual *realized* future flood events. This is especially true when realized flooding affects areas that are not particularly flood-prone, which may become increasingly pertinent as flooding incidence responds to climate change.

Our results also suggest that there is significant scope for further adaptation in our setting. A large majority of firms have access to alternative suppliers that are nearby, in the same industry and subject to lower flood risk than their flooded suppliers. Using our estimated model, we also find that the majority of locations would be able to reduce the variance of cost increases induced by flooding without increasing average costs, by changing their supplier mix to source relatively more from less flood-prone locations. These findings point to the potential for policies that overcome barriers to adaptation to help firms to realize the benefits available from cost-effective improvements in resilience.

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 leads to adaptive adjustments along location, supplier and route choice margins, with complex system-wide effects as a result of 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, which will in turn be a key factor in determining 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 empirical setting and 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 Setting and data

The empirical setting for our analysis is Pakistan, one of the world's most vulnerable countries to the effects of extreme weather (Eckstein et al., 2021; Guha-Sapir et al., 2022), where rapid industrialization is proceeding alongside increasing vulnerability to the effects of climate change. Floods are preeminent among these, and result in 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 estimate 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 that they reduce the flood risk of firms' premises and supply network dependencies. We describe key features of each dataset here; further details on data construction are provided at Appendix C.

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 reported firm sales, purchases, exports and imports. 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.[3] 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 in 2011 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. 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.

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

The resulting data represents a large fraction of the economic aggregates reported in national accounts (Pakistan Bureau of Statistics, 2025). In the restricted sample, aggregate manufacturing value added accounts for 89% of reported manufacturing GDP in the last year of the sample. Total value added in our restricted sample accounts for approximately 20% of total GDP, since the reported aggregates include sectors which are generally not subject to VAT—agriculture, certain services, and the informal sector. Industry and product codes are not available for all firms in the sample, but among those firms for which a sector can be identified, 37% are classified as manufacturing firms, 29% retail/ wholesale, 20% services, 9% agriculture and 4% other.

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.[4] 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. Seventy two percent of firms, accounting for 74% of sales, are in urban areas (Esri, 2025), predominantly concentrated in the major cities of Karachi and Lahore. For 60% of firms, sufficient address information is available to geocode addresses in 2011 and 2019 separately.

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

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

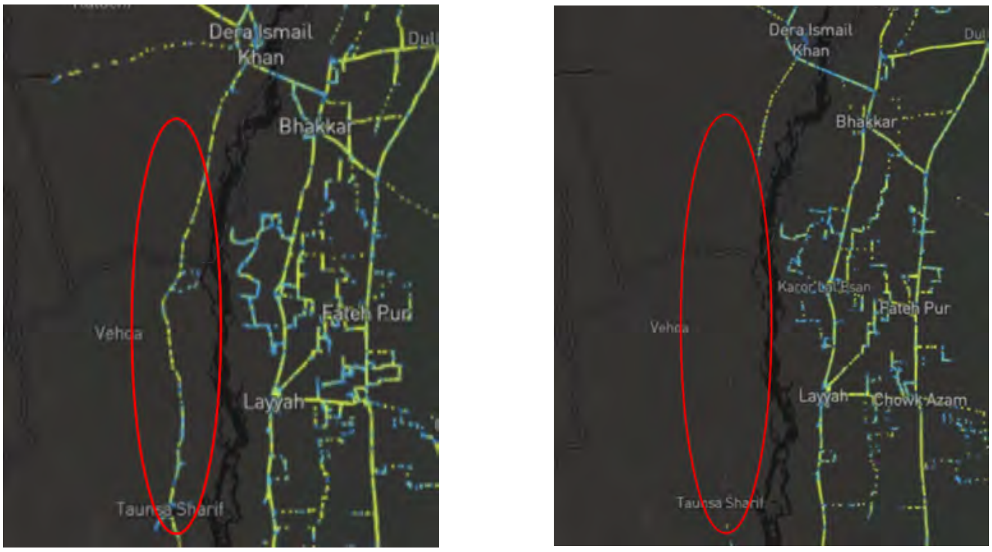
Notes: Flood risk in panel (c) is defined as the maximum across fluvial and pluvial flood risk, both measured as the expected flood depth in meters for a 1 in 100 year return period.

[4]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.

2.2 GPS tracker data from commercial trucks

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.

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 (denoted by color gradient in km/h) 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 (circled in red), which at 09:15 on 31 July 2015 was reported by Pakistan's National Disaster Management Authority (2015) to have been hit by floodwater which "swept away a 300-foot portion of the highway" (Dawn.com, 2015). The left hand panel shows normal traffic, reflected in continuous GPS signals, running along the encircled north-south highway in the four days leading up to the flood. 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 construct firm-pair-route level measures of travel speeds and disruption over time. To do so, we obtain OpenStreetMap 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 using the closest edge within 10 meters of the observation coordinates.[5] 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

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

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. This method overcomes selection bias in the speeds reported by the trackers themselves arising from the fact that GPS trackers are disproportionately likely to report when vehicles are starting, stopping, braking, or turning. We aggregate speeds first to the day-truck-edge level, and then by taking the mean to the week-edge level, also calculating the number of truck-day observations within each week-edge ("day-truck count"). Figure A.1 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 (UNOSAT, 2022). This service provides satellite imagery of major flood events in response to requests from organizations such as UN entities, member states, government offices and NGOs, most often to aid disaster response efforts.[6] These images allow us to map the exact location of floods, from which we extract a reference water layer comprising rivers, lakes and other existing bodies of water (Geofabrik GmbH, 2021).

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.2. We capture flooding of firm locations using the maximum share of a 2km radius circular buffer surrounding the firm's geocoded location that is flooded during a given flood event. Using a small buffer around a firm's geocoded location reflects the fact that there can be local imprecision in firm geocodes, and that local flooding may affect firms through, for instance, local labor market impacts as well as premises or capital destruction. As described in Table A.1, using this definition 30% of firms in the sample are ever flooded during the sample period and 5% are flooded more than once. Nineteen percent of firms ever experience flooding of a supplier, where we define supplier firms as those that accounted for more than 10% of their purchases over the preceding three months. In a given flood, flooding of a firm's own premises and that of its suppliers are not extremely closely correlated, allowing us to distinguish the impacts of these two types of exposure separately: for a firm flooded (not flooded) in a given flood event, the probability that at least one of their suppliers is flooded is 23% (2%). Appendix F.6 shows that results are qualitatively robust to choosing alternative buffer radii of 1km and 3km.

[6] 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 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. Matching the floods in our data with those in the EM-DAT dataset by province and date allows us to classify floods into riverine flood, flash flood and general flood categories; results are not statistically significantly different across these categories.

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 to identify the share of each road edge that is flooded. 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

Data on flood risk come from Fathom-Global, which uses a global flood hazard model combined with detailed terrain and hydrography data. The resulting datasets capture 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, at a resolution of 90 meters.[7] 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 the other return periods are shown in Figure A.3. These maps demonstrate a significant degree of overlap between flood-prone locations and areas with a high density of firms and roads, shown in Panels (a) and (b) 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.4. 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.5.

3 Floods and supply chain disruption

In this section, we present motivating evidence for the disruptive impacts of flooding on firm activity and road transportation. 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 and under-developed disaster insurance market.[8] Analyzing the dynamics of the direct destructive effects of floods will also help in interpreting the results of our subsequent analysis of firm adaptation.

3.1 Direct impacts of firm flooding

We first consider the impact of flooding of a firm's premises on its sales and purchases. These are 'direct' impacts of flooding, in the sense that they affect the firm via its own production, in contrast to

[7] 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 such as dams and levees.

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

our later examination of 'indirect' effects via supply chain linkages. We use 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 $\text{FloodExtent}_{i,t}$ 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.[9] Event dummies are binned at each endpoint of the event window (i.e. for lags and leads beyond 12 months). 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. 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.

The results of estimating this specification, shown in Figure 3, display reductions in both the sales and purchases of flood-hit firms in the direct aftermath of flooding.[10] The immediate impacts are statistically significant and economically large. While the reported coefficients display the estimated effect for a unit change in the maximum share of the firm's 2km buffer flooded (i.e. for a buffer moving from not at all flooded to entirely flooded), this is a much larger flooding extent than observed in practice. To benchmark the magnitude of the coefficient estimates in this and subsequent specifications, we therefore discuss effect sizes for both the mean treated firm across firms experiencing *any* flooding (which typically experiences flooding of only a small share of its 2km buffer) and for a severely flooded firm that experiences flooding of 10% of its buffer area (an acute level of flooding only experienced by 1% of firms).

During the month of impact, for the mean treated firm – which sees only 1.3% of its 2km buffer flooded – sales decline by 1.3% and purchases by 0.5%. Impacts are much stronger for firms that experience severe flooding, with firms whose buffers are 10% flooded experiencing sales declines of 9.6% and purchases declines of 3.7%. Figures B.1 and B.2 show 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; these suggest that strongly flooded firms see their sales and purchases decline most. Figure B.3 reveals that flooding depresses sales and purchases broadly across sectors, with the most pronounced effects for manufacturing, retail and wholesale firms, and intuitively weaker effects for services. While it is challenging to make comparisons across settings and shock types, the magnitude of these impacts is in line with estimated effects from natural disaster and conflict shocks in other contexts (Gröschl and

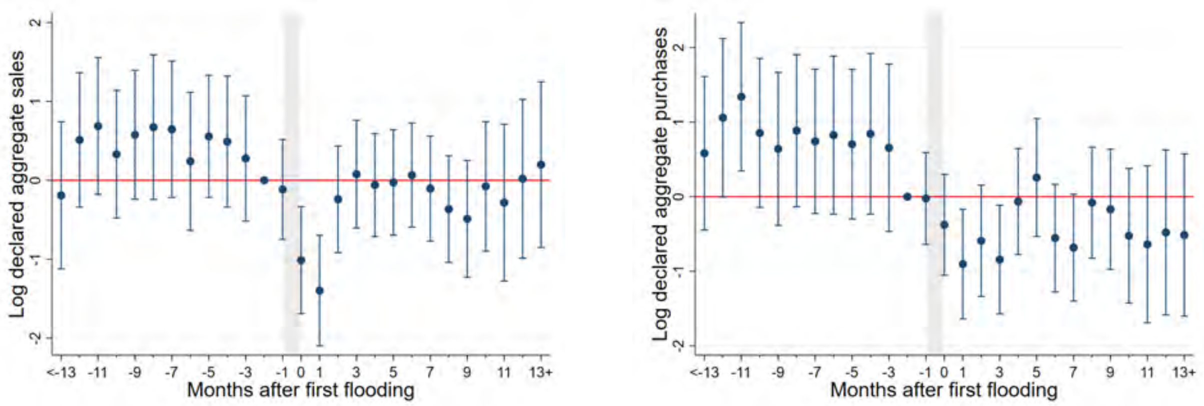
[9]Results are robust to replacing month-year fixed effects with district-month-year fixed effects or Fathom flood risk decile-month-year fixed effects, as demonstrated in Figures A.6 and A.7, respectively. In Appendix F.1, we consider the robustness of results to using alternative estimators to address potential challenges associated with two-way fixed effects regressions including treatment lags and leads with variation in treatment timing. Very similar results obtain when controls for suppliers' flooding are also included.

[10]Reassuringly, trends are flat 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.

Sandkamp, 2023; Del Prete et al., 2023).[11]

These large immediate declines are relatively short-lived. Sales and purchases quickly revert to close to the pre-exposure levels: while the point estimates are slightly lower than pre-flood levels, the magnitudes are small and no coefficients are statistically significantly different from pre-exposure levels for either outcome from four months after flooding. Given this significant recovery relative to the immediate decline, the small and statistically insignificant longer-term reductions are unlikely to be driven by continued direct disruptive impacts of the shock, but may reflect flooded firms (or their supply chain partners) undertaking adaptive adjustments which are, on average, costly (consistent with the empirical results in Section 4 and the model in Section 5). Reversion to pre-flood levels is especially clear for manufacturing firms, and firms that rely less heavily on relationship-specific inputs and which may therefore be less likely to incur the costs of adaptation.

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.9 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 but statistically insignificant positive impact on firm exit in the direct aftermath of flooding, while strong effects are observed for some individual flood events.

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. Our GPS data allows us 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, with treatment centered around

[11] Our firm data does not include profits, costs, quantities or prices, so we cannot estimate impacts on these alternative measures of firm operations directly. In Figure A.8, we examine impacts on profits using available data on sales and materials purchases and using parameter estimates from De Loecker et al. (2016). We find that profits are temporarily depressed following floods, driven by lower sales with a relatively flat sales-to-purchases ratio.

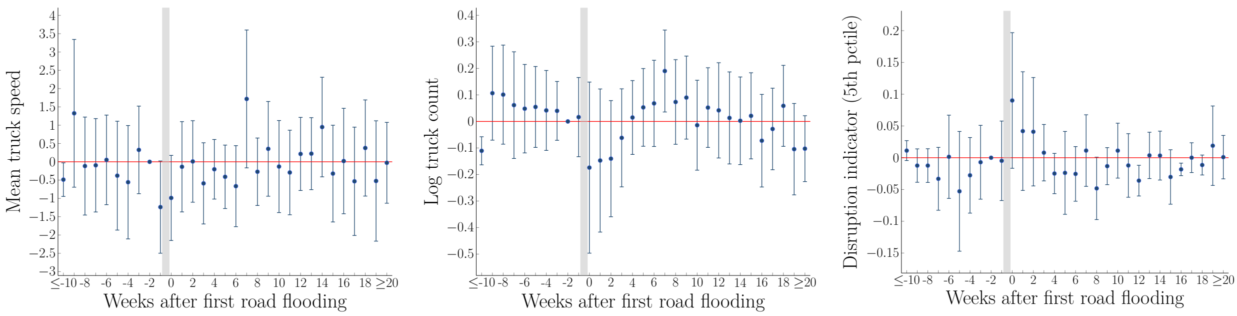
the first week of observed flooding in a particular year, using the following specification:

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

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 '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.[12]

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. Control group means are 31.6 km/h (mean speed), 4.1 (average log number of trucks), and 5% (average probability of disruption).

The results of these specifications paint a consistent picture of sizable but brief disruptions to traffic induced by flooding of roads. Mean truck speeds at the road edge-week level decline by a marginally statistically significant 1km/hr in the week in which flooding is recorded, and return to pre-flooding levels by the following week. Point estimates for day-truck counts, shown in panel (b), show a decline in the range of 14-17%, 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 9pp in the week in which flooding is recorded, with reversion within a fortnight.

The results in this section suggest that floods have sizable disruptive impacts on firm operations and road traffic. While effects on firm exit are likely mostly permanent, the direct disruptive impacts of floods on intensive margin sales and purchases as well as road traffic are transient, lasting for a matter of only months or weeks, respectively. This dynamic pattern is informative for our understanding of potential adaptive responses: if firms' changes in production choices show more persistence than the

[12]The day-truck count is the number of different trucks traveling 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 specification 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.

short-lived direct disruptive effects of flooding, these long-term responses could reflect firms' changed understanding of the risk they face.

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 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.

These adaptation margins may capture both firms' forward-looking decision-making to reduce their future vulnerability to flooding, and mechanical reductions in flood risk if, for instance, flooded firms (which have higher average flood risk) see reductions in flood risk on average if they move, even if they relocate randomly across space. Both forward-looking and mechanical responses reduce firms' flood risk and are therefore of interest in understanding firm adaptation to flood risk. Separating mechanical from forward-looking adaptation is, however, 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, 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. Defining firm relocation based on a threshold of 10km gives a more plausible relocation rate of 13%, so we use this as the threshold for defining a firm 'move'.[13]

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

[13] Results are consistent using other thresholds, as shown in Tables A.4 to A.6. Table A.7 also shows the robustness of results to restricting attention to firms that only have one listed address.

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 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. Given that no firms in the sample see flooding of the entirety of their 2km buffer ($FloodExtent_i = 1$, which corresponds to the main estimated effect in Table 1), we again report effect sizes for both the mean treated firm among those experiencing any flooding, and a severely flooded firm experiencing inundation of 10% of its buffer. In the specification with district fixed effects (district × Fathom flood risk decile fixed effects), mean flooding (which inundates 1.15% of a firm's buffer) increases the relocation probability by 0.26pp (0.31pp) on average, relative to the 12.94% probability of moving by more than 10km among non-flooded firms. For firms that experience severe flooding affecting 10% of their buffer, there is a much stronger effect of 2.42pp.

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

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	2.081***	2.537***	-179.9**	-21.20
	(0.798)	(0.851)	(88.63)	(39.90)
Average effect of mean flooded buffer	0.261pp	0.311pp	-3.652cm	-0.430cm
Average effect of 10% flooded buffer	2.420pp	2.914pp	-17.990cm	-2.120cm
District FE	Yes		Yes	
District × Fathom 1 in 100 FE		Yes		Yes
R^2	0.046	0.067	0.126	0.468
N	43,848	43,395	5,737	5,587

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on a 10km-relocation indicator 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. The flood risk regressions only include firms which moved by >10km. Standard errors (in parentheses) are clustered at the district level. Average effect of mean (10%) flooded buffer refers to the average estimated effect for a firm experiencing the mean level of flooding among treated firms in the estimation sample (flooding of 10% of its 2km radius buffer). 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:

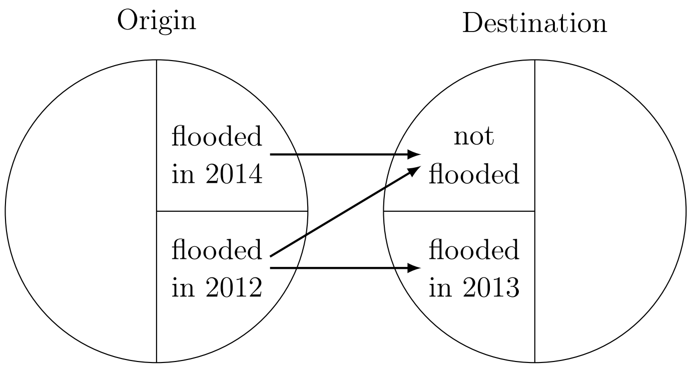
$$\triangle \text{FloodRisk}_i = \beta \text{FloodExtent}_i + \alpha_{zd} + \varepsilon_i \tag{4}$$

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 2.03% of its buffer flooded) sees a 3.65cm reduction in expected 1 in 100 year flood depth, while severely flooded firms see a reduction of 18cm. These changes correspond to large percentage reductions relative to the average expected 1 in 100 year flood depth of 39cm among firms that experience any flooding during the sample period. Column (4) of Table 1 also displays a negative effect when restricting to within district-risk decile variation, with an intuitive reduction in magnitude and statistical significance. Table B.1 shows that smaller firms, which intuitively may be expected to be more footloose, are differentially likely to relocate towards less flood-prone areas following floods.[14]

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.[15] 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?

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



We examine this using the following gravity Poisson specification:

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

where the unit of observation ot_odt_d is the area of an origin district o first flooded in year-month t_o paired with the area of a destination district d which was either first flooded in year-month t_d or never flooded. $X_{ot_odt_d}$ denotes relocation flows capturing the number of firms moving by more than 10km from area ot_o to area dt_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_{dt_d} are fixed effects capturing destination areas flooded at time t_d; and $\mathbb{1}\left(t_o - t_d > 12\right)$ 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.

[14] Appendix B shows that this pattern of heterogeneity is not driven by a higher propensity for adaptive relocation among young firms, single versus multi-branch firms, or firms in industries that on average have lower fixed assets.

[15] 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, consistent with the evidence in Table 1. If that was not the case, the coefficient in equation (5) is unlikely to be non-zero. For locations in destination districts that are never flooded, t_d is set to a time period after the sample period. We drop origin locations not flooded during the study period, and location pairs without relocation flows.

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.[16]

Table 2. Impact of destination flood history on relocation flows

	Number of Firms Moved
Dest. flooded 12mo prior	-0.733***
	(0.252)
Origin × Destination FE	Yes
Origin × Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10km
N	1,539

Notes: The table reports Poisson pseudo-maximum-likelihood estimates of the effect of destination flood history on relocation flows following equation (5). Standard errors (given in parentheses) are clustered at the origin-destination level. The sample is restricted to firms whose 2011 and 2019 locations are known and >10km apart. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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.[17] 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., 2019; 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

[16] Appendix Table A.8 reports results for equivalent specifications where we consider firms relocating from origin district regions that are flooded more than 24 or 36 months (rather than 12 months) after destination district regions. The finding that firms take past flooding into account when deciding where to move remains robust in these specifications. This suggests that flooding has very persistent impacts on in-migration of firms, and reduces the likelihood that results are driven by, for instance, reduced firm profitability or labor market effects in the aftermath of flooding. Consistent with this, analysis of firm entry patterns at the district level reveals depressed entry in the month following flooding, but quick recovery thereafter.

[17] 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 F.9. Supplier diversification results further restrict the sample to cases where buyer and seller reports coincide exactly.

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; $\text{FloodExtent}_{i,t}$ 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.[18]

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. $\text{SellerFlood}_{b,t}$ 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.[19] $\text{SellerFlood}_{b,t-\tau}$ 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. $\text{OwnFlood}_{b,t}$ 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 are shown in Figure 6. The specification from equation (6) finds no evidence for diversification in response to flooding of a firm's own premises (panel (a)). Firms do, however, temporarily increase the number of their suppliers in response to supplier flooding (panel (b)). 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. Severely affected firms, with a maximum flooded buffer share of 10% among their suppliers, see a larger increase of 13.4%. The response is relatively short-lived, with reversion to pre-exposure levels within a year. This is consistent with firms making up for missing or lost inputs by temporarily purchasing from new suppliers, but does not indicate that firms make long-term adaptive adjustments by diversifying their supplier base.

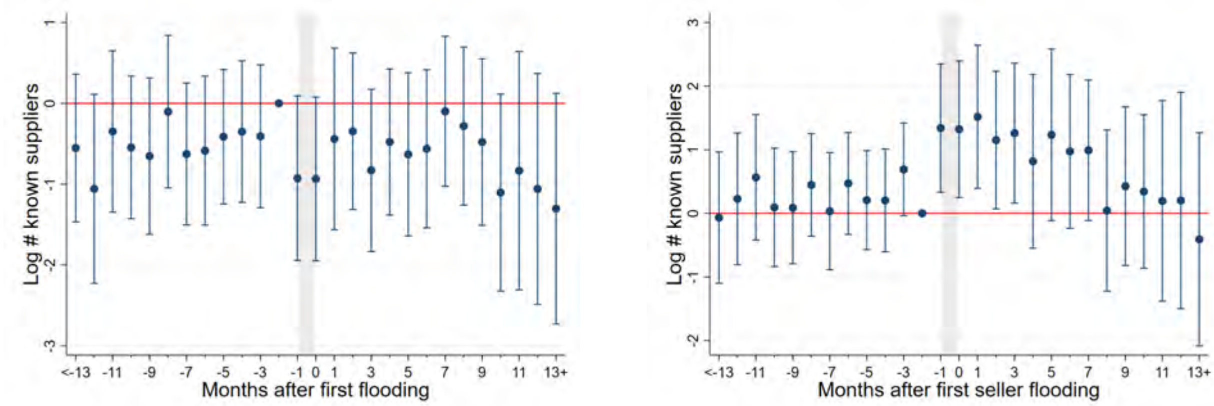
Beyond changes in the *number* of a firm's suppliers, another potential margin of adaptation is to change the *characteristics* of their suppliers by shifting towards a portfolio of suppliers less prone to flooding. We consider two dimensions of such a decision. In the next subsection, we examine how far

[18] 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 total number of suppliers, as shown in Figure A.10.

[19] 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 F.8.

flood-affected firms shift the composition of their suppliers towards suppliers located in less flood-prone regions. In the subsequent subsection, we consider whether floods affecting transportation routes also induce firms to reduce dependence on suppliers reached via flood-prone routes.

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 Flood risk of suppliers

Does exposure to flooding induce firms to source from less flood-prone suppliers? We start by demonstrating that there is significant potential for firms to adapt by choosing less flood-prone suppliers, and then demonstrate that this is an important margin used for adaptation in practice.

We consider the potential for firms to adapt via their choice of suppliers by examining how likely it is that firms whose suppliers are affected by flooding can easily substitute towards safer suppliers. Appendix Table A.11 reports the probabilities that alternative *non-flooded* and *less flood-prone* suppliers in the same 2-digit industry exist within 25, 50, and 100km of the buyer firm. We also consider separately this probability restricting attention to suppliers in the same 2-digit industry that are both less flood-prone and larger, to avoid potential concerns that, for instance, smaller firms could not produce inputs of correspondingly high quality. The results reveal substantial potential for adaptation: for instance, there is a 97% probability that a non-flooded alternative supplier in the same industry exists within 25km, and a 92% (77%) probability that a less flood-prone (less flood-prone and larger) alternative supplier in the same industry exists within 25km.

In order to test how far flood-affected firms exploit this potential by shifting their sourcing towards less flood-prone suppliers, we study changes in the risk profile of a buyer firm's suppliers around the time of flooding of the buyer itself, or flooding of any of their suppliers (again based on the preceding 3-month window). 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. We compare changes in the supplier mix of flood-exposed firms relative to those that are not flood-exposed, around the time of a flood, using the following empirical specification:

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

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 at least 10% of b's purchases over the previous three months; and $\alpha_{d(b)t^*}$ are buyer district × time fixed effects. We additionally report results using buyer district × time × buyer 1 in 100 year flood risk decile or buyer district × time × buyer industry fixed effects. 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:

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

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 $(t_1, t_2]$.

Table 3. Impact of flooding on supplier flood risk

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-4.893	-8.296	-6.813
	(9.585)	(9.148)	(11.34)
Suppliers' max flood extent	-62.71***	-64.58***	-74.24***
	(15.72)	(16.06)	(17.84)
Average effect of mean flooded supplier buffer in cm	-0.927	-0.955	-1.098
Average effect of 10% flooded supplier buffer in cm	-6.271	-6.458	-7.424
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0116	0.0319	0.0611
N	144,566	143,857	139,302

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 all 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 flooding of their suppliers by shifting towards less flood-prone suppliers. The magnitudes are sizable and quite consistent across specifications including different fixed effects. In the central specification including district × time fixed effects, the mean treated observation (which sees a maximum flood extent among its sellers' buffers of 1.48%) experiences a 0.93cm reduction in the sales-weighted average supplier flood risk for a 1 in 100 year flood event. Where suppliers are more severely flooded (with a supplier maximum flooded buffer share of 10%), the sales-weighted average supplier flood risk decreases by 6.27cm. This compares to a sales-weighted average flood risk among treated firms' suppliers of 27.01cm.

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.

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.[20] While the coefficient on the supplier treatment is smaller than in Table 3 (meaning that some of the reduction in supplier risk is driven by reduced purchases from the flooded supplier), 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 their suppliers not disrupted by flooding. In terms of magnitudes, the mean treated firm sees a 0.42cm reduction in the sales-weighted average flood risk among its non-flooded suppliers, while this reduction is 2.8cm for a more severely-affected firm whose suppliers' maximum flooded buffer share is 10%.

Heterogeneity in firms' propensity to shift their sourcing towards less flood-prone suppliers is examined in Appendix B, which reveals intuitive patterns. Adaptive shifts in supplier choice are more pronounced among smaller firms (Tables B.2 and B.3) and single-branch relative to multi-branch firms (Tables B.5 and B.6). This is consistent with smaller firms having smaller and less complex supply chains – such that changes in supplier networks may be less costly and disruptive – and with multi-branch firms having greater resilience to disruption from floods via hedging risk across diversified locations and reallocating activity to unaffected plants (Castro-Vincenzi et al., 2024). Adaptive supplier choice is also more pronounced among firms in industries that require more relationship-specific inputs, as shown in Tables B.8 and B.9. Here input relationship-specificity is constructed as the weighted average of relationship-specificity of input industries as in Boehm et al. (2024) (where product-level relationship-specificity is from Rauch, 1999); this pattern of heterogeneity is robust to instead considering the output specificity of a firm's maximally flooded supplier in order to restrict attention to cases where the disrupted input is specific. This result is intuitive if it is more difficult for firms that purchase relationship-specific goods to find suitable suppliers, so that flooding of upstream suppliers will likely be more costly.[21] Tables B.10 and B.11 demonstrate that firms whose suppliers are affected by flooding increase their share of purchases from new suppliers, while Tables B.12 and B.13 suggest that they also source more from suppliers with multiple branches, which may be less exposed to flooding impacts given their ability to substitute to other sites.[22]

[20] Here we define suppliers that are not hit by a flood shock as those that see less than 5% overlap of their 2km buffer with the flood polygons, since these firms do not experience direct disruptions to sales or purchases from flooding (see Figures B.1 and B.2). Appendix Table A.9 shows that qualitatively similar results are obtained using alternative thresholds of 10% or 1%

[21] Dimensions of firm heterogeneity along which we do not find evidence for heterogeneous adaptive supplier choice include firm age, frequency of purchases, baseline supplier diversification, industry-level average inventory ratios, shipment frequency, and output market concentration.

[22] Firms whose suppliers are flooded do not switch towards suppliers that are more diversified, larger or more distant from the buyer firm; nor do these firms increase their share of sales from suppliers used by their competitors.

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-9.662	-8.296	-11.61
	(9.584)	(8.643)	(11.40)
Suppliers' max flood extent	-28.16***	-29.29***	-27.25***
	(9.524)	(8.929)	(10.24)
Average effect of mean flooded supplier buffer in cm	-0.416	-0.433	-0.403
Average effect of 10% flooded supplier buffer in cm	-2.816	-2.929	-2.725
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0091	0.0313	0.0587
N	144,423	143,714	139,164

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 that are not flooded (defined as $\leq$ 5% overlap of the 2km buffer and the flood polygon). Appendix Figures B.1 and B.2 show that the main sample restricted to firms with an overlap in this range exhibits no effect of flooding on sales and purchases, respectively. Appendix Table A.9 shows robustness checks for varying thresholds in the main specification. 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We consider the persistence of the shift towards less flood-prone suppliers among flood-affected firms, using the following specification:

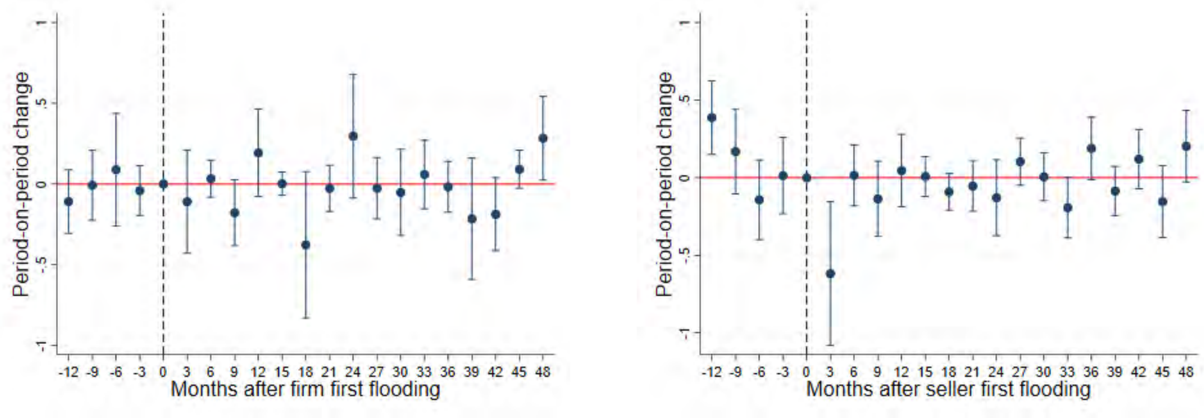
$$\Delta y_{bt} = \sum_{\substack{\tau=-12 \\ \text{s.t.} \frac{\tau}{3} \in \mathbb{Z}, \tau \neq 0}}^{48} \beta_{1,\tau} \text{SellerFlood}_{b,t-\tau} + \sum_{\substack{\tau=-12 \\ \text{s.t.} \frac{\tau}{3} \in \mathbb{Z}, \tau \neq 0}}^{48} \beta_{2,\tau} \text{OwnFlood}_{b,t-\tau} + \alpha_{d(b)t} + \varepsilon_{bt} \tag{10}$$

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 the window 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 (again defined as those accounting for more than 10% of b's purchases over the three month window preceding the flood event) during the relevant flood event; and $\text{OwnFlood}_{b,t-\tau}$ is the share of b's buffer flooded during that event. When analyzing the effects of firms' own flooding, the relevant flood ($\tau = 0$) is the firm's first direct flood event, controlling for potential concurrent flooding of the firm's suppliers. When we instead consider the impacts of flooding of a firm's suppliers, the relevant flood ($\tau = 0$) is instead the firm's first supplier flood event, controlling for potential concurrent flood exposure at the firm's premises. $\alpha_{d(b)t}$ are buyer-district-by-time fixed effects.[23]

[23] We include ever-treated observations only at the lags of interest $\tau_{(t)} = -12, -9, ..., 45, 48$. Including them in every time period but omitting the treatment outside the lags of interest would confound $\widehat{\alpha_{d(b)t}}$ as these observations would effectively serve as control observations.

Given this specification, a short-lived shift towards less flood-prone suppliers would yield an initial negative coefficient of interest $\beta_{1,\tau}$ (or $\beta_{2,\tau}$) , 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.

Figure 7. Dynamic impact of flooding on supplier flood risk



(a) Own flooding

(b) Supplier flooding

Notes: The panels plot OLS estimates of the effect of own and supplier flooding (separately) on the change in suppliers' sales-weighted average flood risk in equation (10), following the first firm direct flooding event for panel a), and the first supplier flood event for panel b). 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 7b 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.[24] A persistent response is also evident when restricting attention to non-flooded suppliers, as shown in Figure A.11. Figure 7a shows no effect of flooding of a firm's own premises, consistent with the results in Table 3.

4.4 Flooding of supply routes

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

[24]Figure F.56 presents results excluding firms which experience flooding of a supplier 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.

flooded firms' sales and purchases have recovered.[25] We estimate event study regressions of the form:

$$y_{bst} = \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{36} \beta_\tau \text{ShareRouteFlooded}_{bs,t-\tau} + \eta_{\text{age}(b,s),t} + \alpha_{bs} + \alpha_{bt} + \alpha_{st} + \varepsilon_{bst} \tag{11}$$

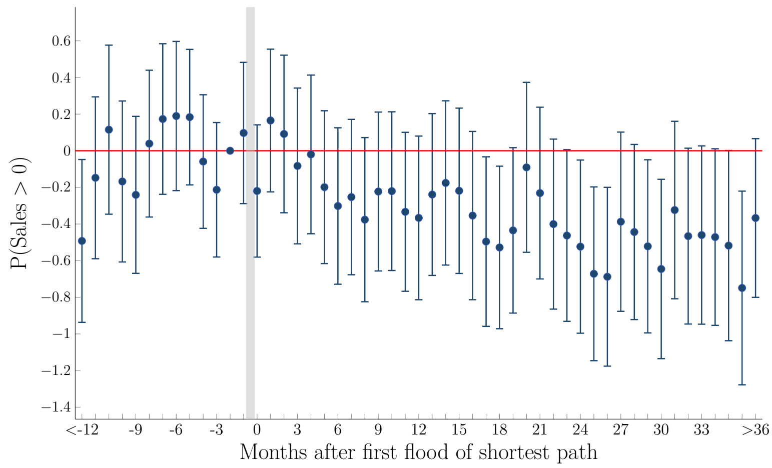
where y_{bst} is an outcome at the buyer-seller-time level (sales in the (b, s) relationship during month-year t, or an indicator variable denoting whether sales are positive); and $\text{ShareRouteFlooded}_{bst}$ is the share of the ordinary-time (i.e. during non-flooded weeks) shortest-time route between 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.12). α_{bs}, α_{bt}, and α_{st} are, respectively, buyer-seller, buyer-time, and seller-time fixed effects. 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 to ensure that transactions correspond to shipments of physical goods; results are however robust to lifting this restriction (Appendix Table F.33).

Figure 8 shows the 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 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.13). 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.

[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.

[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-months 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 Robustness

Appendix F 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 F.1); excluding industries for which supply disruptions of the nature considered in the analysis may not be pertinent (Appendix F.2-F.4); considering only transaction observations where buyer and seller reports coincide exactly (Appendix F.5); using buffers of radius 1km or 3km, rather than 2km, to define flood exposure and risk (Appendix F.6); and considering floods with return periods of 1 in 10 or 1 in 50 rather than 1 in 100 years (Appendix F.7). The central results are all qualitatively robust to these alternative specifications.

4.6 Discussion of potential mechanisms

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. Several alternative mechanisms may underlie these adaptive responses.

One possible mechanism is that floods lower the fixed cost of making changes that the firm may already have wished to make, such as relocating to safer areas, or force firms to experiment with new suppliers, resulting in lasting changes as in Larcom et al. (2017). Such a mechanism cannot, however, account for the finding in Table 4 that supplier flooding induces buyers to shift their *non-flooded* supplier mix towards less flood-prone firms, or flood-induced supplier diversification in Section 4.2.

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).

Alternatively, floods may increase 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., 2023), 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).

While mechanisms predicated on experience-based updating should imply persistent responses, availability heuristics would predict larger impacts from more recent floods. The evidence in Section 4.1 for adaptive relocation is consistent with a permanent response. 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 8), without evidence of attenuation in either case. While behavior may revert over longer timescales, the fact that these adaptive responses persist for as long as is measurable in our data appears inconsistent with salience effects being first-order in the medium-run.

5 Quantifying the aggregate impacts of adaptation

While the reduced form results in Section 4 identify evidence for adaptation, a simple aggregation of these estimates is unlikely to provide an accurate assessment of their economy-wide impacts. This is because aggregate effects will reflect general equilibrium forces (for instance, firm cost increases driven by flooding of their suppliers as well as direct damages) and firm connections via multi-step linkages (for instance, flood exposure of the suppliers of a firm's suppliers, and so on). In this section, we develop a quantitative spatial model of production network formation and adaptation which models general equilibrium and indirect effects explicitly, in order to estimate the aggregate impacts of adaptation for the resilience of the economy to future floods.

5.1 Theoretical model

The model builds on recent two-stage models of production network formation under uncertainty (Kopytov et al., 2024) 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. Given the challenges in distinguishing rational from heuristic updating of flood beliefs empirically (see Section 4.6), we use a flexible framework that does not require us to take a stance on the nature of firm beliefs or the learning process.

Before flood shocks are realized, firms search for suppliers taking into account their beliefs over the flood risk of potential suppliers. Once floods have occurred, firms then choose suppliers to minimize costs conditional on the outcomes of their search. Extreme value distribution assumptions (following Oberfield, 2018 and Boehm and Oberfield, 2020, 2022) yield tractable gravity expressions for sourcing shares. We use these gravity equations alongside expressions for cost indices in changes (the "exact-hat" approach pioneered by Dekle et al., 2007) to estimate how far post-flood adaptation observed in our sample affects the damages imposed by subsequent floods. Full derivations are included in

Appendix D.

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 given by β_n and assumed constant given our focus on firms' adaptive decisions:

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

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.

5.1.3 Production

Production combines a primary factor (equipped labor) with an intermediate input which is sourced from a supplier. There are two stages in the production process: (i) search for suppliers, and (ii) sourcing and production. In the first stage, firms in each location n exert bilateral search efforts m_{ni} to search for suppliers from different locations i, maximizing expected profits given their beliefs over flood risk across locations. This search process 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 which of these techniques they will use to produce to maximize profits. We start by describing the second stage, where technique draws and shock realizations are taken as given.

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 Cobb-Douglas production function in equipped labor and intermediate inputs:

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

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 the deterministic time-invariant productivity of 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. α is the cost share of intermediate inputs.

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:

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

Firms choose the technique ϕ which minimizes marginal cost and maximizes profits.

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 bilateral sourcing shares in 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 i and that yield a match-specific productivity z greater than a threshold $\bar{z}$ is Poisson distribution with mean $m_{ni}\bar{z}^{-\zeta}$, where m_{ni} describe bilateral search efforts 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:

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

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:*

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

where location-specific cost indices $\bar{c}_n$ satisfy:

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

Sourcing shares follow the common gravity form, with search efforts m_{ni} as bilateral trade flow shifters:

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

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

First stage: search for suppliers. The first stage of the firms' production problem endogenizes search efforts m_{ni} as the optimal ex-ante investments in the face of uncertainty over flood outcomes. 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. They face a resource constraint $\bar{m}$ on the total resources available for supplier search, characterized by a general function g. In the first stage, a firm j in location n chooses search efforts m_{ni} to solve:

$$\begin{aligned} \max_{(m_{ni})_i} \; & \mathbb{E}\left(\lambda \pi_j(m_{n1}, \ldots, m_{nN}) | \mathcal{I}_n\right) \\ \text{s.t.} \quad & g(m_{n1}, \ldots, m_{nN}) = \bar{m} \qquad \text{and} \qquad m_{ni} \geq 0 \quad \text{for all } i \end{aligned} \tag{16}$$

We assume that g is such that the solution matrix $\mathbf{m}(\mathcal{I}) = (m_{ni}(\mathcal{I}_n))_{ni}$ 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 supplier 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 or search efforts m in response to flood shocks can be characterized as a function of shocks, elasticities, and observed pre-shock equilibrium outcomes. Denoting ratios of a variable in one equilibrium to another by hats ($\hat{x} = x_{post}/x$) yields:

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

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

$$\hat{\bar{c}}_n\left(\mathbf{X}, \hat{\mathbf{b}}, \hat{\mathbf{m}}\right) = \hat{b}_n^{-1}\left[\sum_i \frac{X_{ni}}{X_n} \hat{m}_{ni} \hat{\bar{c}}_i\left(\mathbf{X}, \hat{\mathbf{b}}, \hat{\mathbf{m}}\right)^{-\zeta}\right]^{-\alpha/\zeta} \tag{18}$$

5.1.5 Dynamics

The static economy described above is played out in each time period. Time periods are linked by the dynamics of firm 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). We do not impose restrictions on the nature of firm beliefs beyond the requirement that firms in each location update beliefs in the same way, in order to preserve ex-ante homogeneity of firms within locations as specified in the model. In our estimation of the model below, we ensure consistency with the empirical results in Section 4 by defining locations according to flood exposure of a firm's suppliers.

5.2 Quantitative implementation

This section describes how we take the model in Section 5.1 to the data in our empirical setting, and estimate the aggregate impacts of flood shocks. Section 5.3 then estimates how post-flood adaptation—identified in the model as enduring changes in sourcing behavior driven by updated firm beliefs about flood risk—influences the network's aggregate vulnerability to future flooding.

To estimate the model, we define 'locations' as groups of firms. Locations are defined separately for each flood event based on two firm characteristics, which 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 2km buffer in the flood event under consideration. This reflects the evidence in Table 4 that firms whose suppliers are flooded update their beliefs differentially, while the firm's own flood status has no significant impact on firm beliefs.[27] Second, the definition of locations accounts for the district in which the firm is located, to permit heterogeneity in beliefs according to the proximity of flooding. Locations are therefore groups of firms that share both characteristics: district, and supplier flood status. Sales transactions between firms in each location are aggregated to this level.

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, during which the flood reduces TFP in affected locations in line with the dynamics of direct flood impacts in Section 3. 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. 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. Technological productivity levels a_n, elasticity parameters and trade costs τ_{ni} are assumed constant over the three periods of each flood event.

Flood shocks b and ξ are realized independently across flood events. To quantify the consequences of adaptive changes in search decisions, we require a parameterization of location-level productivity shocks induced by flooding. We assume the following form for how these shocks b_n are related to $\overline{\text{ShareFlooded}}_n$, the share of firms in n experiencing flooding of more than 10% of their 2km buffer:

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

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

$$\widehat{\left(\frac{X_{nit}}{X_{nt}}\right)} = \exp\left(-\zeta \log \hat{c}_i + \frac{\zeta}{\alpha} \log \hat{\bar{c}}_n + \frac{\zeta}{\alpha} \log \hat{b}_n\right) \tag{20}$$

Here variables with hats denote changes from the pre-flood period to the flooded period, and the changes in cost indices $\hat{\bar{c}}$ are implicitly defined as a function of shocks $\hat{b}$ and pre-period sourcing shares by:

$$\hat{\bar{c}}_n = \hat{b}_n^{-1} \left[\sum_i \frac{X_{ni}}{X_n} \hat{\bar{c}}_i^{-\zeta}\right]^{-\alpha/\zeta} \tag{21}$$

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.[28] We set the input share α equal to the average annual share of reported purchases to sales, which is 0.77.[29] The trade elasticity ζ is calibrated to be

[27] 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.

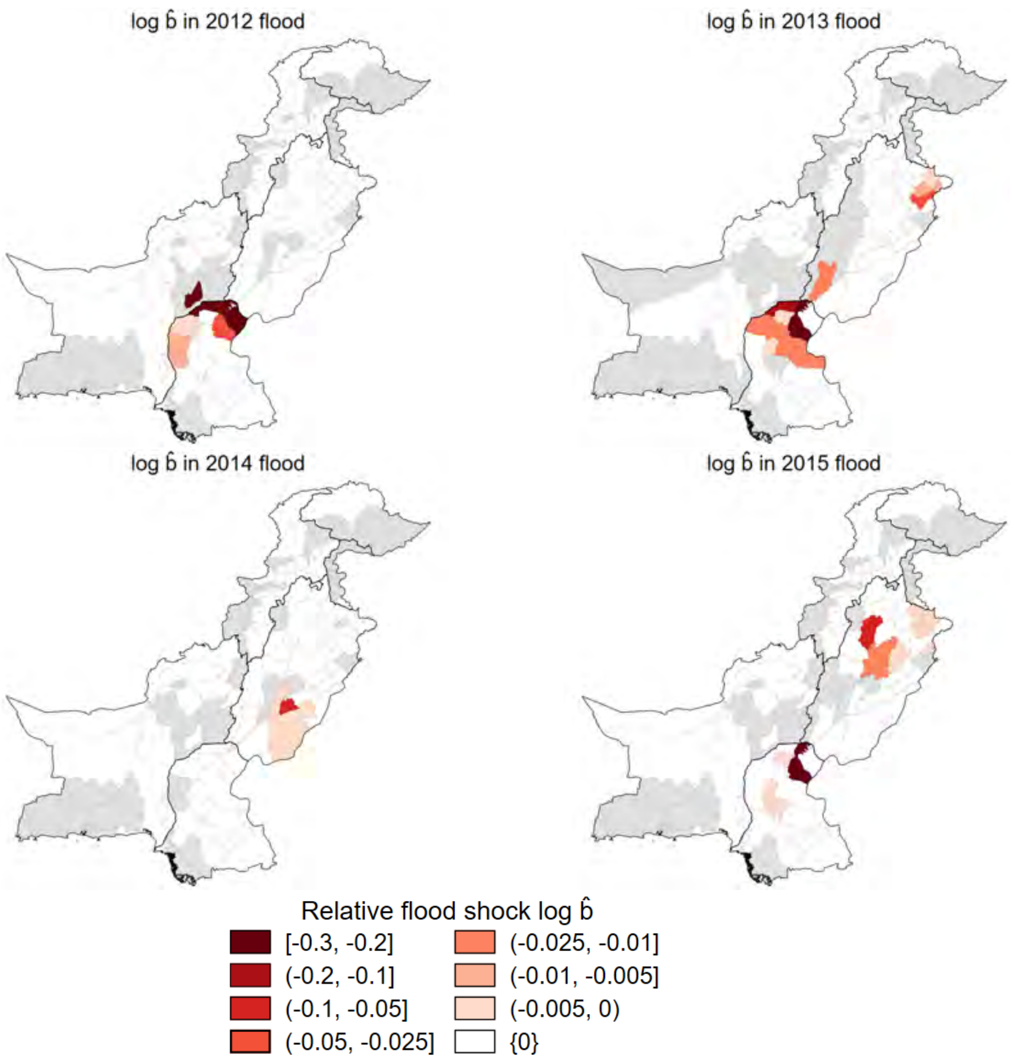
[28] We ensure that all observations of shares are finite and reduce the influence of outliers by estimating Equation (20) on the set of cell pair × events (n, i, t^*) where, prior to the flood, the purchases of n from i account for at least half a percent of n's purchases, and winsorizing the change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

[29] In this calculation we ignore firms that report fewer than three times in a year, and firms that have purchase-to-sales

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 2km buffer would experience a 30% reduction in TFP. This estimate of η, together with the observed share of firms in each location n experiencing flooding of more than 10% of their 2km buffer, yields the productivity cost b_n of each flood in each location from equation (19). These values are aggregated to the district level and mapped for each flood event in our sample 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%.

Figure 9. Estimated productivity shocks from floods in sample

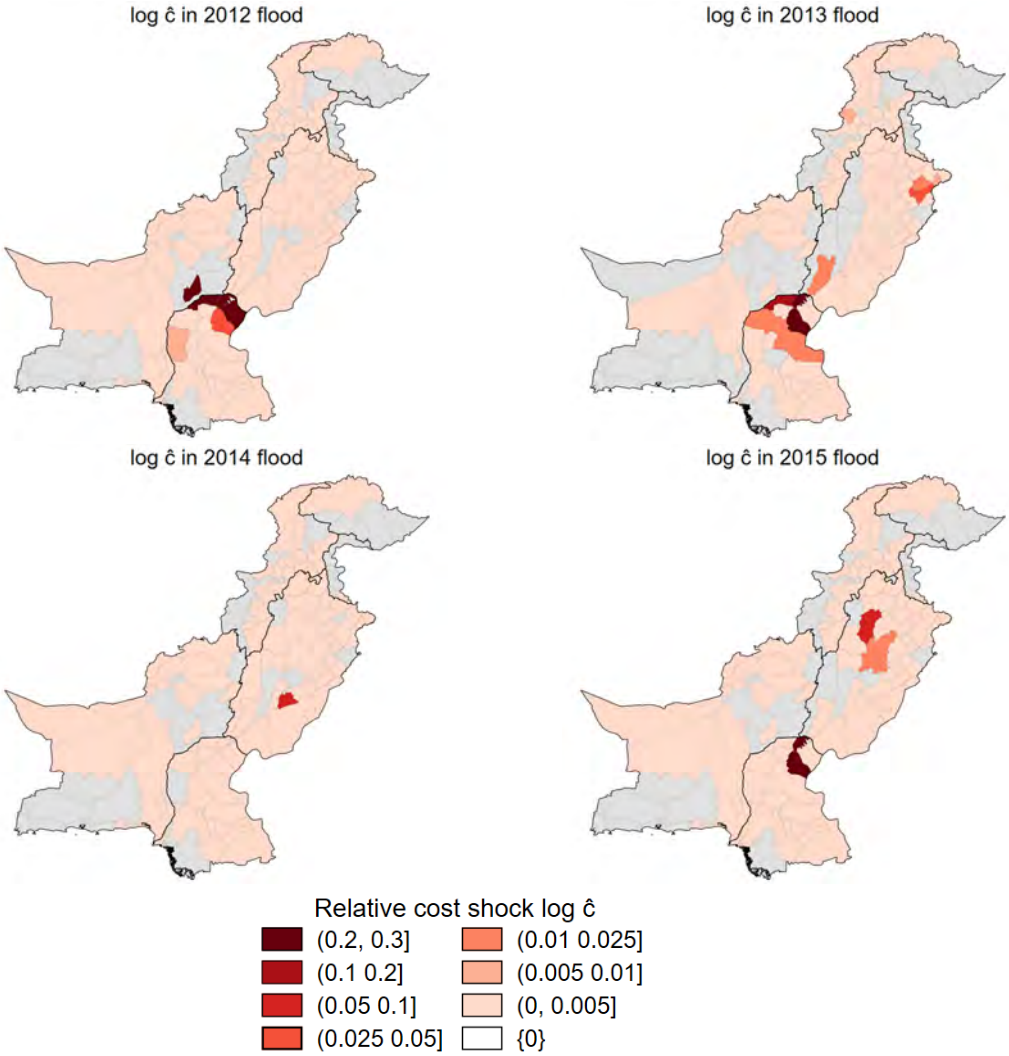


Notes: The figure maps the productivity shocks $\log \hat{b}$ estimated from equation (19) as described in this section. We obtain $\log \hat{b}$ at the district level by taking the average across both locations in the district weighted by pre-flood period sales to households.

The impact of flooding on firm costs extends 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.

ratios exceeding 3. This value is larger than most materials shares reported in the literature because purchases from firms can also include capital.

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.[30]

5.3 Estimating the aggregate impacts of adaptation

In this section, we use the estimates from Section 5.2 to quantify the impacts of observed post-flood adaptation for the aggregate damages from subsequent floods. We quantify this by calculating the costs of a subsequent flood with and without incorporating the adaptive sourcing changes induced by a prior flood. These changes in sourcing decisions reflect the aggregate effect of upstream firms exiting or

[30]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).

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.

Equation (21) yields cost changes $\hat{\hat{c}}$ induced by flooding using estimates of the flood shock $\hat{b}$ and the baseline sourcing shares X_{ni}/X_n. To simulate the role that adaptation following a prior flood plays in changing the costs of a subsequent flood, we solve this equation once under the sourcing shares that prevailed before adaptation to the prior flood, and once under the post-adaptation sourcing shares, and compare the resulting cost increases induced by the subsequent flood.

We consider the example of adaptive changes in sourcing shares undertaken following the observed flood in 2012, and estimate the impacts of these changes in shaping the damages imposed by subsequent floods in the sample. This 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.[31] 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 activity *towards* areas that would subsequently be affected by the 2014 floods, and as a result damages from the 2014 floods would have been 3.5% *lower* without adaptation following the 2012 flood.[32]

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 do not necessarily move activity from areas that will be exposed in 2014, and in fact 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 for the 2015 floods. As such, the pattern of gains and losses from adaptation 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.

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 benefiting from the prior adaptation. Conversely, aggregate damages in a 2015 flood scenario would have been 1% higher without adaptation following the 2012 floods, with only 66% of locations seeing benefits from adaptation.

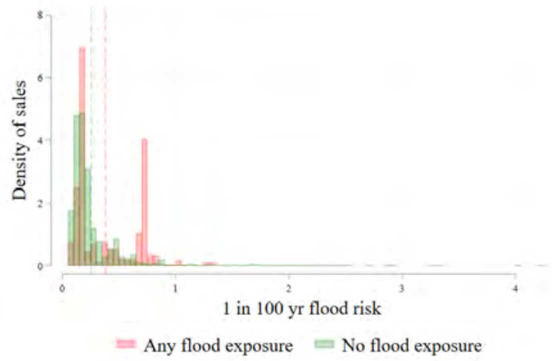
The heterogeneous impacts of adaptation following the 2012 flood across subsequent floods in the sample raises a question as to the conditions under which post-flood adaptation to reduce flood *risk* may be expected to help or hurt in the face of individual future disasters. Some guidance on this question can come 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

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

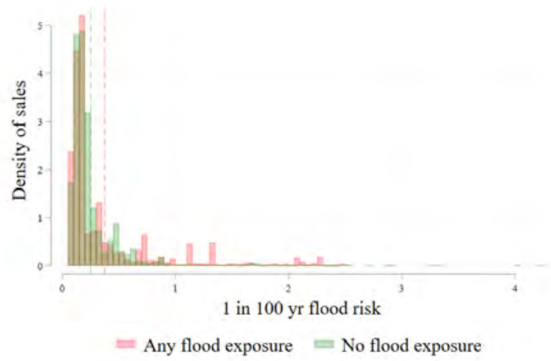
[32] Noisy measurement of these sourcing shares attenuates the impacts of these adaptive changes. Estimates obtained using manufacturing firms only—for which sourcing shares tend to be more stable—are a few percentage points larger but of the same order of magnitude.

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 shows 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.10). 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 occur for idiosyncratic events that affect areas that are not especially flood prone.

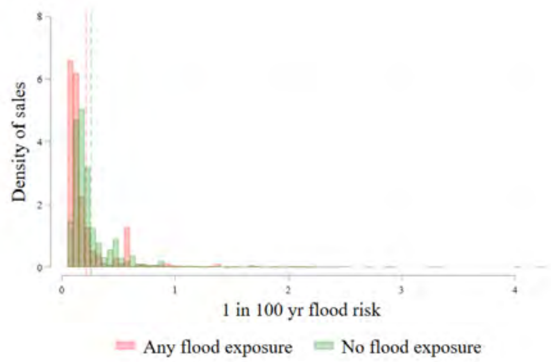
Figure 11. Density of sales across 1 in 100 year flood risk by flood exposure



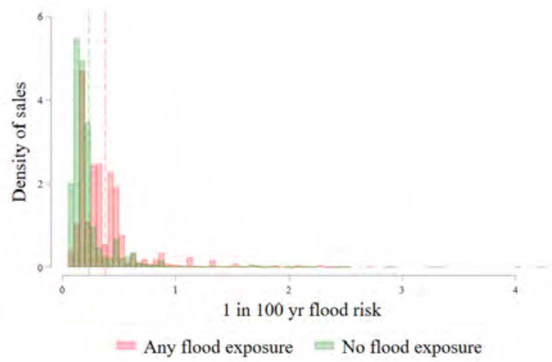
(a) 2012



(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.

5.4 Evaluating the potential for adaptation

The analysis above reveals that adaptive sourcing adjustments can yield benefits from reduced future flood exposure. In a final structural exercise, we evaluate the economy's remaining potential to reduce the impact of climate-related shocks by adjusting supply chains. Concretely, we use the model to calculate how many locations could adjust their input sourcing shares by a small amount, $d\log(X_{ni}/X_n)$, such that there is a decrease in the variance of cost changes induced by flood shocks, $Var_{\hat{b}}(\hat{c}_n)$, while ensuring that expected costs $\mathbb{E}(c_n)$ do not increase. This gives a measure of the potential for locations to shift towards suppliers that result in lower exposure to cost variability from flooding, but which do not increase expected costs on average.

For this exercise, we calculate the variance and expectation over the joint distribution of flood shocks across locations, parameterized using a longer time series of historical flood data in Pakistan as described in Appendix E. We implement this exercise[33] at the level of the spatial aggregates used for the 2015 flood event (as described in Section 5.3) in order to estimate the remaining potential for adaptation at the end of our sample period; similar but slightly larger results obtain using the baseline sourcing shares from 2012.

The results of these simulations indicate that 82% of locations could reduce cost variability from flooding by altering their supply chain exposure without increasing expected costs on average.[34] This significant scope to reduce the volatility associated with climate shocks without incurring large costs highlights the opportunity for policies that support firms in realizing this potential for cost-effective adaptation.

6 Conclusion

The impact of climate change depends crucially on the ability of economic agents and systems to adapt to its effects. The results of this paper suggest a consequential role for adaptation by firms. We demonstrate that natural disaster events — a key manifestation of climate change — can also be important in influencing its impacts by inducing firm-level adaptation in their production and network linkage decisions. Floods result in only temporary disruption to production and transportation links, but 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. To quantify this, we develop a spatial equilibrium model of firm production and sourcing decisions under imperfect information about flood risk. Flood shock realizations percolate through the spatial production network and raise the cost of production. The model allows us to evaluate the impact of flood realizations both with and without adaptive supplier sourcing changes. Estimating these effects reveals that firms' adaptive behavior following floods observed in our sample has quantitatively meaningful implications for the damages imposed by future flood events on the aggregate economy.

These findings open up a research agenda on how far private adaptation may shape future climate damages. First, as statistical models of the distribution of extreme weather events under different climate change scenarios evolve, the frameworks developed here can be used to evaluate the dynamic impact of adaptation events across the full distribution of future flood risk. Second, adaptation is triggered by a multitude of events, not just disaster episodes as studied here, raising important policy questions about whether complementary approaches might also 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? Third, adaptive responses by firms likely interact with those of households and the public sector, and a better understanding of these inter-dependencies will

[33] See Appendix D.2 for the precise mathematical definition of the problem and the computational strategy.

[34] In our model, firms may of course not attempt to minimize the variance of cost increases, but may target other moments that depend on their risk aversion and stochastic discount factor. Firms may also not realize these potential gains if they do not know the true distribution of flood shocks.

be required to estimate aggregate impacts. Finally, our results relating to firms' imperfect information about climate risk highlight the need for further analysis of their expectations about long-range climate trajectories, including to better understand whether belief updating and adaptive behaviors attenuate over time as major flood events become more common (Belasen and Polachek, 2008). Given sharply deteriorating projections of natural disaster incidence as climate change proceeds, understanding the nature, determinants, and implications of firm adaptation will be crucial in projecting and responding to future damages.

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Appendix

Contents

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	30%			
Share of firms ever flooded >5% of 2km buffer	2%			
Share of firms ever flooded >10% of 2km buffer	1%			
Share of firms flooded more than once	5%			
Share of firms ever had important recent supplier flooded	19%			
Share of firms had important recent supplier flooded more than once	3%			
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		

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. We impose standard restrictions on all firms including transaction partners. For the self-reported and all aggregated transaction variables, we do not restrict transaction partners to the standard sample in the table or the analyses. The flooding of an important recent supplier follows the definition of the supplier flooding treatment variable. It refers to 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 months in which a given transaction measure is positive are computed as the standard deviation across firms of the share of year-months in which the measure is positive for that firm. 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 (positive transaction)	15,473,279	
Buyer-seller-pairs ever reported	1,657,933	
Share active pairs among all 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 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 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

All sales and purchases are denominated in Pakistani Rupee (PKR) before logging. Transactions refer to buyer-seller-year-month observations with a positive transaction value. 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 posititve amount to the firm in a given quarter. Years refer to fiscal years, which last from July through June.

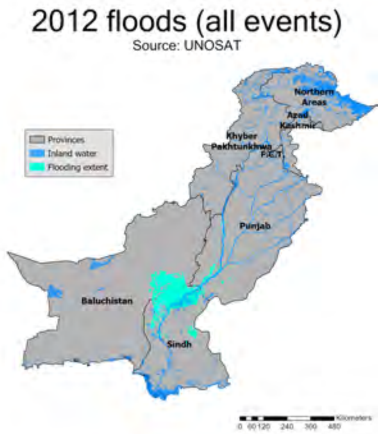
Figure A.1. Comparison of calculated and reported truck speeds in Lahore

(a) Calculated speeds, 2015 (b) Reported speeds, 2010

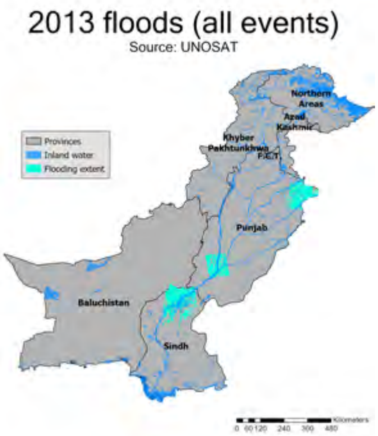
Notes: Panel (a) maps computed 2015 speeds and panel (b) maps 2010 speeds reported in Japan International Cooperation Agency (2012) for the same area in Lahore.

Figure A.2. Flood extent maps during sample period

(a) 2011: Aug.-Sep.



(b) 2012



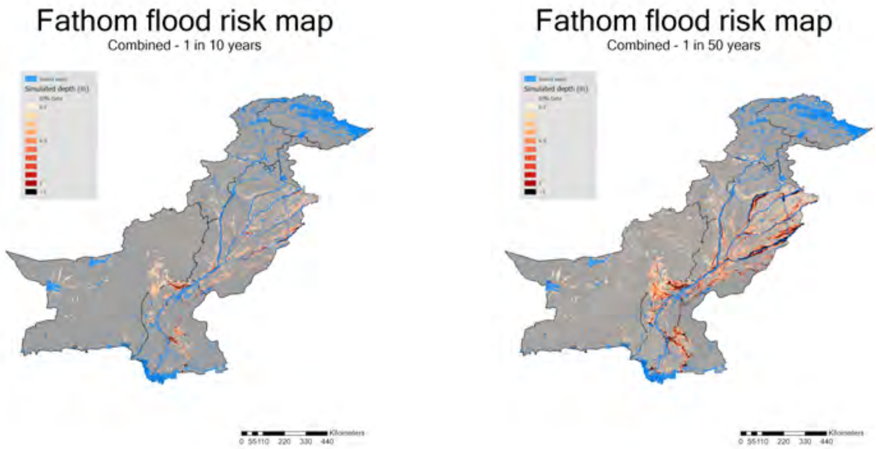
(c) 2013

(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.3. Fathom flood risk maps of Pakistan for return periods of 10 and 50 years

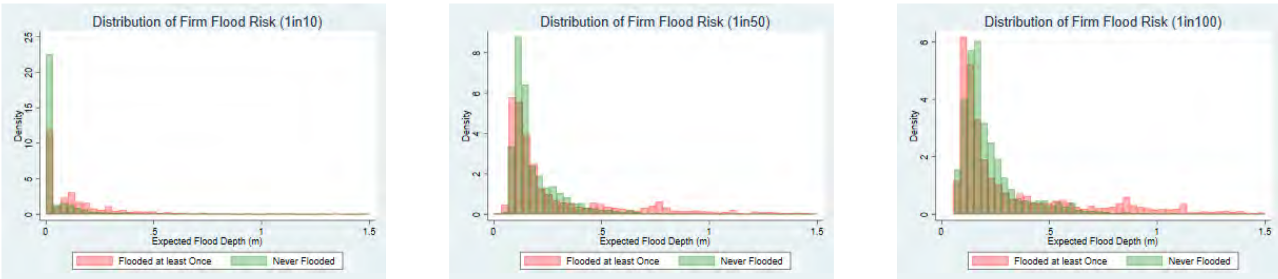


(a) 1 in 10 years return period

(b) 1 in 50 years return period

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.4. Distribution of firms by Fathom flood risk



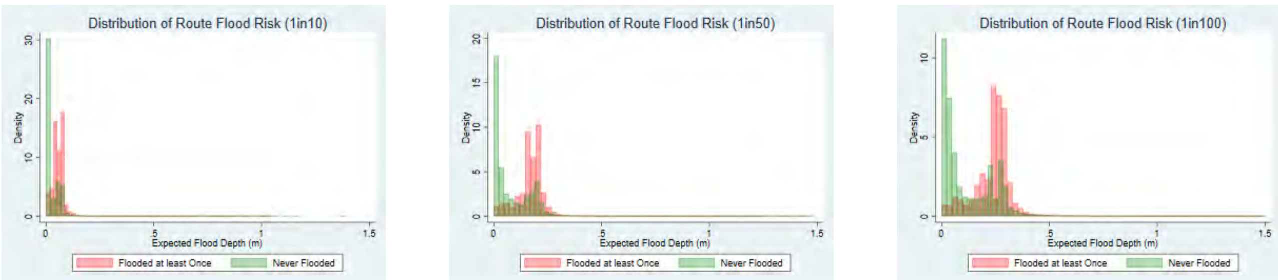
(a) 1 in 10 years return period

(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.5. Distribution of firm-pair routes by Fathom flood risk



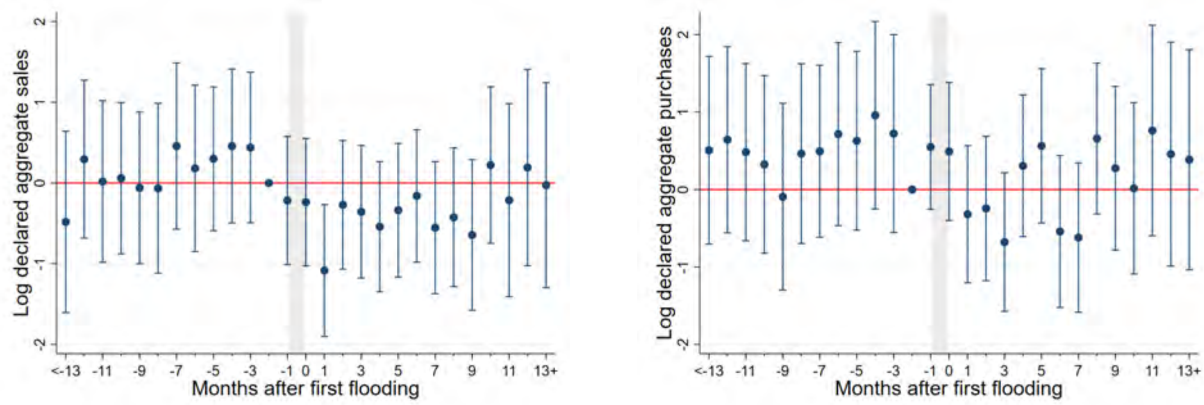
(a) 1 in 10 years return period

(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.

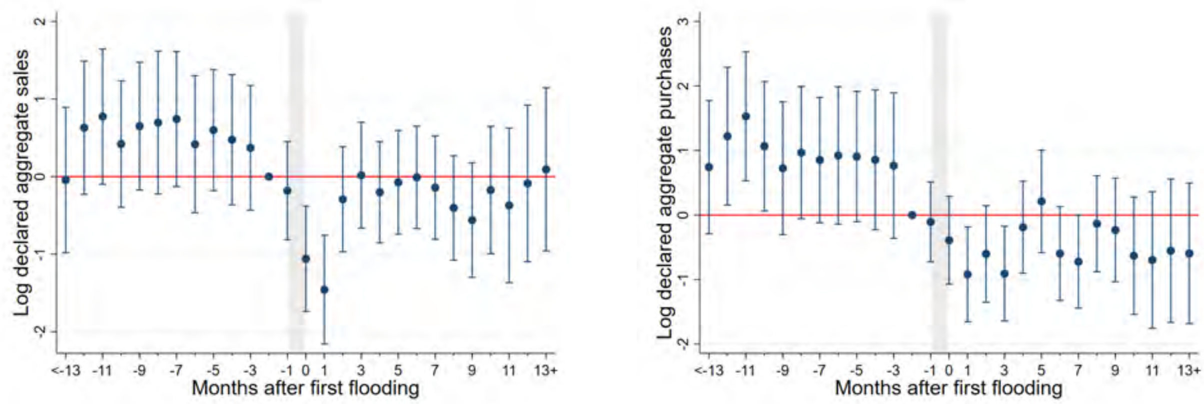
Figure A.6. Impact of flooding on firm sales and purchases using district × time FEs



(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.

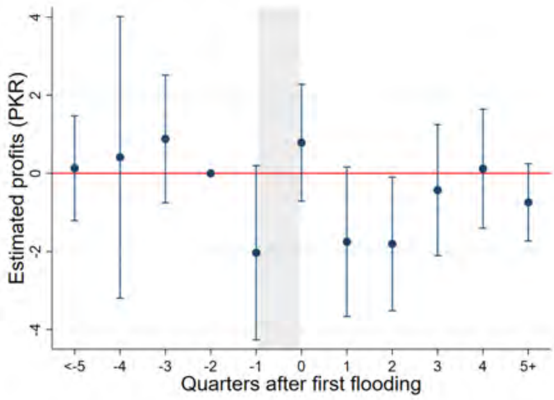
Figure A.7. Impact of flooding on firm sales and purchases using flood-risk-decile × time FEs



(a) Log sales (b) Log purchases

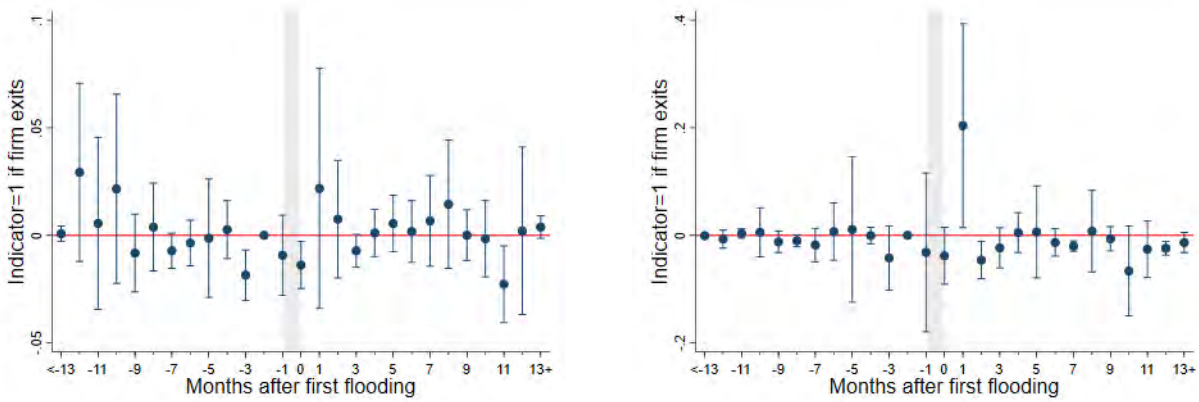
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases following equation (1). Here, we use flood-risk-decile × time FEs instead of time FEs. The flood risk decile is defined as the decile of a firm's expected flood depth in meters for a 1 in 100 year return 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.8. Impact of flooding on firm estimated profits



Notes: The panel plots the PPML estimates of the effect of flooding on estimated quarterly profits with firm and quarter(-year) fixed effects. The timing of treatment is constructed as the first quarter of observed flooding, where quarters are fixed. The treatment variable is the maximum flood extent of the quarter aggregated from the firm-month panel. Estimated profits are calibrated using industry-specific material elasticities from Table 3 of De Loecker et al. (2016), with negative profits recoded as zeroes. The sample includes manufacturing firms from industries in which material elasticities are available. We trim the top and bottom 2 percent of observations based on estimated profits, and drop firms that reported negative estimated profits throughout the entire panel period. The unit of observation is a firm-quarter-year. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure A.9. 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:

$$y_{it} = \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_\tau \text{FloodExtent}_{i,t-\tau} + \alpha_{dt} + \varepsilon_{it} \tag{22}$$

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. Standard errors are clustered at the district level.

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 >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	0.906	2.054***	0.860	0.873	2.101**	1.689*
	(0.680)	(0.719)	(0.832)	(0.622)	(0.903)	(0.910)
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	0.006	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 table reports logit estimates of the effect of flooding on a 0, 5, or 15km-relocation indicator following equation (3). Observations are firms fully geocoded in 2011 and 2019. 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.5. Impact of flooding on flood risk of firm's location (no, 0, 5, 15km move restrictions)

	Δ Flood Risk (cm)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max share of 2km buffer flooded	-138.1*	-188.8*	-216.2*	-212.3**	-55.32*	-70.93	-43.82	-42.38
	(78.49)	(110.1)	(121.8)	(81.38)	(32.18)	(46.89)	(52.35)	(39.39)
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	0.085	0.163	0.190	0.268	0.430	0.504
N	43,866	29,684	10,623	3,780	43,754	29,567	10,487	3,630

Notes: The table 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 regardless of relocation or which moved by more than 0, 5, or 15km. Standard errors (in parentheses) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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	-1.769***	-0.821***	-0.815***
	(0.289)	(0.223)	(0.292)
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	1,758	1,615	1,437

Notes: The table reports Poisson pseudo-maximum-likelihood estimates of the effect of destination flood history on relocation flows following equation (5). Standard errors (given in parentheses) are clustered at the origin-destination level. The sample is restricted to firms whose 2011 and 2019 locations are known and >0, 5, or, 15km apart. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7. Impact of flooding on firm relocation and location flood risk (single business register address)

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	1.635*	1.635**	-170.1**	-9.517
	(0.893)	(0.775)	(82.77)	(34.80)
District FE	Yes		Yes	
District × Fathom 1 in 100 FE		Yes		Yes
R^2	0.051	0.075	0.141	0.503
N	29,532	28,990	3,634	3,494

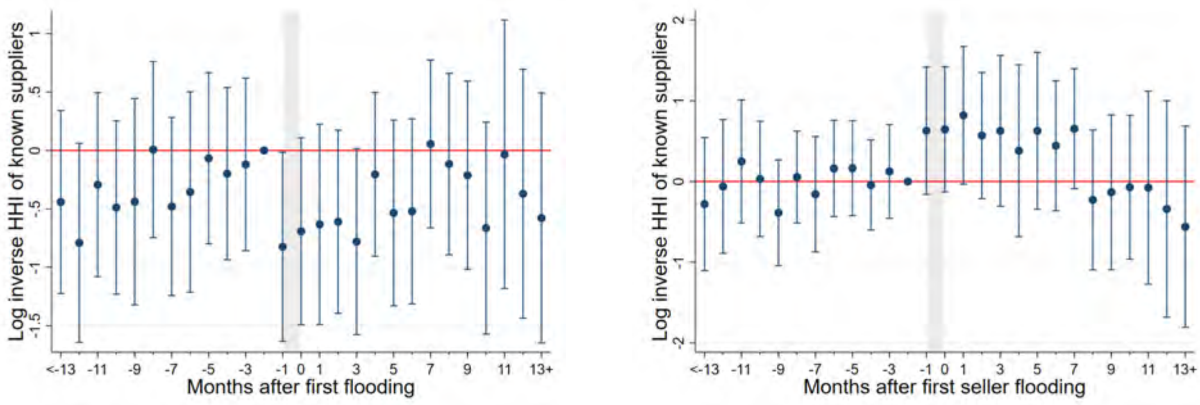
Notes: Columns (1) and (2) display logit estimates of the effect of flooding on a 10km-relocation indicator. Columns (3) and (4) report OLS estimates of the effect of flooding on moving firms' change in flood risk. Observations are firms fully geocoded in 2011 and 2019 for which the business register records a single address. The flood risk regressions only include firms which moved by >10km. Standard errors (in parentheses) are clustered at the district level. Average effect of mean (10%) flooded buffer refers to the average estimated effect for a firm experiencing the mean level of flooding among treated firms in the estimation sample (flooding of 10% of its 2km radius buffer). R^2 refers to McFadden's Pseudo R^2 for columns (1) and (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8. Impact of destination flood history on relocation flows (24- and 36-month treatment)

	Number of Firms Moved	
	(1)	(2)
Dest. flooded 24mo prior	-0.700	
	(0.480)	
Dest. flooded 36mo prior		-1.443**
		(0.657)
Origin × Destination FE	Yes	Yes
Origin × Flood Event (month) FE	Yes	Yes
Flood Event of Destination FE	Yes	Yes
Move Distance Restriction	>10km	>10km
N	1,539	1,539

Notes: The table reports Poisson pseudo-maximum-likelihood estimates of the effect of destination flood history on relocation flows. Standard errors (given in parentheses) are clustered at the origin-destination level. The sample is restricted to firms whose 2011 and 2019 locations are known and >10km apart. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.10. Supplier Diversification: Impact of flooding on suppliers' log inverse HHI



(a) Own flooding

(b) Supplier flooding

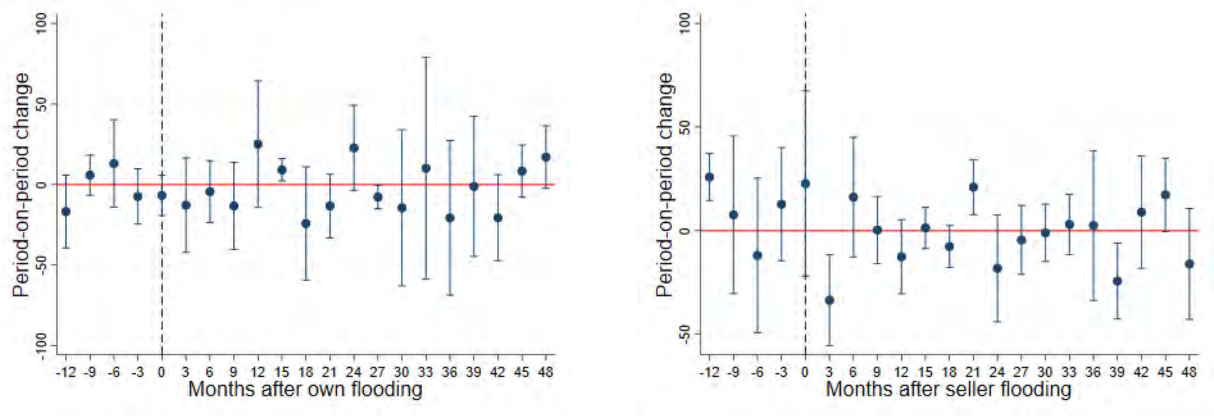
Notes: Panels (a) and (b) plot OLS estimates of the effect of own flooding and supplier flooding on the log inverse Herfindahl index of a buyer's suppliers in a given month following equations (6) and (7), respectively. Observations are firm-month-years whose 2011 and 2019 addresses are known and ≤ 10km 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.9. Impact of flooding on supplier flood risk: varying supplier flood threshold

	Δ Flood Risk of Suppliers Flooded by					
	$\leq$ 1%			$\leq$ 10%		
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	-9.034	-7.971	-11.66	-7.148	-6.724	-9.231
	(9.605)	(8.545)	(11.52)	(9.740)	(8.701)	(11.69)
Suppliers' max flood extent	-15.52*	-16.01*	-13.09	-48.47**	-50.29***	-50.65**
	(8.959)	(8.370)	(9.880)	(18.95)	(19.38)	(21.20)
Time × District FE	Yes			Yes		
Time × District × Risk decile FE		Yes			Yes	
Time × District × Industry FE			Yes			Yes
R^2	0.0093	0.0329	0.0588	0.0099	0.0311	0.0587
N	144,003	143,288	138,748	144,494	143,785	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%, or $\leq$ 10%. 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.11. Dynamic impact of supplier and own flooding on flood risk of $\leq$ 5% flooded suppliers



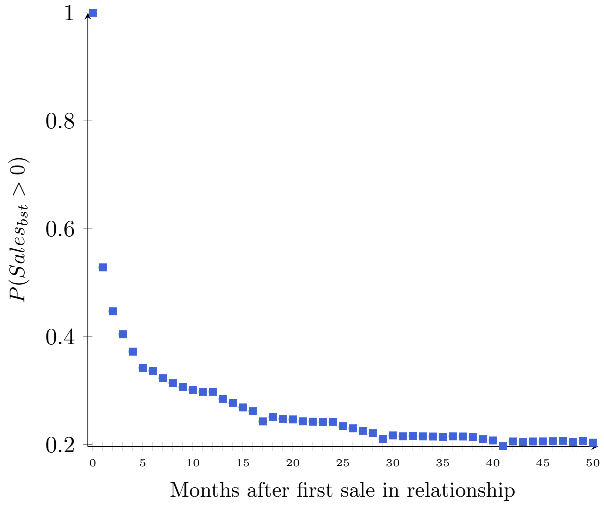
(a) Own flooding (b) Supplier flooding

Figure A.11 plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own 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:

$$\Delta y_{b(t^*+l)} = \beta_1 OwnFlood_{bt^*} + \beta_2 SellerFlood_{bt^*} + \alpha_{d(b)t^*} + \epsilon_{bt^*} \tag{23}$$

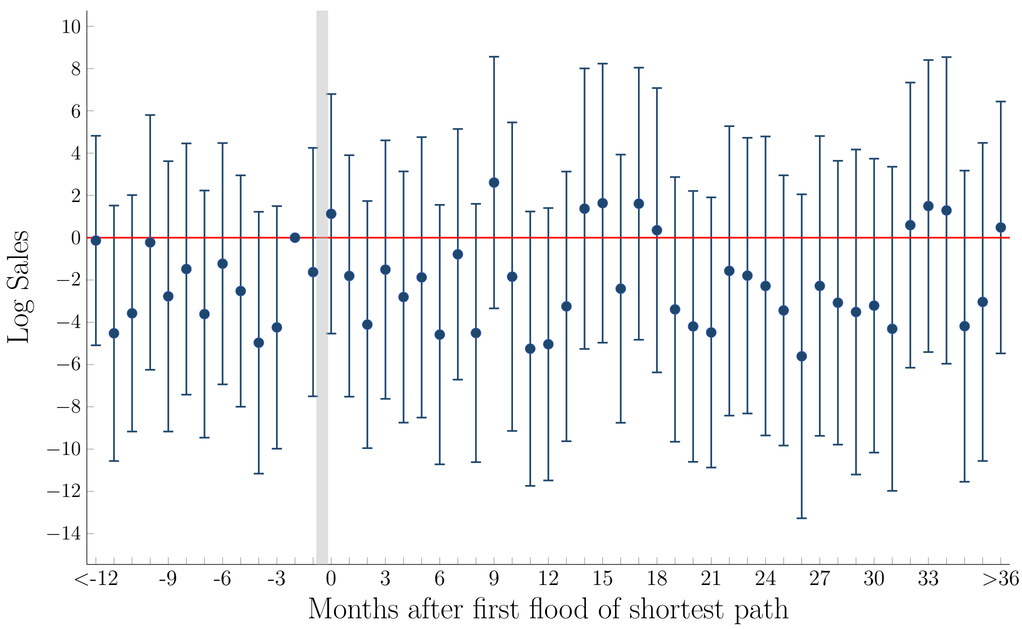
where t^* denotes the month-year of a flood event; $OwnFlood_{bt^*}$ is the maximum share of buyer b's 2km buffer that is flooded at t^*; $SellerFlood_{bt^*}$ is the maximal maximum share of the 2km buffer flooded at t^* across all sellers which account for $\geq$ 10% of b's purchases over the previous 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^*. We note that this allows both the buyer-flood-year-month sample and the set of suppliers entering the dependent variable to change across lags. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure A.12. Probability of having positive sales in the relationship, by month after first sale



Notes: 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.13. No impact of road flooding on intensive margin sales in buyer-seller relationship



Notes: 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.10. 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. Values are rounded to nearest percentage point.

Table A.11. Adaptation potential

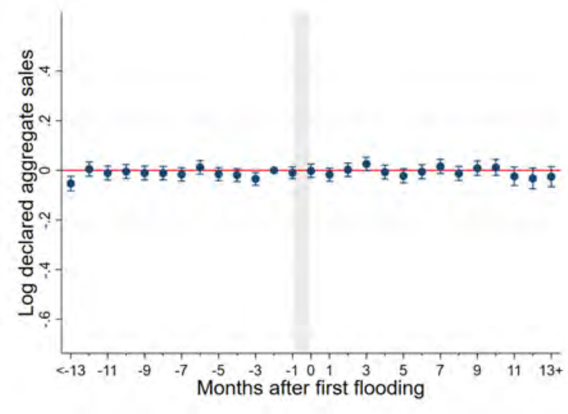
	Radius r, in km		
	25	50	100
Prob. that a non-flooded alternative supplier exists within r	97%	98%	99%
Prob. that a less flood-prone alternative supplier exists within r			
$< 1.0 \cdot \text{FloodRisk}_s$	92%	95%	97%
$< 0.9 \cdot \text{FloodRisk}_s$	90%	93%	95%
$< 0.8 \cdot \text{FloodRisk}_s$	86%	90%	93%
$< 0.7 \cdot \text{FloodRisk}_s$	79%	83%	86%
$< 0.6 \cdot \text{FloodRisk}_s$	63%	68%	70%
$< 0.5 \cdot \text{FloodRisk}_s$	51%	55%	58%
Prob. that a less flood-prone, larger alternative supplier exists within r			
$< 1.0 \cdot \text{FloodRisk}_s$	77%	80%	83%
$< 0.9 \cdot \text{FloodRisk}_s$	73%	77%	79%
$< 0.8 \cdot \text{FloodRisk}_s$	68%	72%	75%
$< 0.7 \cdot \text{FloodRisk}_s$	61%	64%	67%
$< 0.6 \cdot \text{FloodRisk}_s$	49%	52%	55%
$< 0.5 \cdot \text{FloodRisk}_s$	40%	42%	45%

Note: The sample consists of all firm-supplier-time combinations (b, s, t^*) where b has purchased from s within 12 months prior to t^* and s has a nonzero overlap of its 2km buffer with a flood polygon at t^*. 'Alternative supplier' denotes firms from the same two-digit industry as s. For each (b, s, t^*), we calculate probabilities that an alternative supplier exists within $r$km ($r \in \{25, 50, 100\}$) radius of b. 'Less flood-prone' is measured using the 1-in-100 year Fathom flood risk measure, using multiple thresholds relative to the flood risk of s. Firm size is measured by the total sales over the sample period.

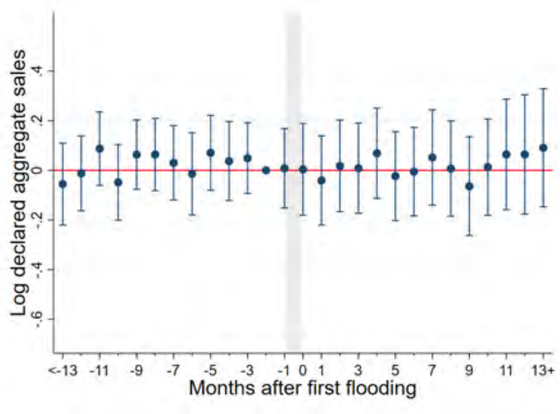
B Heterogeneity analysis

B.1 Flood severity

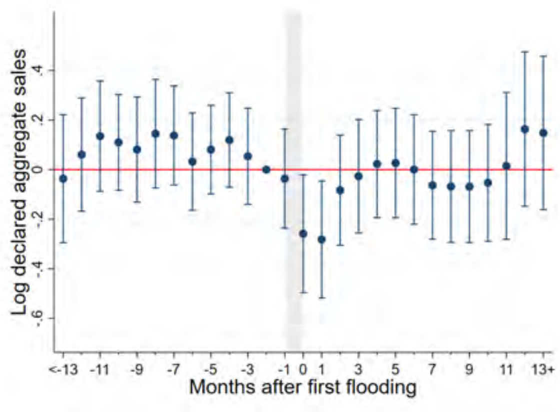
Figure B.1. Impact of binned own flooding on firm sales



(a) 0-5%



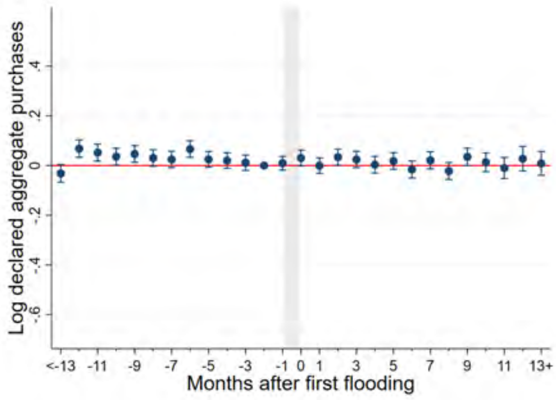
(b) 5-10%



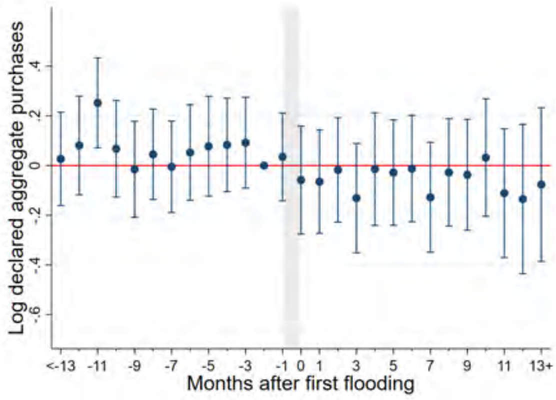
(c) >10%

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.

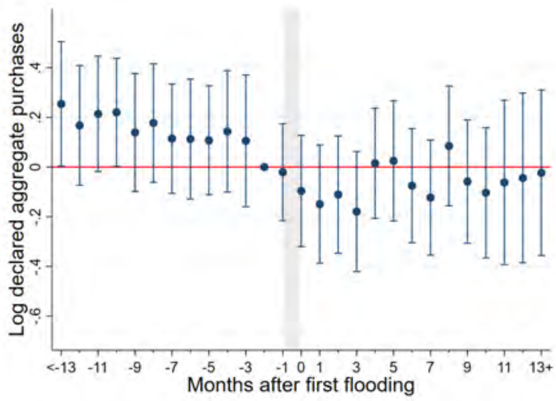
Figure B.2. Impact of binned own flooding on firm purchases



(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.

B.2 Firm size

Table B.1. By sales volume: Impact of flooding on firm relocation and location flood risk

	Move Dummy				Δ Flood Risk (cm)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max share of 2km buffer flooded	1.212*	3.171**	1.628**	6.666***	-93.18	-373.1*	16.74	-154.4
	(0.697)	(1.478)	(0.688)	(1.824)	(61.44)	(198.5)	(28.22)	(174.5)
Sales sample	High	Low	High	Low	High	Low	High	Low
District FE	Yes	Yes			Yes	Yes		
District × Fathom 1 in 100 FE			Yes	Yes			Yes	Yes
R^2	0.045	0.052	0.070	0.082	0.159	0.161	0.498	0.513
N	14,542	14,518	14,185	13,932	1,897	1,887	1,769	1,781

Notes: Columns (1) through (4) display logit estimates of the effect of flooding on a 10km-relocation indicator following equation (3). Columns (5) through (8) 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 with average yearly declared sales in the upper (High) or lower (Low) tercile. 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) through (4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2. By sales volume: Impact of supplier flooding on flood risk of all suppliers

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	-17.70	2.284	-16.51	-9.322	-22.87*	-11.21
	(12.51)	(10.46)	(11.24)	(12.82)	(13.47)	(21.02)
Suppliers' max flood extent	-42.28***	-149.0**	-43.49***	-163.8**	-52.63***	-160.8**
	(9.682)	(70.98)	(9.357)	(77.77)	(9.427)	(78.39)
Sales sample	High	Low	High	Low	High	Low
Time × District FE	Yes	Yes				
Time × District × Risk decile FE			Yes	Yes		
Time × District × Industry FE					Yes	Yes
R^2	0.0275	0.0219	0.0675	0.0563	0.1058	0.0969
N	59,071	36,500	58,352	35,919	55,465	33,978

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 all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart with average yearly declared sales in the upper (High) or lower (Low) tercile. Standard errors (in parentheses) are clustered at the time × district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3. By sales volume: Impact of supplier flooding on flood risk of ≤5% flooded suppliers

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	-19.81	-9.075	-16.52	-7.823	-22.41*	-17.22
	(12.99)	(9.925)	(11.32)	(10.69)	(13.53)	(21.45)
Suppliers' max flood extent	-17.93*	-44.77	-19.81**	-44.46	-18.98**	-42.85
	(10.02)	(31.98)	(9.413)	(32.69)	(8.590)	(30.70)
Sales sample	High	Low	High	Low	High	Low
Time × District FE	Yes	Yes				
Time × District × Risk decile FE			Yes	Yes		
Time × District × Industry FE					Yes	Yes
R^2	0.0249	0.0163	0.0679	0.0516	0.1057	0.0921
N	59,012	36,450	58,290	35,870	55,411	33,930

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 that are not flooded (defined as ≤ 5% overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart with average yearly declared sales in the upper (High) or lower (Low) tercile. Standard errors (in parentheses) are clustered at the time × district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Single vs. multiple branches

Table B.4. By multiple branches: Impact of flooding on firm relocation and location flood risk

	Move Dummy				Δ Flood Risk (cm)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max share of 2km buffer flooded	2.373	1.559*	3.323	1.396*	-213.1**	-155.9**	-148.2**	-1.550
	(1.771)	(0.938)	(2.419)	(0.754)	(94.74)	(77.43)	(71.43)	(36.92)
Branch sample	Multiple	Single	Multiple	Single	Multiple	Single	Multiple	Single
District FE	Yes	Yes			Yes	Yes		
District × Fathom 1 in 100 FE			Yes	Yes			Yes	Yes
R^2	0.037	0.054	0.064	0.080	0.252	0.137	0.523	0.486
N	5,523	29,918	5,225	29,386	1,015	3,673	933	3,547

Notes: Columns (1) through (4) display logit estimates of the effect of flooding on a 10km-relocation indicator following equation (3). Columns (5) through (8) 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, which the business register indicates have a branch (Multiple) or have no branch (Single). 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) through (4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5. By multiple branches: Impact of supplier flooding on flood risk of all suppliers

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	35.42*	-12.21	-2.393	-14.11	31.49	-12.79
	(18.96)	(10.35)	(19.17)	(9.774)	(31.62)	(11.71)
Suppliers' max flood extent	-54.01***	-66.38***	-56.45***	-67.21***	-71.33***	-77.40***
	(13.23)	(19.66)	(14.65)	(20.25)	(13.12)	(22.25)
Branch sample	Multiple	Single	Multiple	Single	Multiple	Single
Time × District FE	Yes	Yes				
Time × District × Risk decile FE			Yes	Yes		
Time × District × Industry FE					Yes	Yes
R^2	0.0267	0.0139	0.0673	0.0384	0.1139	0.0714
N	19,195	107,709	18,688	106,955	16,988	103,491

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 all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart and which the business register indicates have a branch (Multiple) or have no branch (Single). Standard errors (in parentheses) are clustered at the time × district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6. By multiple branches: Impact of supplier flooding on flood risk of ≤5% flooded suppliers

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	18.22	-14.78	-19.30	-13.13	2.200	-14.91
	(13.33)	(10.15)	(15.50)	(8.569)	(14.31)	(10.16)
Suppliers' max flood extent	-21.59**	-30.10**	-15.65*	-29.97***	-13.54	-28.73***
	(8.884)	(12.41)	(8.406)	(11.48)	(8.623)	(10.60)
Branch sample	Multiple	Single	Multiple	Single	Multiple	Single
Time × District FE	Yes	Yes				
Time × District × Risk decile FE			Yes	Yes		
Time × District × Industry FE					Yes	Yes
R^2	0.0295	0.0114	0.0727	0.0380	0.1131	0.0690
N	19,177	107,599	18,667	106,844	16,977	103,376

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 that are not flooded (defined as $\leq$ 5% overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart and which the business register indicates have a branch (Multiple) or have no branch (Single). Standard errors (in parentheses) are clustered at the time × district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.4 Input specificity

Table B.7. By input specificity: Impact of flooding on firm relocation and location flood risk

	Move Dummy				Δ Flood Risk (cm)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max share of 2km buffer flooded	1.306	2.166***	2.725	2.951***	-354.0**	-110.5*	-58.22	7.965
	(1.444)	(0.782)	(1.707)	(0.960)	(145.5)	(57.86)	(74.83)	(32.86)
Input specificity	High	Low	High	Low	High	Low	High	Low
District FE	Yes	Yes			Yes	Yes		
District × Fathom 1 in 100 FE			Yes	Yes			Yes	Yes
R^2	0.051	0.046	0.081	0.075	0.204	0.153	0.509	0.501
N	13,306	13,317	12,853	12,909	1,792	1,830	1,681	1,711

Notes: Columns (1) through (4) display logit estimates of the effect of flooding on a 10km-relocation indicator following equation (3). Columns (5) through (8) 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 with input specificity in the upper (High) or lower (Low) tercile. 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) through (4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.8. By input specificity: Impact of supplier flooding on flood risk of all suppliers

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	18.75*	-9.873	24.99*	-17.38	25.94*	-15.63
	(10.58)	(14.96)	(12.96)	(13.22)	(15.01)	(14.89)
Suppliers' max flood extent	-117.0***	-37.93***	-114.6***	-42.53***	-103.6***	-61.19***
	(29.90)	(11.78)	(30.57)	(11.67)	(27.98)	(13.80)
Input specificity	Specific	Unspec	Specific	Unspec	Specific	Unspec
Time × District FE	Yes	Yes				
Time × District × Risk decile FE			Yes	Yes		
Time × District × Industry FE					Yes	Yes
R^2	0.0177	0.0266	0.0529	0.0665	0.1076	0.1078
N	38,616	53,066	38,002	52,192	36,038	49,600

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 all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart with input specificities in the upper (Specific) or lower (Unspec) tercile. Standard errors (in parentheses) are clustered at the time × district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.9. By input specificity: Impact of supplier flooding on flood risk of $\leq$5% flooded suppliers

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	12.38	-13.38	16.55	-19.71	21.59	-18.76
	(10.89)	(13.58)	(13.54)	(12.64)	(15.66)	(12.88)
Suppliers' max flood extent	-48.26**	-8.491	-45.24**	-12.22*	-34.21**	-13.62**
	(20.85)	(6.861)	(20.11)	(6.437)	(16.25)	(6.932)
Input specificity	Specific	Unspec	Specific	Unspec	Specific	Unspec
Time × District FE	Yes	Yes				
Time × District × Risk decile FE			Yes	Yes		
Time × District × Industry FE					Yes	Yes
R^2	0.0164	0.0251	0.0517	0.0654	0.1042	0.1076
N	38,594	53,004	37,980	52,124	36,016	49,542

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 that are not flooded (defined as $\leq$ 5% overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart with input specificities in the upper (Specific) or lower (Unspec) tercile. Standard errors (in parentheses) are clustered at the time × district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.5 Impact of supplier flooding on share of purchases from new suppliers

Table B.10. Impact of supplier flooding on share of purchases from all first-time suppliers

	Δ Share of New Supplier Purchases		
	(1)	(2)	(3)
Own max flood extent	0.0755	0.0157	0.160***
	(0.0752)	(0.0925)	(0.0541)
Suppliers' max flood extent	0.308***	0.297***	0.271**
	(0.110)	(0.111)	(0.121)
Average effect of mean flooded supplier buffer	0.005	0.004	0.004
Average effect of 10% flooded supplier buffer	0.031	0.030	0.027
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.5128	0.5186	0.5373
N	144,566	143,857	139,302

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in purchase shares from new suppliers among all 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.11. Impact of supplier flooding on share of purchases from < 5% flooded first-time suppliers

	Δ Share of New Supplier Purchases		
	(1)	(2)	(3)
Own max flood extent	0.0817	0.0327	0.155***
	(0.0763)	(0.0935)	(0.0553)
Suppliers' max flood extent	0.435***	0.432***	0.416***
	(0.0997)	(0.101)	(0.107)
Average effect of mean flooded supplier buffer in cm	0.006	0.006	0.006
Average effect of 10% flooded supplier buffer in cm	0.044	0.043	0.042
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.5130	0.5188	0.5374
N	144,423	143,714	139,164

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in purchase shares from new suppliers among suppliers that are not flooded (defined as $\leq$ 5% overlap of the 2km buffer and the flood polygon) . 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.6 Impact of supplier flooding on share of purchases from multi-branch suppliers

Table B.12. Impact of supplier flooding on share of all multiple-plants suppliers

	Δ Share of Multibranch Supplier		
	(1)	(2)	(3)
Own max flood extent	0.112	0.115	0.162*
	(0.0797)	(0.0768)	(0.0874)
Suppliers' max flood extent	0.0528	0.0352	0.0634
	(0.0770)	(0.0784)	(0.0858)
Average effect of mean flooded supplier buffer	0.001	0.001	0.001
Average effect of 10% flooded supplier buffer	0.005	0.004	0.006
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0042	0.0166	0.0449
N	130,152	129,454	125,370

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in the share of purchases from multi-branch suppliers among all 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

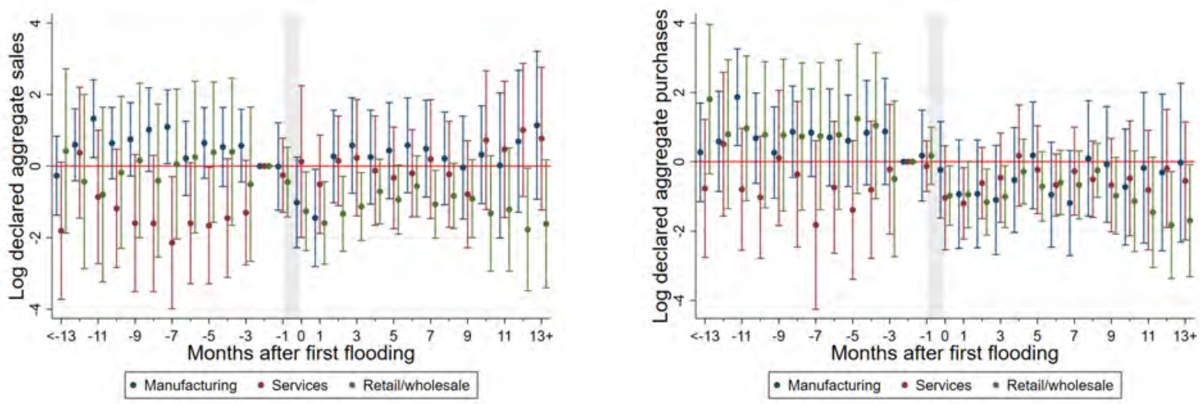
Table B.13. Impact of supplier flooding on share of < 5% flooded, multiple-plants suppliers

	Δ Share of Multibranch Supplier		
	(1)	(2)	(3)
Own max flood extent	0.0980	0.104	0.143*
	(0.0776)	(0.0757)	(0.0815)
Suppliers' max flood extent	0.130**	0.133**	0.157***
	(0.0545)	(0.0523)	(0.0605)
Average effect of mean flooded supplier buffer in cm	0.002	0.002	0.002
Average effect of 10% flooded supplier buffer in cm	0.013	0.013	0.016
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE		Yes	
Time $\times$ District $\times$ Industry FE			Yes
R^2	0.0044	0.0169	0.0449
N	130,044	129,347	125,266

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in the share of purchases from multi-branch suppliers among all suppliers that are not flooded (defined as $\leq$ 5% overlap of the 2km buffer and the flood polygon) . 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 $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.7 By sector and industry

Figure B.3. By sector: 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 in the indicated sector. The 95% confidence intervals rely on standard errors clustered at the firm-level.

C Data Appendix

C.1 Firm transaction data

The firm transactions data are described in Section 2.1. Here we describe additional cleaning steps for this dataset.

We drop all observations where the transactions value `trvat` is exactly `99999999999999` or 10^{14}, as they are likely invalid, as well as firms with invalid registration number and/or tax identifiers (e.g., invalid format, lengths, `"99999"`). In the firm-pair panel that captures monthly sales from a seller firm to a buyer firm, we drop all transactions that occur within a firm (where the buyer and the seller firm are the same).

The raw data files sometimes feature multiple transactions of the same reporting party (buyers or sellers) that have the exact same PKR transaction value ("duplicates"). The frequency of such duplicates increases sharply in November 2014. We implement the following procedure to deal with duplicates. Denoting Seller (S) and Buyer (B):

1. Drop S-only-reported transactions $T = (b, s, x, t)$ that satisfy the following condition: there exists another transaction (to the same buyer b, at time t, but from a different firm s') that has the same seller-reported transaction value x, and this relationship is also reported by the buyer b (possibly with a different reported transaction value).

2. Drop S-only-reported transactions $T = (b, s, x, t)$ that satisfy the following condition: there exists another transaction (to the same buyer b, at time t, but from a different firm s') that is B- and S-reported and has the same buyer-reported transaction value x (possibly with a different seller-reported transaction value).

These first two steps take out S-only-reported observations where one of the duplicates is trustworthy in the sense that it is reported by both buyer and seller. The remaining duplicates are those where we do not have such a duplicate that is clearly preferable:

3. For each firm, calculate the fraction f of its S-only-reported sales transactions that are B-duplicates (over the course of its whole life). Drop all S-only-reported B-duplicates transactions of firms that have this fraction above 90% and report more than five S-only-reported sales transactions and are before November 2014.

4. Drop all S-only-reported B-duplicates transactions $T = (b, s, x, t)$ where b and s never report any transactions that are confirmed by both parties.

After this step, there is no remaining discernible break in November 2014.

C.2 Firm addresses

Firm address information was obtained from multiple lists from the Federal Bureau of Revenue, including the Pakistan Active Taxpayer Portal and Business Register.[35]

Duplicate identifier–address pairs or empty addresses were dropped. When duplicate firms with multiple identifiers had different addresses, both were kept. The variable "address_type" was used

[35] Portal link: https://e.fbr.gov.pk/esbn/Service.aspx?PID=YAkaq8jRWzAjzvb3k8criw==

to differentiate address types and branch numbers, single-field sources are "business" address by default. For sources with multiple address fields, the additional fields often contained leftover strings, outdated addresses, or status notes. Irrelevant entries were cleaned and supplemental address fields were concatenated if they were shorter than 30 characters (95th percentile of address string length) since these were found to contain continuations of the main address field. Longer entries were retained as separate addresses for geocoding.

The resulting dataset is in long form, with multiple possible addresses per firm. Using the list of cities/municipalities and alternative Urdu romanization, obtained by aggregating municipality data from public sources[36], we performed a fuzzy string match on the address strings for the city names, before merging in the corresponding city geocodes for the string's highest match score. We allow up to seven city or alternative-name matches per address string and, after geocoding, select the city closest to the firm's geocode. This procedure identified cities for 90% of addresses.

A first round of geocoding firm addresses was conducted in 2019 on a partial set of addresses. Once additional addresses were obtained, a second round of geocoding was conducted for all addresses in 2021. Both rounds used Google Maps API, although the results are not necessarily identical due to differences in string cleaning procedures and changes to the Google Maps API. We use geocodes from both rounds, prioritizing 2019 geocodes since these were manually verified, and using 2021 geocodes if 2019 geocodes are not available or valid. 2019 geocoding was conducted in Excel.[37] 2021 geocoding was conducted in Python by directly querying the Google Maps API.[38]

After obtaining geocoding results, we drop geocodes outside of Pakistan and geocodes whose province does not match the province in the address strings. We then identify a set of plausible municipalities/cities from the address strings and drop geocodes that are more than 25km from any of these. Lastly, we prioritize 2019 geocodes over 2021 geocodes and prioritize the address sources by completeness and trustworthiness.

C.3 Flood data

Flooding data in Pakistan was obtained from UNOSAT over the period 2010-2019, as described in Section 2.3.[39] UNOSAT flood data have been used in a number of papers assessing flooding in Pakistan and assessed to be generally accurate in representing flood extents.[40] These studies note that, although the UNOSAT data include shortcomings such as 1) uncertainty due to cloud interception, 2) potential failures to capture peak inundation, and 3) overestimation of maximal flood extent, the data are generally reliable. The UNOSAT data capture the most severe flood events in Pakistan, as measured by the number of deaths and displacements reported in other sources. For instance, compared to the EM-DAT natural disaster database (EM-DAT, 2022), the UNOSAT data excludes 10 floods over 2010-2015, most of which are flash floods or relatively minor in terms of casualties; all flood events associated with over 100 deaths and 25,000 displacements are captured. The geographic coverage of

[36]For cities, we use the list obtained from LatitudeLongitude.org (`https://latitudelongitude.org/pk/`) and for tehsils (sub-district units), we use the OCHA administrative map of Pakistan (`https://data.humdata.org/dataset/cod-ab-pak`).

[37]This procedure can no longer be implemented efficiently for large queries due to restrictions in the Google Maps API, but a guide can be found here: `https://www.adventuresincre.com/auto-populate-latitude-longitude-excel/`.

[38]More details about the Google Maps API can be found here: `https://developers.google.com/maps/documentation/geocoding/overview`.

[39]The last flood event observed during our study period is in 2015, reflecting the fact that UNOSAT did not receive a request for their service in the years 2016, 2017, 2018 or 2019.

[40]For example, see Sayama et al. (2012), Jilani et al. (2007), Ushiyama et al. (2014), as well as analyses for popular reporting in the New York Times (Burgess and Tse, 2010; Gall, 2010).

the UNOSAT data appears best in the heavily-populated provinces of Punjab and Sindh, and worst in northern areas.

C.4 Flood risk data

Flood risk data from Fathom-Global (Fathom-Global, 2022) are described in Section 2.4. The raw raster values represent the expected depth in meters of flooding for the return period of the specific flood type. We treat missing cells (raw value -9999) as "0" in our raster, as suggested by FATHOM staff, and treat base water cells (raw value 999) as empty cells ("NODATA").

We create a 2km radius buffer around each firm geocode and erase the baseline water layer to yield a "cropped buffer". We calculate the weighted average FATHOM depth index for each return period and cropped buffer using the formula below, where i is the centroid of the raster pixel for each return period:

$$\text{Firm flood risk} = \frac{\sum_{i \in cropped\_buffer} Depth_i}{N_{i \in cropped\_buffer}}$$

C.5 Constructing the aggregated cell panel

For the purpose of model estimation, we construct a panel that aggregates firms into "cells" by district and supplier flood exposure status (for each flood year of our study period). These cells encompass the geographic distribution of Pakistan, and are grouped such that every cell has at least one firm. We calculate an aggregate cell-level flood risk as the average Fathom flood risk across all firms in a given cell. We aggregate transaction flows between cells in the 6 months before, 6 months immediately after, and from 6 to 12 months after each flood event. We additionally calculate cell-level measures of flood incidence capturing flood extent and the share of flooded firms.

C.6 GPS tracker data from commercial trucks

Data from GPS trackers installed in commercial trucks is described in Section 2.2. Here we described additional steps in data preparation and cleaning.

C.6.1 Constructing road network graph from shapefile

OpenStreetMap data on Pakistan's road network was retrieved from HotOSM, and cropped to Pakistan's country outline shapefile from GADM.[41]

Vertices are defined as the endpoints of roads and the intersections of roads. The endpoints are defined as the starting coordinates and the ending coordinates. In our implementation, intersections of two roads can be `Point` or `MultiPoint`. Roads are divided at vertices into smaller segments which we call edges. For each vertex pair, we check if there is an edge between them. If there is no edge between them, they are classified as not adjacent. If there is exactly one edge between them, they are classified as adjacent vertices, and the distance between them is the length of the edge. If there is more than one edge, we select the shortest edge as the connecting edge, and the distance between this vertex pair is the length of the connecting edge. We adopt Dijkstra's algorithm with Fibonacci heaps to solve this directed shortest path problem.

[41] Pakistan GADM shapefile access link: https://biogeo.ucdavis.edu/data/gadm3.6/shp/gadm36_PAK_shp.zip

C.6.2 Cleaning GPS tracker data

Deduplicate truck id

In the raw GPS data, the field `Masterid` and `Vehicle_Number` gives us information about truck identifiers. If we use the Cartesian product of these two variables as a truck id, there appears to be some duplication (i.e. two truck ids reporting the same pings all the time). At the same time, we want to avoid removing pings that accidentally coincide in time and location because of the precision of tracking devices.

We find all truck id pairs (denoted A and B) that have duplicates and count the number of duplicates ($|A \bigcap B|$). We then count the total number of pings for each truck id in the pair ($|A|$ and $|B|$).

- When $|A| > |A \bigcap B| < |B|$, we mark A and B as NOT duplicates.
- When $|A| \approx |A \bigcap B| < |B|$, all of A's pings are covered by B's. We mark A as the duplicate that needs to be removed (and vice versa).
- When $|A| \approx |A \bigcap B| \approx |B|$, meaning that A and B perfectly duplicate each other, we mark either one of A or B as a duplicate that needs to be removed.
- $|A| \approx |A \bigcap B|$ or $|A \bigcap B| \approx |A|$ is defined as True when

  $$99\%|A| \leq |A \bigcap B| \leq 100\%|A|$$

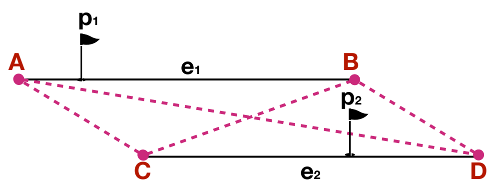
  is satisfied and False otherwise.

We remove all pings associated with truck ids marked as duplicates.

Compute the ping-pair distance

We project the GPS tracker signals ("pings") onto our edges, discarding all pings that are more than 10 meters away from the nearest edge. For each ping, we find the previous ping, and transform our data set from the ping level to the consecutive ping-pair level. For each observation, we denote the first ping as p_1 and the second ping as p_2. We denote the edge that the p_1 is projected onto as e_1, and the edge that p_2 is projected onto as e_2.

Case 1: $e_1 \neq e_2$



Projected onto different edges

When both e_1 and e_2 are twoway, we define the shortest path on the graph as:[42]

$$|p_1 p_2| := \min\{p_1ACp_2, p_1ADp_2, p_1BCp_2, p_1BDp_2\}$$

[42] We denote the shortest path on the graph between p_1 and p_2 as $|p_1p_2|$. In more precise notation, $\min\{X\}$ here can be considered as $\text{argmin}_{x\in X}\text{length}(x)$.

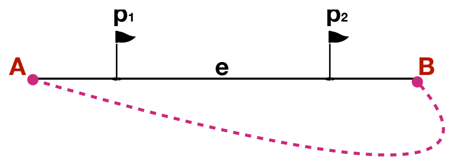
When e_1 is oneway (e.g. $\overrightarrow{AB}$), we define the shortest path as:

$$|p_1p_2| := \min\{p_1BCp_2, p_1BDp_2\}$$

The definition is similar when e_2 is oneway or the direction is different. When both edges are oneway, the shortest path is the only path between p_1 and p_2. For example, when e_1's direction is $\overrightarrow{AB}$ and e_2's direction is $\overrightarrow{CD}$:

$$|p_1p_2| := p_1BCp_2$$

Case 2: $e_1 \equiv e_2$



Projected onto the same edge

When e is twoway:

$$|p_1p_2| := \min\{p_1p_2, p_1ABp_2\}$$

When e is oneway and the direction is $\overrightarrow{AB}$:

$$|p_1p_2| := p_1p_2$$

When the direction is $\overrightarrow{AB}$:

$$|p_1p_2| := p_1ABp_2$$

Detecting possible errors

Since the GPS data contains noise in the location information, pings may be projected onto the wrong road, or the wrong side of a multi-lane road. This can result in (i) the computed shortest path being very long, creating a handful of outliers, and (ii) the computed shortest paths traversing edges that they shouldn't. Euclidean distance is likely a better proxy for true distance in such situations. We mark observations that satisfy:

$$\text{Computed shortest distance} > 3 \times \text{Euclidean distance}$$

as ping-pairs with a possibly erroneous projection, and in these cases replace the computed shortest distance with the Euclidean distance.

Disaggregating into edges

For each consecutive ping-pair, we find the shortest distance and the edges traversed. For a consecutive ping-pair that spans multiple edges, we weight edges using the ratio of the distance traversed on that edge out of the total distance; this assumes that the truck drove at a constant speed between ping-pairs. For a handful of ping-pairs that could be erroneous, we assign only to the edges that the pings are projected onto, assigning equal weight to each.

Aggregating on the edge × day × truck level

We define the midpoint of the `Recorddatetime` of a consecutive ping-pair as the representative timestamp for this ping-pair. We obtain the date information from the timestamp. All consecutive ping-pairs (denoted as i) are linked to three key categorical variables: `edge`, `truck_id`, and `date_`. For each edge × day × truck group G, we define the speed of G as:

$$\text{computed speed}_G = \frac{\sum_{i \in G} \text{Computed shortest distance}_i}{\sum_{i \in G} \text{Time elapsed}_i}$$

We also define the reported speed on edge × day × truck as:

$$\text{reported speed}_G = \frac{\sum_{i \in G} \text{reported speed}_i * \text{Time elapsed}_i}{\sum_{i \in G} \text{Time elapsed}_i}$$

Fill missing counts

In order to distinguish missing day-truck counts for an edge-time driven by "no trucks" versus poor data coverage during certain periods, we set a lower coverage limit to identify "invalid" time windows. Based on a coverage histogram where each observation is the ratio of valid edges in a year-week, we choose a cutoff value of 0.5, and discard year-weeks below this. We fill with zeros missing counts of edges that appear at least once in the dataset of that year.

C.6.3 Buyer-seller-week level route disruption and floods

Flood-disruption variable

We start from the event study dataset at the edge-week level. We construct three edge-week level variables named pctx_flood_disrupted where x $\in \{1, 3, 5\}$

$$\text{pctn\_flood\_disrupted}_{it} = \begin{cases} 1 & \text{if nth\_pct\_disrupted}_{it} = 1 \text{ and FloodedRatio}_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

Data on buyer-seller-week level

To construct graphs that enable us to compute the least time (rather than distance) route, we update edge weights based on travel time between two vertices. The initial graph is g_0. We are interested in graphs during the non-flooded year-weeks and flooded year-weeks.[43] For non-flooded year-weeks, for an edge i, we take the average speed of i through all year-weeks where no flood is recorded in any part of Pakistan. For flooded year-week t', we select the speed on edge i during year-week t' as the speed used to construct the graph. We obtained 12 sets of speed (non-flooded speed, the speed in 2012-37, 2012-38, 2012-39, 2013-33, 2013-34, 2013-35, 2014-37, 2014-38, 2015-31, 2014-32, 2014-33), which correspond to 12 graphs indexed by g.

We exclude edges that are stationary (i.e. have a speed of zero). They are treated the same as edges that never appear in the corresponding time window or are not valid: the two vertices they

[43] Though no satellite picture of flooding in week 2015-32 is recorded, it is considered flooded because 2015-31 and 2015-33 are all flooded.

connect are considered disconnected.

We update the graph weights for the 12 new graphs:[44]

$$\text{weight}(i; g) = \frac{\text{length}(i)}{\text{speed}(i; g)} = \frac{\text{weight}(i; g_0)}{\text{speed}(i; g)} \tag{25}$$

To solve all g, we obtained the lowest travel time between any vertex-pair. Using a similar method to that used to compute the shortest route between pings, we compute the least time route between a buyer-seller pair p for each g, and the ratio $w_{i,p}$ that each edge i in the path contributed to the total length of the path. Denote the total number of buyer-seller pair as P, and total number of edges I.[45] We can write this data as a vector of I-by-P matrices $\mathbf{A}_g$:

$$[\mathbf{A}_g]_{g\in G} = [\mathbf{A}_{\text{non-flooded}} \quad \mathbf{A}_{\text{2012-37}} \quad \cdots \quad \mathbf{A}_{\text{2015-33}}]^T$$

where

$$\mathbf{A}_g = [w_{i,p}]_{i\in I, p\in P} \text{ with path } p \text{ evaluated in graph } g$$

and

$$w_{i,p} = \frac{\text{the distance covered on edge } i}{\text{total distance of path } p}$$

The data in the event study dataset can also be written as a vector of I-by-T matrix $\mathbf{B}_v$, where T is the total number of year-weeks, and $v \in V$ is some column of data (for example, flood_extent, pct1_disrupted, pct3_flood_disrupted):

$$[\mathbf{B}_v]_{v\in V} = \left[\mathbf{B}_{\text{flood\_extent}} \quad \mathbf{B}_{\text{pct1\_disrupted}} \quad \cdots \quad \mathbf{B}_{\text{pct5\_flood\_disrupted}}\right]^T$$

where

$$\mathbf{B}_v = [v_{i,t}]_{i\in I, t\in T}$$

The construction of route disruption and flood variables is essentially the outer product of $[\mathbf{A}_g]_{g\in G}$ and $[\mathbf{B}_v]_{v\in V}$

$$[\mathbf{A}_g]_{g\in G} [\mathbf{B}_v]_{v\in V}{}^T = \begin{bmatrix} \mathbf{A}_1^T\mathbf{B}_1 & \cdots & \mathbf{A}_1^T\mathbf{B}_V \\ \vdots & \ddots & \vdots \\ \mathbf{A}_G^T\mathbf{B}_1 & \cdots & \mathbf{A}_G^T\mathbf{B}_V \end{bmatrix} \quad \text{(PG-by-TV)}$$

where $\mathbf{A}_g^T\mathbf{B}_v$ is a P-by-T matrix. The element in the result defined by tuple (p,g,t,v) is the value of variable v at year-week t for the path p evaluated in the graph g. In the data frame we construct, each row corresponds to a buyer-seller-year-week (i.e. $p\times t$ level), and each column corresponds to a variable name and the graph that everything is evaluated under (i.e. $g\times v$ level). For graph g that is constructed out of the speed data of some year-week $t(g)$, we compute only elements $(p, g, t(g), v), g \in G$, and set elements $(p, g, T \setminus t(g), v), g \in G$ to missing. For a graph g that is constructed out of the mean speed of non-flooded year-weeks, we compute this for all $t \in T$.

Missing values arise due to the following reasons:

- Buyer and seller are not connected in the graph g. This is always accompanied by a lowest travel

[44] weight$(i; g)$ denotes the weight of edge i in graph g. speed$(i; g)$ denotes the speed of i that is assigned in the construction of g.

[45] In this section we use the uppercase letters P, I, T, G, V to denote the set or the number of elements in the set, and the lowercase p, i, t, g, v to denote the element or the index of the element.

time of `inf`. If all paths are connected, $\mathbf{A}^T\mathbf{1} = \mathbf{1}$, i.e. the contributions of each edge in the path sum up to one. For disconnected buyer-sellers, their corresponding column in $\mathbf{A}$ sums up to zero, which we flag with NaN.

- For the graph weighted by non-flooded speeds only, not all edges have a valid speed in all year-weeks. As a simple example, consider a case where, for week 1, the valid edges are edge a and edge b; for week 2, the valid edges are edge c and edge d; for week 3, the valid edges are edge a and edge d. A path consists of edge a and b. This path would have real data in week 1 and 3, but not week 2. In week 1, both edges are taken into consideration. In week 3, only edge a is considered, and is assigned full weight since b is absent.

D Theory Appendix

D.1 Proofs of results in the main text

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:*

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

where:

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

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

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

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[46]

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

to get

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

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

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

□

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 $\theta := \alpha/\zeta$. □

D.2 Adaptation potential

Section 5.4 considers the potential for a location n to maginally change its sourcing shares X_{ni}/X_n to reduce the variance of cost shocks in the wake of flood events without seeing changes in expected cost. We model this as an optimization problem where firms choose marginal changes in sourcing shares $\{d\log\left(X_{ni}/X_n\right)\}_{i\in I}$ subject to the constraint that sourcing shares have to add up to one. A location can marignally reduce the variance of cost shocks without increasing expected cost if and only if the

[46] Note that $c_j\xi_j$ does not depend on ξ_j, so X and Y are independent.

linear optimization problem

$$\min_{\left\{d\log\left(\frac{X_{ni}}{X_n}\right)\right\}_{i\in I}} \sum_i \frac{\partial Var_{\hat{b}}\left(\hat{\bar{c}}_n\left(\hat{b}\right)\right)}{\partial \log\left(X_{ni}/X_n\right)} d\log\left(\frac{X_{ni}}{X_n}\right) \tag{26}$$

$$\text{s.t.} \quad \sum_i \frac{\partial \log E_b\left(c\left(b,X\right)\right)}{\partial \log\left(X_{ni}/X_n\right)} d\log\left(X_{ni}/X_n\right) \leq 0 \tag{27}$$

$$\sum_i \frac{X_{ni}}{X_n} d\log\left(\frac{X_{ni}}{X_n}\right) = 0 \tag{28}$$

$$-1 \leq d\log\left(X_{ni}/X_n\right) \leq 1 \qquad \forall i \tag{29}$$

has a solution where the objective function value is negative. Equation (27) is the constraint that expected cost should not increase. Equation (28) is the constraint that sourcing shares should add up to 1. Equation (29) ensures that the solution of the optimization problem remains bounded.

In order to be able to solve this optimization problem, we need to make sure that the coefficients in the objective function and in equation (1) can be expressed in terms of observables (notably X_{ni}/X_n) and parameters that we calibrate (α, ζ, and the distribution of flood shocks $\mathcal{F}_b$).

Lemma 8. *The two expressions*

$$\frac{\partial Var_{\hat{b}}\left(\hat{\bar{c}}_n\left(\hat{b}\right)\right)}{\partial\left(X_{ni}/X_n\right)} \qquad \textit{and} \qquad \frac{\partial \log E_b\left(\bar{c}\left(b,X\right)\right)}{\partial \log\left(X_{ni}/X_n\right)}$$

can be expressed as functions of $\mathcal{F}_b$, α, ζ,and the matrix X_{ni}/X_n only.

Proof. We have that

$$\begin{aligned}
\frac{\partial Var_{\hat{b}}\left(\hat{\bar{c}}_n\left(\hat{b}\right)\right)}{\partial\left(X_{ni}/X_n\right)} &= 2\int \hat{\bar{c}}_n\left(\hat{b}\right) \frac{\partial \hat{\bar{c}}_n\left(\hat{b}\right)}{\partial\left(X_{ni}/X_n\right)} d\mathcal{F}_b(\hat{b}) - 2\left[\int \hat{\bar{c}}_n\left(\hat{b}\right) d\mathcal{F}_b(\hat{b})\right]\left[\int \frac{\partial \hat{\bar{c}}_n\left(\hat{b}\right)}{\partial\left(X_{ni}/X_n\right)} d\mathcal{F}_b(\hat{b})\right] \\
&= 2E_{\hat{b}}\left[\hat{\bar{c}}_n\left(\hat{b}\right) \frac{\partial \hat{\bar{c}}_n\left(\hat{b}\right)}{\partial\left(X_{ni}/X_n\right)}\right] - 2\left[E_{\hat{b}}\hat{\bar{c}}\left(\hat{b},X\right)\right] E_{\hat{b}}\left[\frac{\partial \hat{\bar{c}}_n\left(\hat{b}\right)}{\partial\left(X_{ni}/X_n\right)}\right]
\end{aligned}$$

All three expressions can be evaluated through Monte Carlo integration: for every flood draw $\hat{b} \sim \mathcal{F}_b$, calculating $\hat{\bar{c}}\left(\hat{b},X\right)$ requires solving equation (18) with $\hat{m}_{ni}=1$; the derivative can be evaluated by automatic differentiation.

$$\begin{aligned}
\frac{\partial \log E_b\left(\bar{c}\left(b,X\right)\right)}{\partial \log\left(X_{ni}/X_n\right)} &= \frac{\partial \log\left[\bar{c}\left(1,X\right)\int \hat{c}\left(\hat{b},X\right) d\mathcal{F}_b(b)\right]}{\partial \log\left(X_{ni}/X_n\right)} = \\
&= \frac{\partial \log \bar{c}\left(1,X\right)}{\partial \log\left(X_{ni}/X_n\right)} + \frac{X_{ni}}{X_n} \frac{\partial \log\left[E_{\hat{b}}\hat{\bar{c}}\left(\hat{b},X\right)\right]}{\partial\left(X_{ni}/X_n\right)} \\
&= \frac{\partial \log \bar{c}\left(1,X\right)}{\partial \log\left(X_{ni}/X_n\right)} + \frac{X_{ni}}{X_n} \frac{1}{E_{\hat{b}}\hat{\bar{c}}\left(\hat{b},X\right)} E_{\hat{b}}\left[\frac{\partial \hat{\bar{c}}\left(\hat{b},X\right)}{\partial\left(X_{ni}/X_n\right)}\right]
\end{aligned}$$

The two expectations in the second term were already calculated above. The first term we compute in a number of steps. From

$$(-\zeta)\log \bar{c}_n = \zeta \log\left(a_{n(j)}b_{n(j)}\right) - \zeta \log\left(w^{1-\alpha}\right) + \log\left(\sum_i m_{ni}\tau_{ni}^{-\zeta}\bar{c}_i^{-\zeta}\right)^{\alpha} + \log \Gamma\left(1-\frac{\alpha}{\beta}\right)$$

we take derivatives with respect to $\log m_{ni}$ to obtain

$$\left(\frac{\partial \log \bar{\mathbf{c}}}{\partial \log m_{ni}}\right) = \alpha\left[\mathbf{X}\right]\left(\frac{\partial \log \bar{\mathbf{c}}}{\partial \log m_{ni}}\right) - \left(\frac{\alpha}{\zeta}\right)\left(0,\ldots,\frac{X_{ni}}{X_n},\ldots,0\right)' \tag{30}$$

where $\partial \log \bar{\mathbf{c}}/\partial \log m_{ni}$ is a vector with j-th element $\partial \log \bar{c}_j/\partial \log m_{ni}$, $\mathbf{X}$ is the matrix with (n,i)-th element X_{ni}/X_n, and $\left(0,\ldots,\frac{X_{ni}}{X_n},\ldots,0\right)$ is a vector with only X_{ni}/X_n in the n-the element, and zeros otherwise. Equation (30) is a linear system of equations that can be solved for $\partial \log \bar{\mathbf{c}}/\partial \log m_{ni}$. This means we can solve also for

$$\frac{\partial \log \frac{X_{ni}}{X_n}}{\partial \log m_{ni}} = (-\zeta)\frac{\partial \log \bar{c}_i}{\partial \log m_{ni}} + \zeta \sum_{i'} \frac{X_{ni'}}{X_n}\frac{\partial \log \bar{c}_{i'}}{\partial \log m_{ni}} + 1 - \frac{X_{ni}}{X_n}$$

and hence together,

$$\frac{\partial \log \bar{c}_n}{\partial \log\left(X_{ni}/X_n\right)} = \frac{\frac{\partial \log \bar{c}_n}{\partial \log m_{ni}}}{\frac{\partial \log(X_{ni}/X_n)}{\partial \log m_{ni}}}.$$

□

E Parameterizing the joint distribution of flood shocks across locations

In order to use the model to evaluate the potential for adaptation in Section 5.4, we need to parameterize the joint distribution of flood shocks across locations. The Fathom flood risk data used elsewhere in the paper is not sufficient for this purpose as it only contains moments from the marginal distributions of flood risk in each location, and therefore does not provide information about correlations across locations. For this exercise, we therefore augment the Fathom flood risk data with additional data from the Global Flood Database[47] and EM-DAT (EM-DAT, 2022)[48], which report the centroid and total area of 51 historical floods in Pakistan dating back to 1979.[49]

We use this additional flood data and the following procedure to draw 10,000 potential future summer monsoon season realizations in Pakistan: (i) we draw the number of floods that hit in a given monsoon season from the empirical distribution of the number of floods per summer in the additional flood data; (ii) for each flood, we draw the flood centroid location from the distribution of expected flood depths under a 1 in 10 year flood in the Fathom data; (iii) for each flood, we draw an area from the empirical distribution of flood areas in the additional flood data; and (iv) we consider circles of increasing radii emanating from the centroid drawn in step (ii) until the intersection between the circle and areas of non-zero expected flood depth under a 1 in 10 year flood reaches the area drawn in step (iii). The resultant intersection yields the spatial extent of each simulated flood, and the flood depth in each of the pixels it contains.[50] To aggregate to the level of summer monsoon seasons, we take the union of all simulated floods in a given summer.

This procedure yields a distribution for the spatial extent and depth of flood shocks. We translate these into economic shocks using equation 19 that relates productivity shocks in each location to the average flood exposure of each firm's buffer in a location, together with the estimated value for η.

[47] https://global-flood-database.cloudtostreet.ai/

[48] https://www.emdat.be/

[49] We use data from the Global Flood Database for the full period for which this data is available (2003-2018), and data from EM-DAT for those flood events for which this database contains area estimates from 1979-2002.

[50] The shape of the modeled flood extent will therefore be similar to the shape of high flood risk areas in the Fathom data rather than circular extents.

F Robustness specifications

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

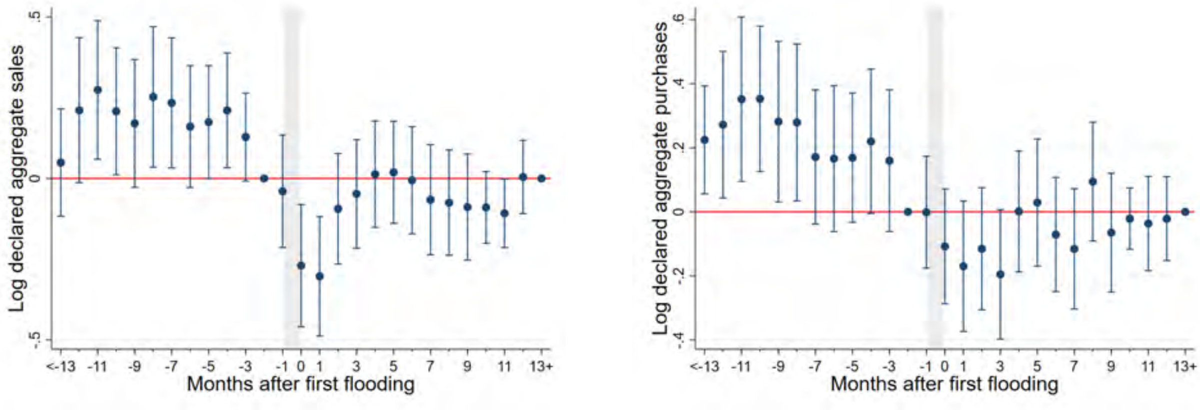
A recent literature has highlighted potential challenges with the use of two-way fixed effects regressions including treatment leads and lags, since variation in treatment timing may give rise to contamination of coefficients on lead or lag terms by effects from other periods (Callaway and Sant'Anna, 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. We do not use this estimator in the preferred specification in the main text since it relies on a binary treatment variable. In order to implement this estimator for robustness specifications, we construct a binary treatment variable as follows. Since Figure B.1 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%, and drop all firms with a treatment variable $\in (0\%, 10\%]$. We use never treated firms as the control cohort.

As an additional test, we present results separately by flood event, restricting 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 flood events lasting two months, we define event time relative to the first month of the event. This specification shuts down variation in treatment timing while using the standard continuous treatment variable, and allows us to explore heterogeneity across flood events. Since the panel begins in July 2011 and ends in June 2018, coefficients for earlier and later periods are omitted. One coefficient in each fiscal year is omitted in the sales, purchases, and log number of supplier regressions because the full set of treatment variables, the firm-fiscal-year fixed effects and the firm-month-of-the-year fixed effects are perfectly collinear when restricting to a single flood event. We include the number of treated firms, $N_{treated}$, with each specification below. These results show that negative impacts of flood events on sales and purchases are observed broadly across all of the flood events in the sample, with the exception of the 2013 flood. Heterogeneity in the impacts of each individual flood event reflects heterogeneity in the extent and location of flooding, as well as the overlap of flood polygons with firm locations.

Robustness analyses in this section are included only for those specifications estimated with two-way fixed effects models.

F.1.1 Impact of flooding on firm sales and purchases

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



(a) Log sales

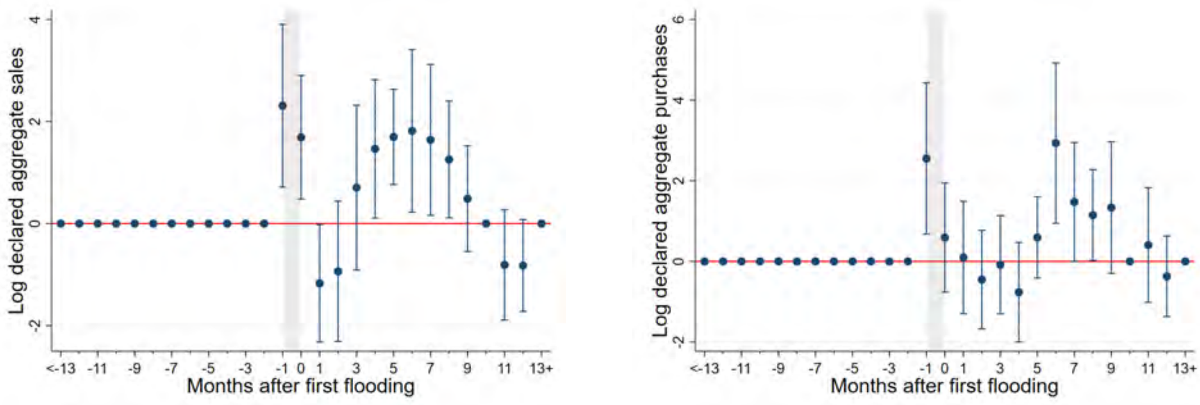
$N_{treated} = 705$

(b) Log purchases

$N_{treated} = 705$

Notes: The panels plot the effect of flooding on log declared sales and purchases. We use the method in 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 F.2. Impact of flooding on firm sales and purchases (Aug-Sep 2011)



(a) Log sales

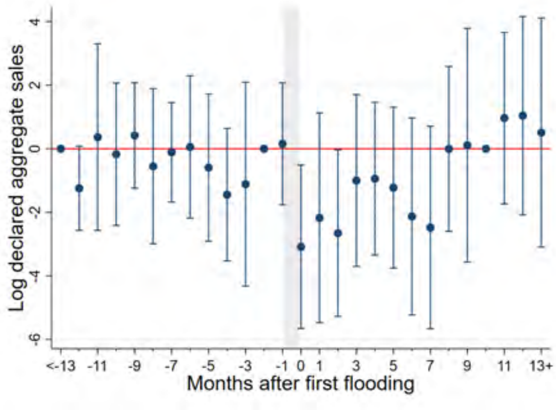
$N_{treated} = 1045$

(b) Log purchases

$N_{treated} = 1045$

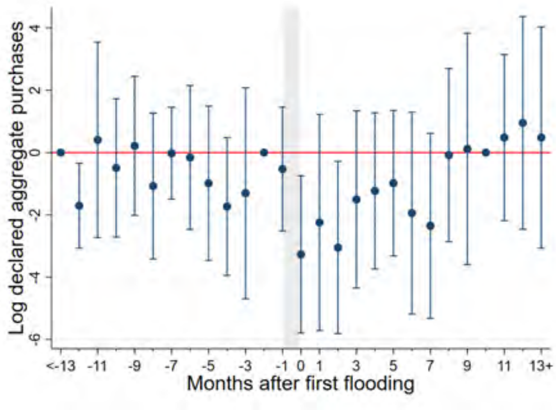
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Aug-Sep 2011 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

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



(a) Log sales

$N_{treated} = 42$

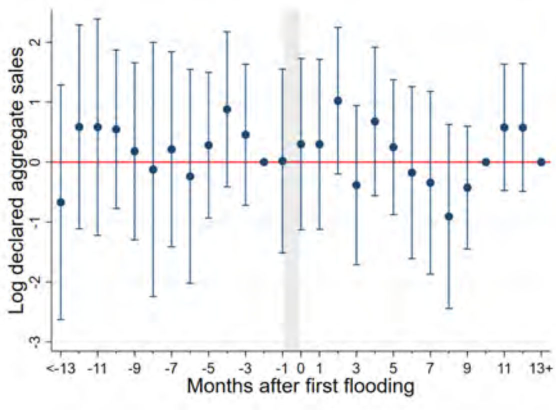


(b) Log purchases

$N_{treated} = 42$

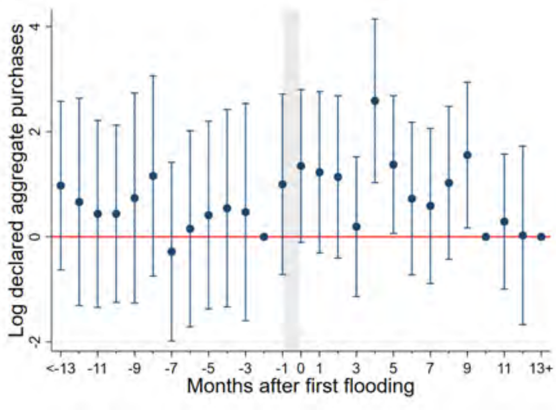
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Sep 2012 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

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



(a) Log sales

$N_{treated} = 3735$

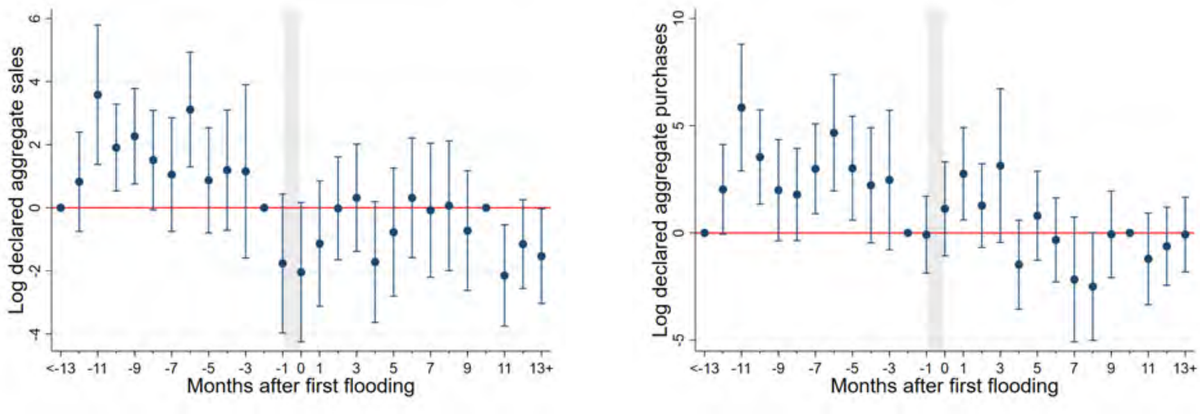


(b) Log purchases

$N_{treated} = 3735$

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



(a) Log sales

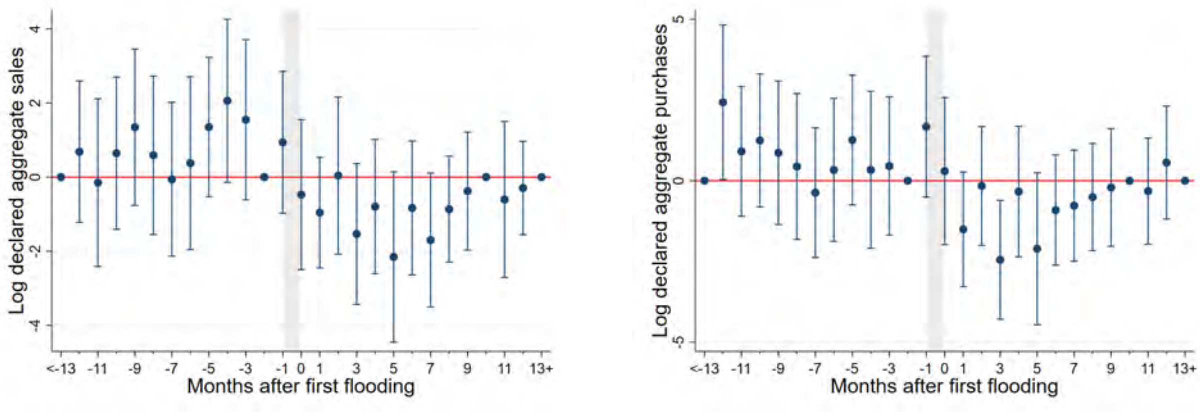
$N_{treated} = 8214$

(b) Log purchases

$N_{treated} = 8214$

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



(a) Log sales

$N_{treated} = 9768$

(b) Log purchases

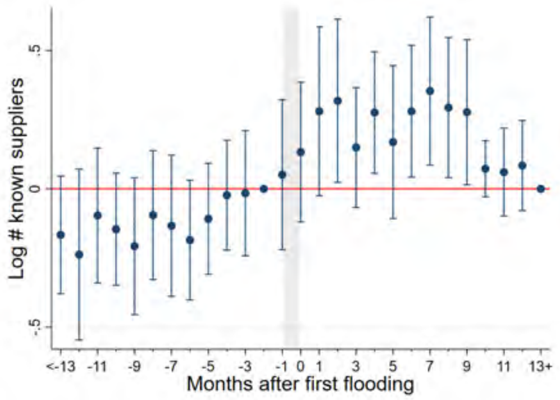
$N_{treated} = 9768$

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.

F.1.2 Supplier diversification

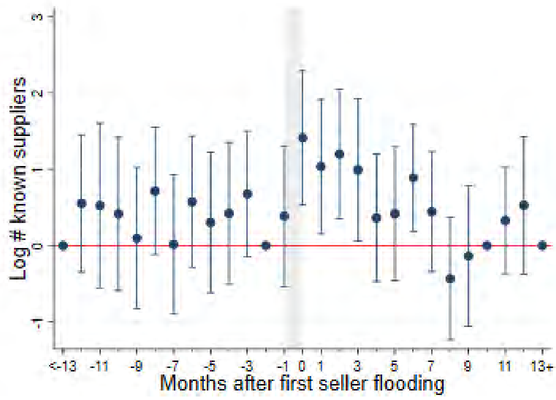
We omit the impact of own flooding in the September 2012 flood in this section since only six firms with a non-missing dependent variable experienced flooding during this episode.

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



(a) Own flooding

$N_{treated} = 227$

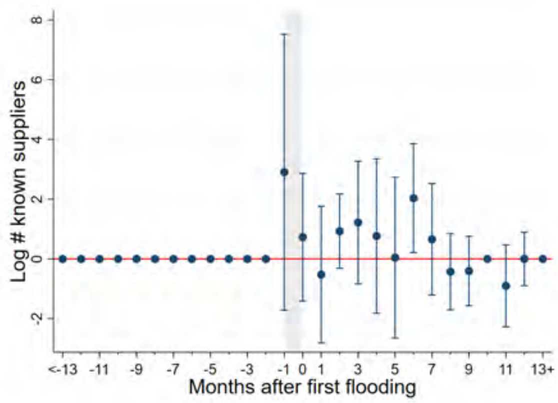


(b) Supplier flooding

$N_{treated} = 125$

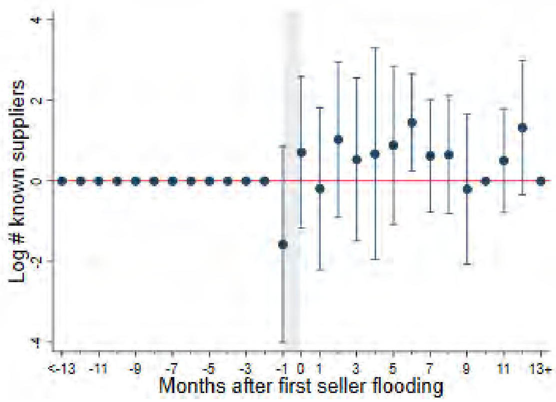
Notes: The panels plot the effect of own flooding or supplier flooding on log number of suppliers. We use the method in Sun and Abraham (2021) to estimate equations (6) and (7), but with a binary treatment variable based on a 10% threshold. Observations are firm-month-years whose 2011 and 2019 addresses 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 F.8. Impact of flooding on log number of suppliers (Aug-Sep 2011)



(a) Own flooding

$N_{treated} = 474$

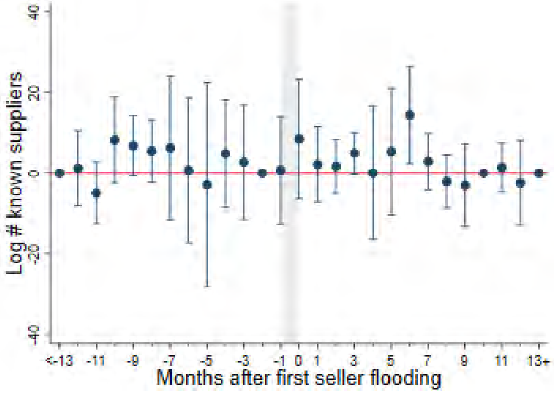


(b) Supplier flooding

$N_{treated} = 281$

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.

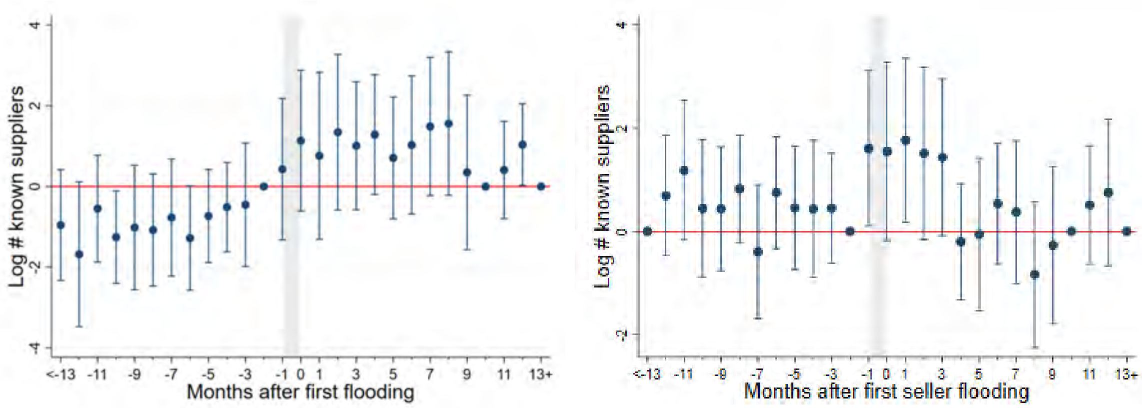
Figure F.9. Impact of supplier flooding on log number of suppliers (Sep 2012)



$N_{treated} = 37$

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



(a) Own flooding

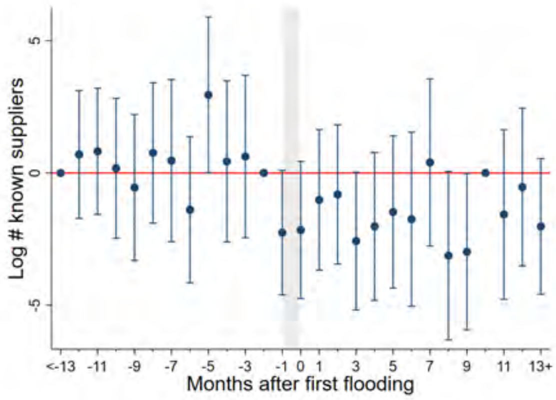
$N_{treated} = 1749$

(b) Supplier flooding

$N_{treated} = 1124$

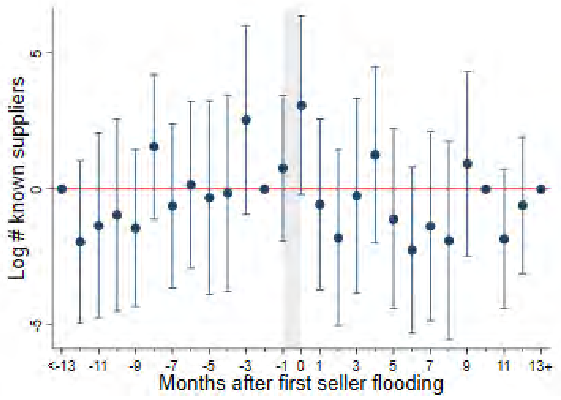
Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on log number of suppliers following equations (6) and (7). Observations are firm-month-years whose 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Aug 2013 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 F.11. Impact of flooding on log number of suppliers (Sep 2014)



(a) Own flooding

$N_{treated} = 4246$

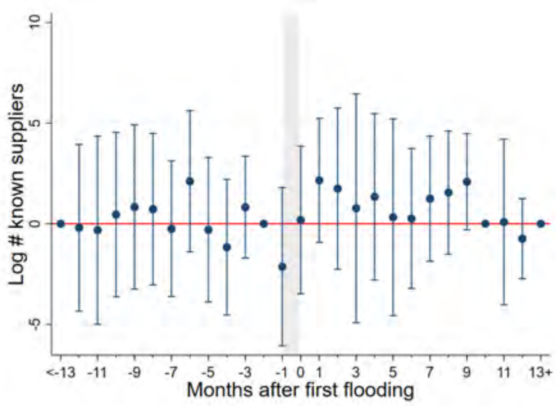


(b) Supplier flooding

$N_{treated} = 1915$

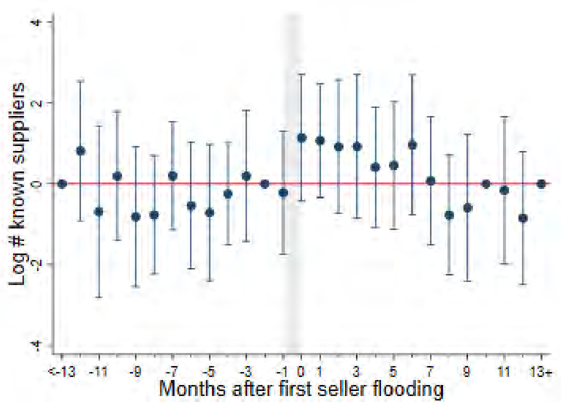
Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on log number of suppliers following equations (6) and (7). Observations are firm-month-years whose 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first treated in the Sep 2014 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 F.12. Impact of flooding on log number of suppliers (Jul-Aug 2015)



(a) Own flooding

$N_{treated} = 4921$



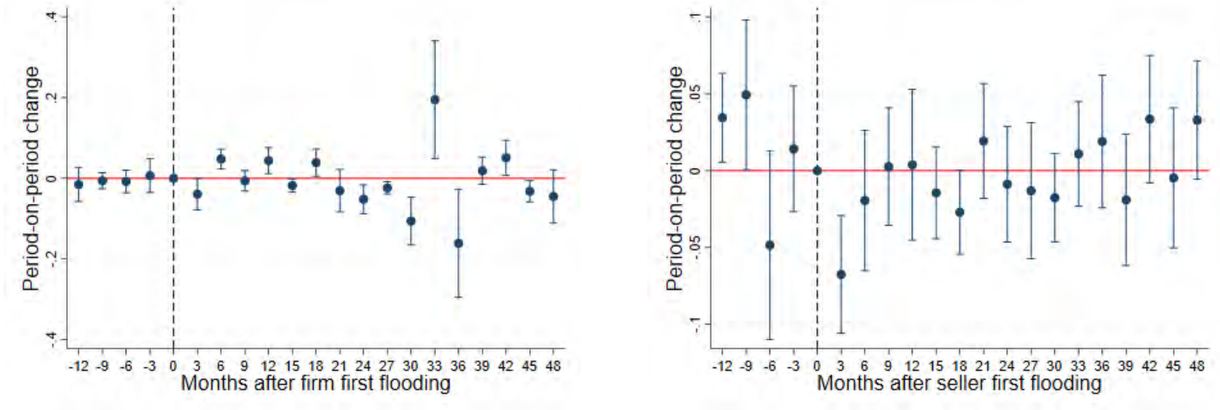
(b) Supplier flooding

$N_{treated} = 1831$

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.

F.1.3 Supplier choice

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



$N_{treated} = 223$

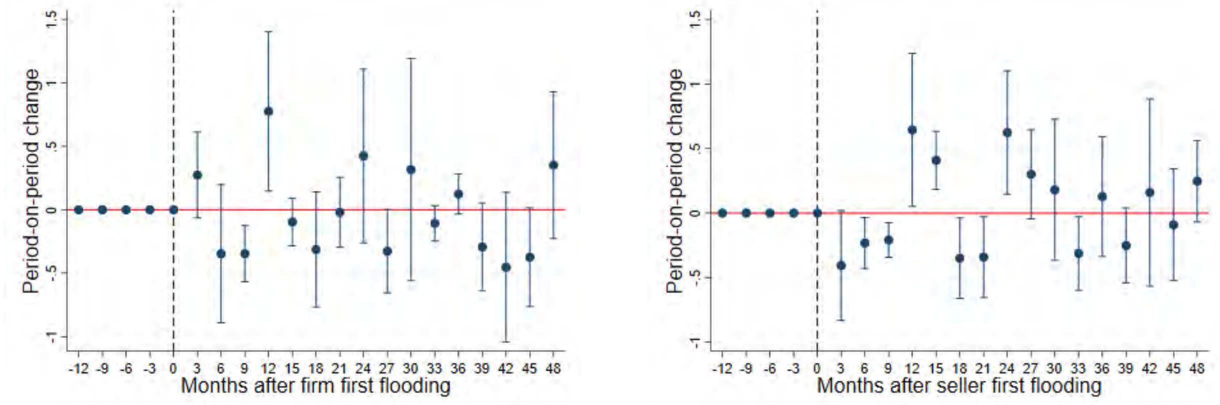
(a) Own flooding

$N_{treated} = 199$

(b) Supplier flooding

Notes: The panel plots estimates of the effect of own and 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 F.14. Dynamic impact of supplier flooding on flood risk of all suppliers (Aug-Sep 2011)



$N_{treated} = 460$

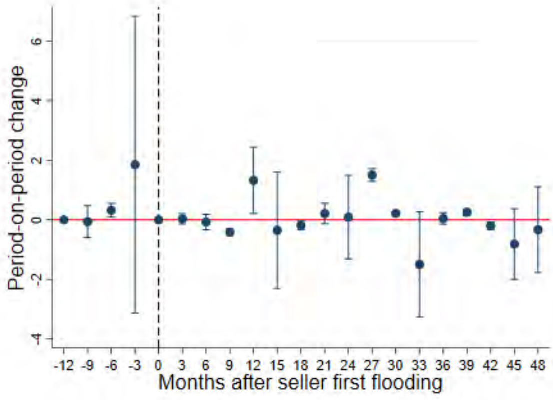
(a) Own flooding

$N_{treated} = 484$

(b) Supplier flooding

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.

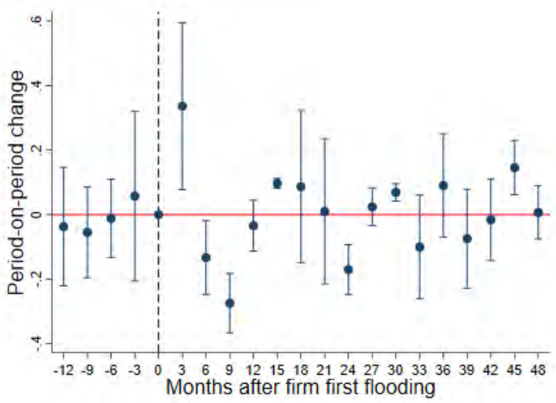
Figure F.15. Dynamic impact of supplier flooding on flood risk of all suppliers (Sep 2012)



$N_{treated} = 50$

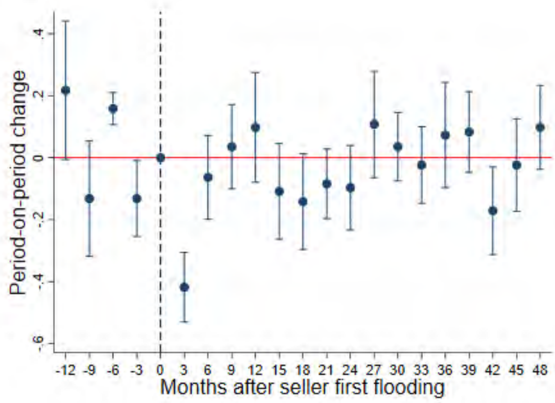
Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first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

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



$N_{treated} = 1604$

(a) Own flooding

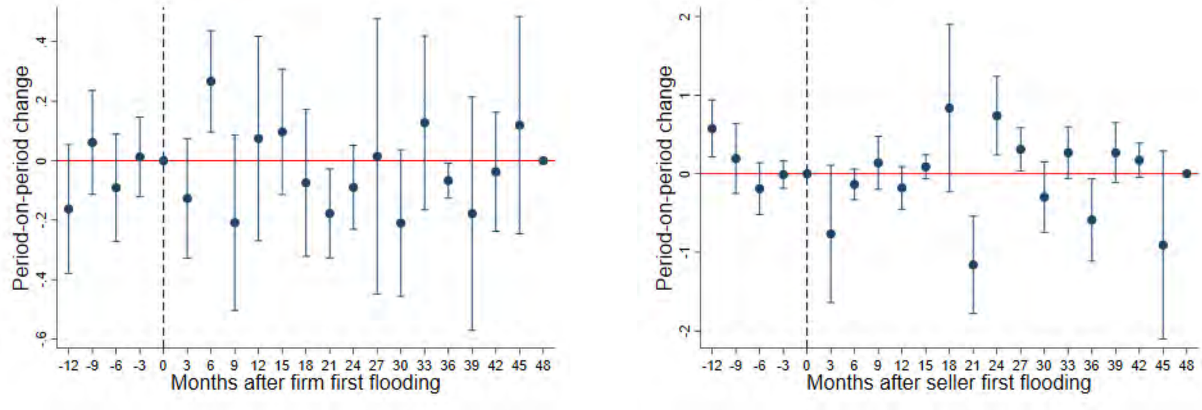


$N_{treated} = 1551$

(b) Supplier flooding

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



$N_{treated} = 4163$

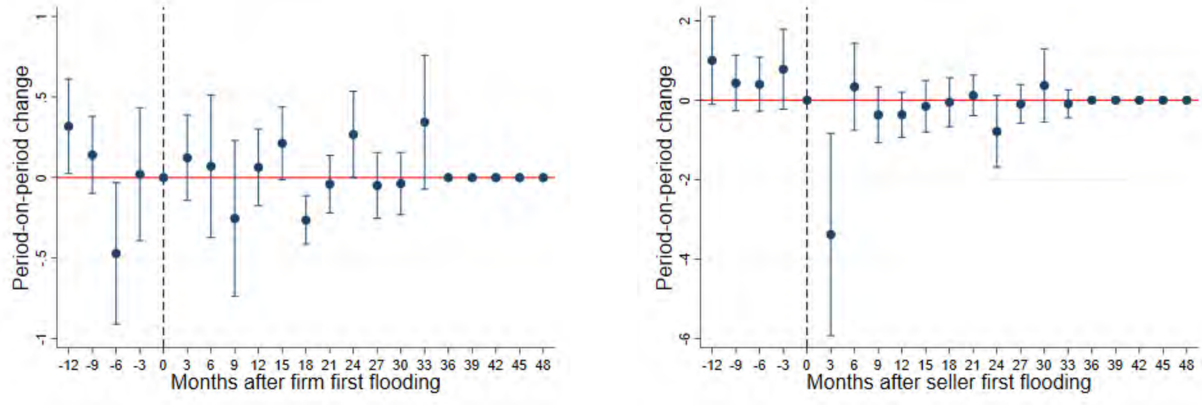
(a) Own flooding

$N_{treated} = 2616$

(b) Supplier flooding

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



$N_{treated} = 4724$

(a) Own flooding

$N_{treated} = 2963$

(b) Supplier flooding

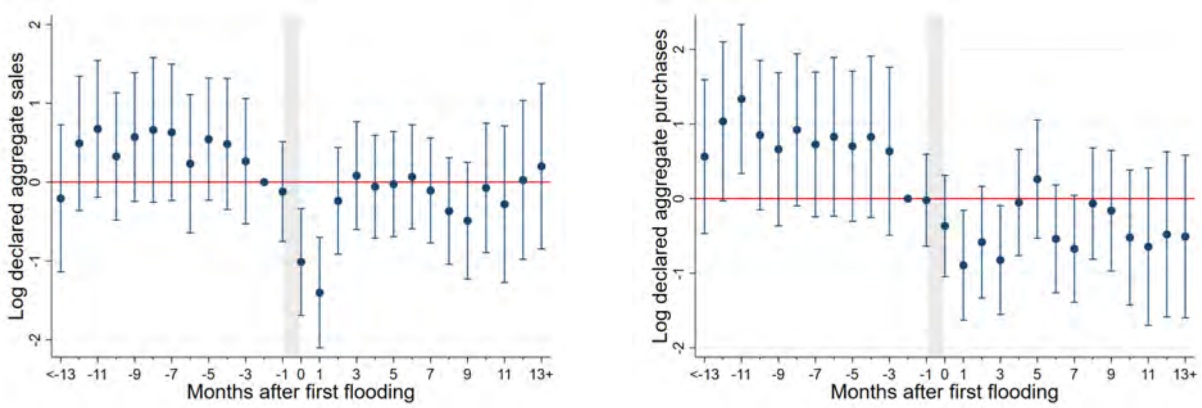
Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq$ 10km apart and which are never treated or first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

F.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.[51] 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.

F.2.1 Impact of flooding on firm sales and purchases

Figure F.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.

F.2.2 Firm location

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

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	2.074***	2.611***	-180.0**	-22.77
	(0.800)	(0.825)	(88.83)	(39.33)
District FE	Yes		Yes	
District × Fathom 1 in 100 FE		Yes		Yes
R^2	0.045	0.068	0.126	0.468
N	43,525	43,074	5,663	5,515

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on a 10km-relocation indicator 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. 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

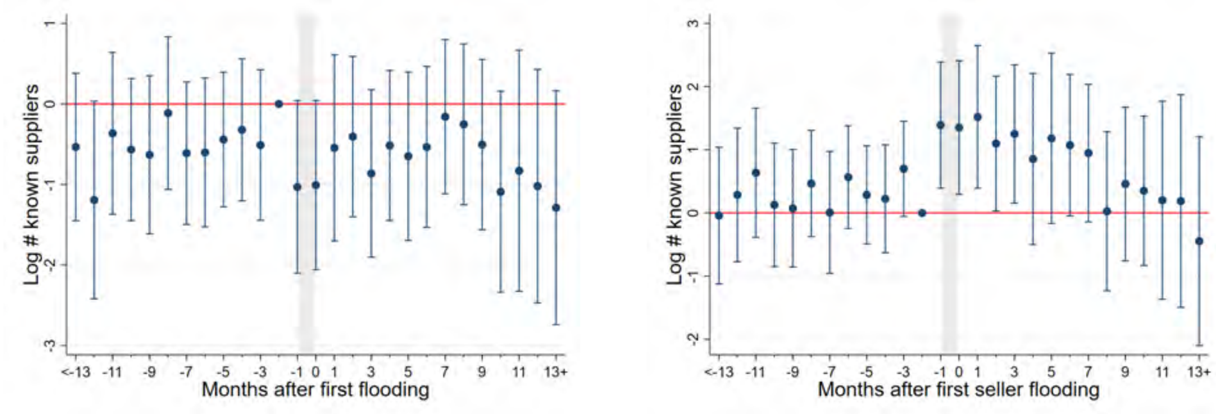
Table F.2. Impact of destination flood history on relocation flows (excl. electricity and gas)

	Number of Firms Moved
Dest. flooded 12mo prior	-0.720***
	(0.249)
Origin × Destination FE	Yes
Origin × Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10km
N	1,521

Notes: The table reports Poisson pseudo-maximum-likelihood estimates of the effect of destination flood history on relocation flows following equation (5). Standard errors (given in parentheses) are clustered at the origin-destination level. The sample is restricted to firms whose 2011 and 2019 locations are known and >10km apart. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

F.2.3 Supplier diversification

Figure F.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, $\leq$ 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.

F.2.4 Supplier choice

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	5.714	-0.473	10.05**
	(4.165)	(3.929)	(4.924)
Suppliers' max flood extent	-62.65***	-65.58***	-75.70***
	(14.91)	(15.66)	(17.28)
Average effect of mean flooded supplier buffer in cm	-0.955	-1.000	-1.154
Average effect of 10% flooded supplier buffer in cm	-6.265	-6.558	-7.570
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0089	0.0245	0.0542
N	138,885	138,169	133,913

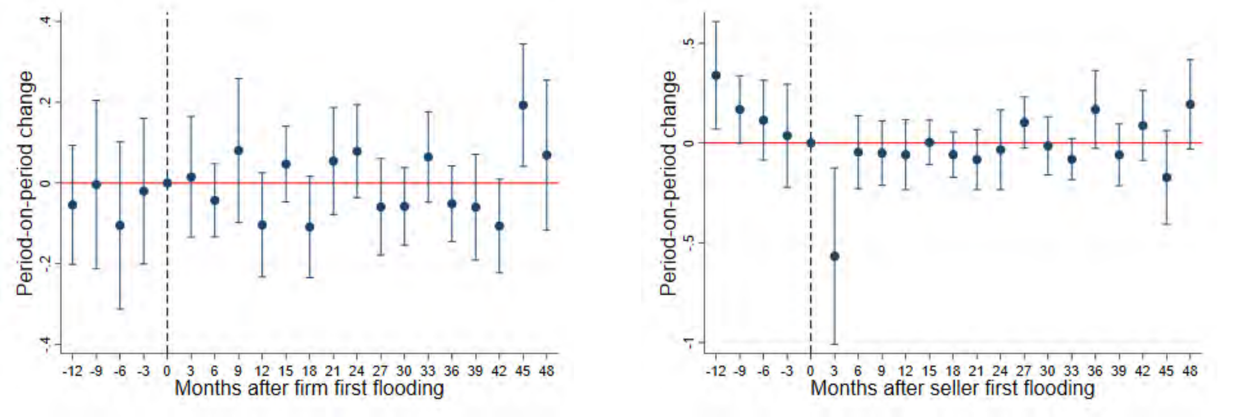
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.4. Impact of supplier flooding on flood risk of non-flooded suppliers (excl. electricity and gas)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	4.182	2.434	7.059
	(3.296)	(3.251)	(4.754)
Suppliers' max flood extent	-21.47***	-22.93***	-21.77***
	(6.192)	(6.515)	(6.455)
Average effect of mean flooded supplier buffer in cm	-0.327	-0.350	-0.332
Average effect of 10% flooded supplier buffer in cm	-2.147	-2.293	-2.177
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0059	0.0214	0.0507
N	138,713	137,996	133,755

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 that are not flooded (defined as ≤ 5% overlap of the 2km buffer and the flood polygon). 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

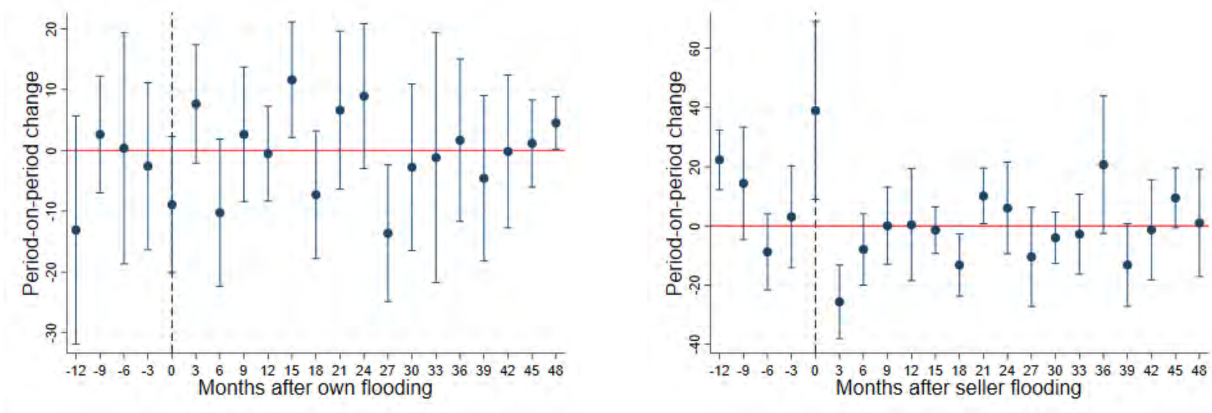
Figure F.21. Dynamic impact of supplier and own flooding on flood risk of all suppliers (excl. electricity and gas)



(a) Own flooding (b) Supplier flooding

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). We exclude electricity and gas producers from buyers and sellers. Observations are firm-year-month pairs 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 F.22. Dynamic impact of supplier and own flooding on flood risk of $\leq$ 5% flooded suppliers (excl. electricity and gas)



(a) Own flooding (b) Supplier flooding

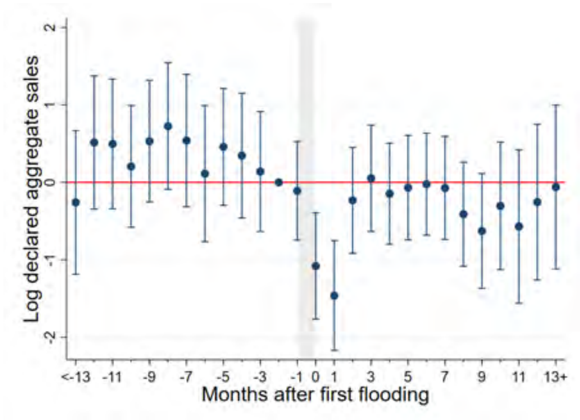
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq$ 5% following equation (23). We exclude electricity and gas producers from buyers and sellers. Observations are firm-by-flood-year-month pairs 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.

F.3 Results excluding capital purchases

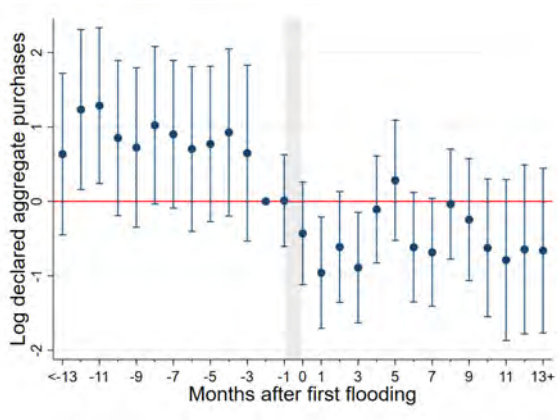
We next consider the robustness of results to excluding transactions involving capital goods, given that lumpy capital purchases are likely to be infrequent and may be less prone to flood-induced supply disruptions. To do so, we remove all transactions in which either the buyer or the seller has a primary product code which maps to a capital good, identified using Part I of the Fifth Schedule of the Customs Act.[52]

F.3.1 Impact of flooding on firm sales and purchases

Figure F.23. Impact of flooding on firm sales and purchases (excl. capital purchases)



(a) Log Sales



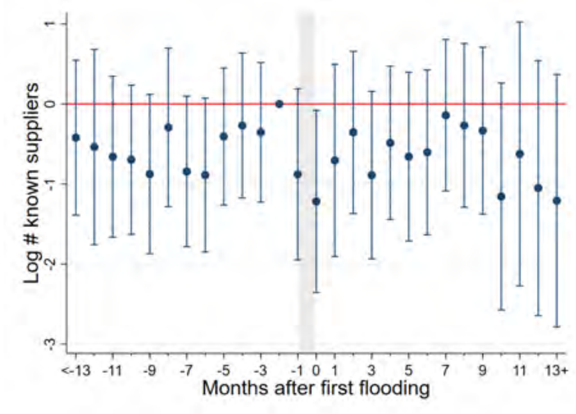
(b) Log Purchases

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.

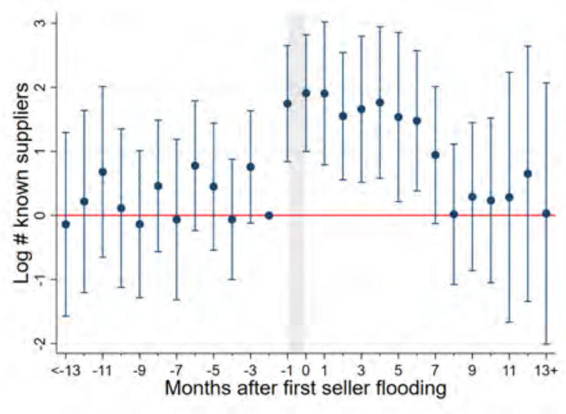
[52] https://www.fbr.gov.pk/categ/customs-tariff/51149/70853/131188

F.3.2 Supplier diversification

Figure F.24. 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, $\leq$ 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.

F.3.3 Supplier choice

Table F.5. Impact of supplier flooding on supplier flood risk (excl. capital purchases)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-6.797	-6.591	-11.13
	(10.50)	(8.430)	(12.32)
Suppliers' max flood extent	-51.94***	-52.59***	-60.07***
	(13.87)	(14.37)	(15.85)
Average effect of mean flooded supplier buffer in cm	-0.791	-0.801	-0.915
Average effect of 10% flooded supplier buffer in cm	-5.194	-5.259	-6.007
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0112	0.0337	0.0671
N	125,091	124,361	120,023

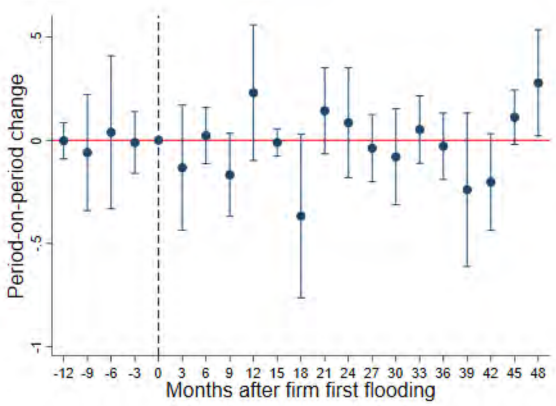
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.6. Impact of supplier flooding on flood risk of non-flooded suppliers (excl. capital purchases)

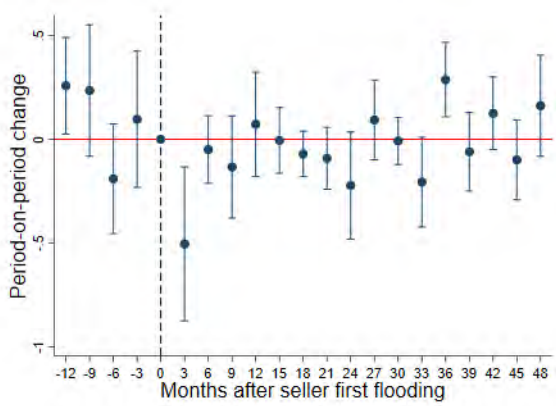
	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-10.96	-7.164	-14.84
	(10.74)	(8.051)	(12.59)
Suppliers' max flood extent	-21.61***	-19.76**	-18.56**
	(7.590)	(7.747)	(9.441)
Average effect of mean flooded supplier buffer in cm	-0.329	-0.301	-0.283
Average effect of 10% flooded supplier buffer in cm	-2.161	-1.976	-1.856
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0100	0.0347	0.0664
N	124,953	124,223	119,893

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 that are not flooded (defined as $\leq$ 5% overlap of the 2km buffer and the flood polygon). 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure F.25. Dynamic impact of supplier flooding on flood risk of all suppliers (excl. capital purchases)



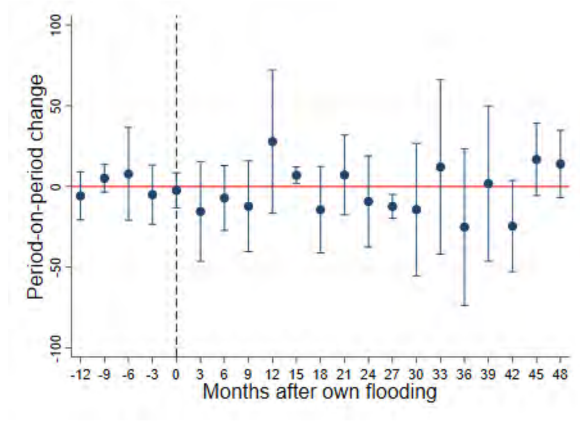
(a) Own flooding



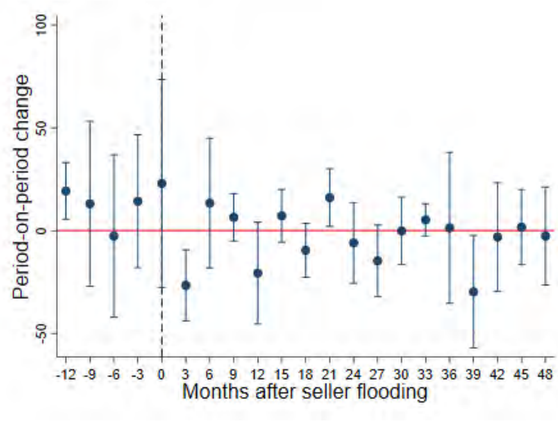
(b) Supplier flooding

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). We exclude firms primarily transacting in capital goods from buyers and sellers. Observations are firm-year-month pairs 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 × district level.

Figure F.26. Dynamic impact of supplier and own flooding on flood risk of $\leq 5\%$ flooded suppliers (excl. capital purchases)



(a) Own flooding



(b) Supplier flooding

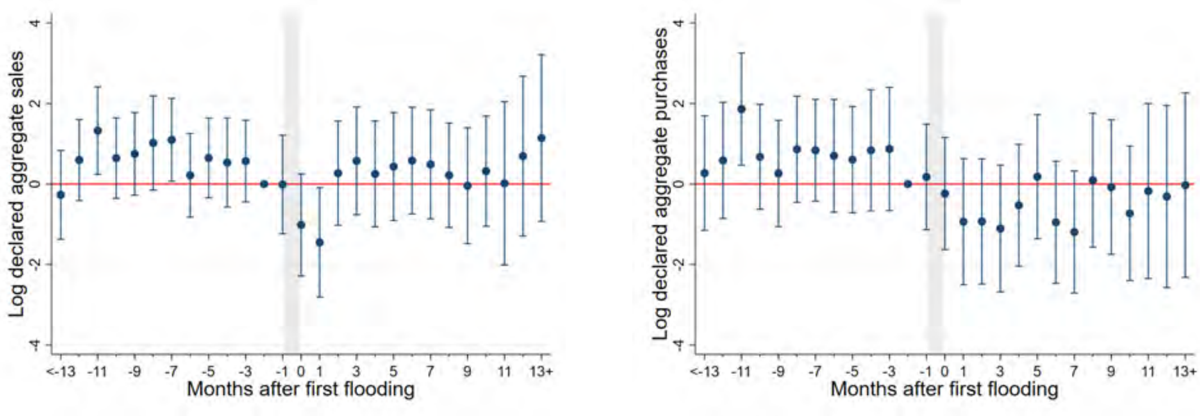
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (23). We exclude firms primarily transacting in capital goods from buyers and sellers. Observations are firm-by-flood-year-month pairs 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.

F.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.

F.4.1 Impact of flooding on firm sales and purchases

Figure F.27. 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.

F.4.2 Firm location

Table F.7. Impact of flooding on firm relocation and location flood risk (manufacturing)

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	1.938*	2.086**	-106.4	1.257
	(1.017)	(0.813)	(77.82)	(44.81)
District FE	Yes		Yes	
District × Fathom 1 in 100 FE		Yes		Yes
R^2	0.052	0.072	0.145	0.467
N	17,422	17,070	2,752	2,645

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on a 10km-relocation indicator 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. 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

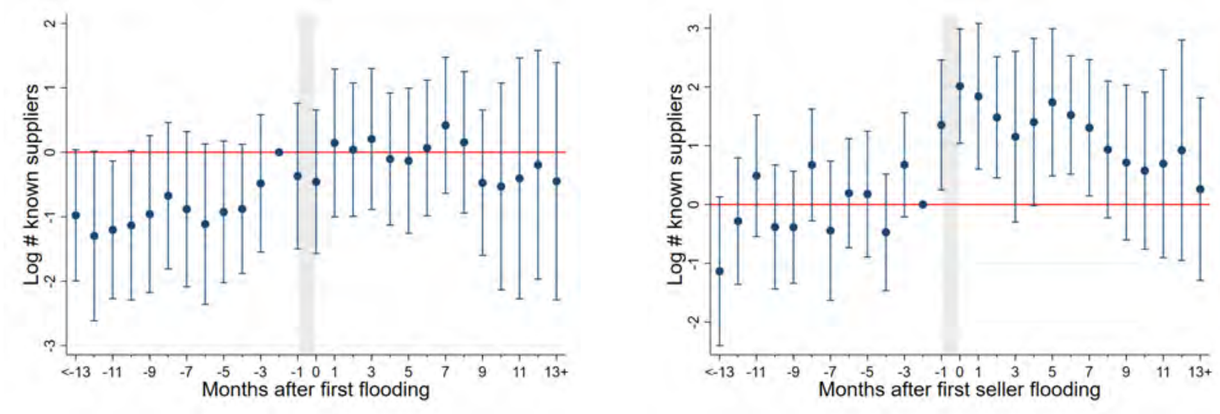
Table F.8. Impact of destination flood history on relocation flows (manufacturing)

	Number of Firms Moved
Dest. flooded 12mo prior	-0.870***
	(0.284)
Origin × Destination FE	Yes
Origin × Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10km
N	834

Notes: The table reports Poisson pseudo-maximum-likelihood estimates of the effect of destination flood history on relocation flows following equation (5). Standard errors (given in parentheses) are clustered at the origin-destination level. The sample is restricted to firms whose 2011 and 2019 locations are known and >10km apart. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

F.4.3 Supplier diversification

Figure F.28. 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 ≤ 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.

F.4.4 Supplier choice

Table F.9. Impact of supplier flooding on supplier flood risk (manufacturing)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	19.77***	22.18***	23.36***
	(6.015)	(6.393)	(8.693)
Suppliers' max flood extent	-66.58***	-65.96***	-66.69***
	(11.76)	(12.18)	(12.07)
Average effect of mean flooded supplier buffer in cm	-1.177	-1.166	-1.179
Average effect of 10% flooded supplier buffer in cm	-6.658	-6.596	-6.669
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0195	0.0472	0.0670
N	52,769	52,259	51,413

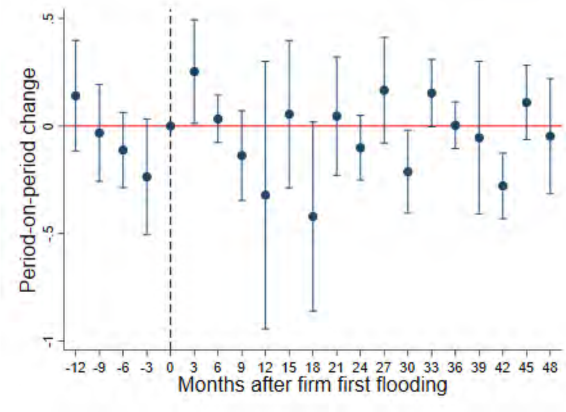
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.10. Impact of supplier flooding on flood risk of non-flooded suppliers (manufacturing)

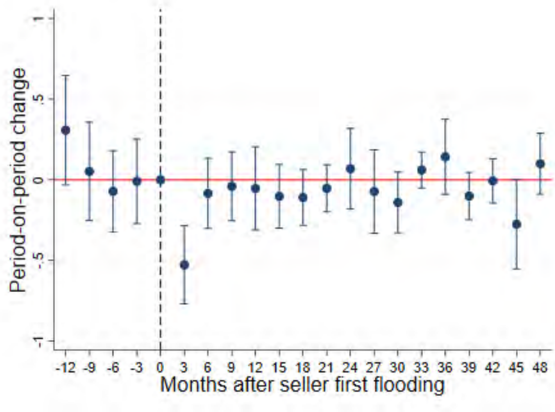
	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	15.62**	17.83**	18.87*
	(7.341)	(8.245)	(9.762)
Suppliers' max flood extent	-21.67**	-21.19**	-20.46*
	(10.59)	(10.65)	(10.44)
Average effect of mean flooded supplier buffer in cm	-0.383	-0.375	-0.362
Average effect of 10% flooded supplier buffer in cm	-2.167	-2.119	-2.046
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0156	0.0417	0.0622
N	52,652	52,142	51,296

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 that are not flooded (defined as $\leq$ 5% overlap of the 2km buffer and the flood polygon). 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure F.29. Dynamic impact of supplier flooding on flood risk of all suppliers (manufacturing)



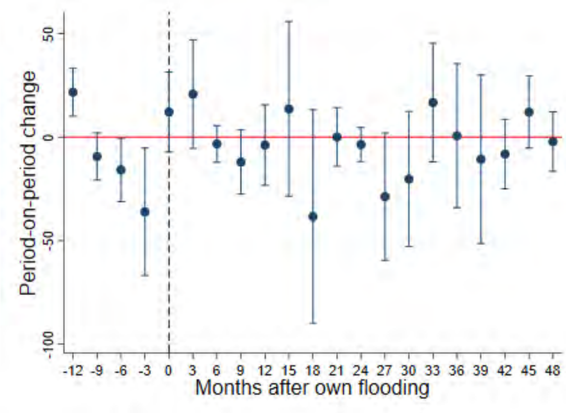
(a) Own flooding



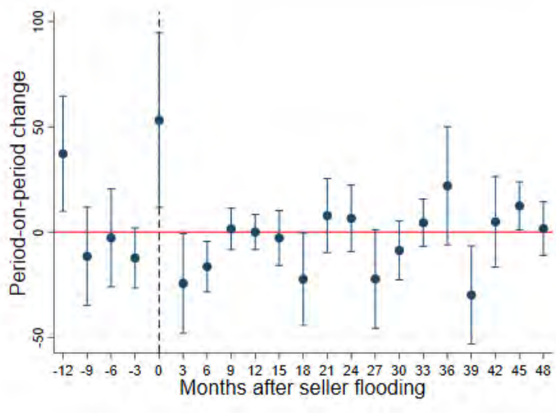
(b) Supplier flooding

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). We restrict buyers and sellers to manufacturing firms. Observations are firm-year-month pairs 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 F.30. Dynamic impact of supplier and own flooding on flood risk of $\leq$ 5% flooded suppliers (manufacturing)



(a) Own flooding



(b) Supplier flooding

Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq$ 5% following equation (23). We restrict buyers and sellers to manufacturing firms. Observations are firm-by-flood-year-month pairs 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.

F.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.

F.5.1 Supplier choice

Table F.11. Impact of supplier flooding on supplier flood risk (coinciding reports)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	4.741	-2.093	6.457
	(9.200)	(13.09)	(9.262)
Suppliers' max flood extent	-97.20***	-95.35***	-94.45***
	(20.48)	(21.04)	(21.62)
Average effect of mean flooded supplier buffer in cm	-1.372	-1.346	-1.334
Average effect of 10% flooded supplier buffer in cm	-9.720	-9.535	-9.445
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0111	0.0297	0.0600
N	86,786	86,198	83,675

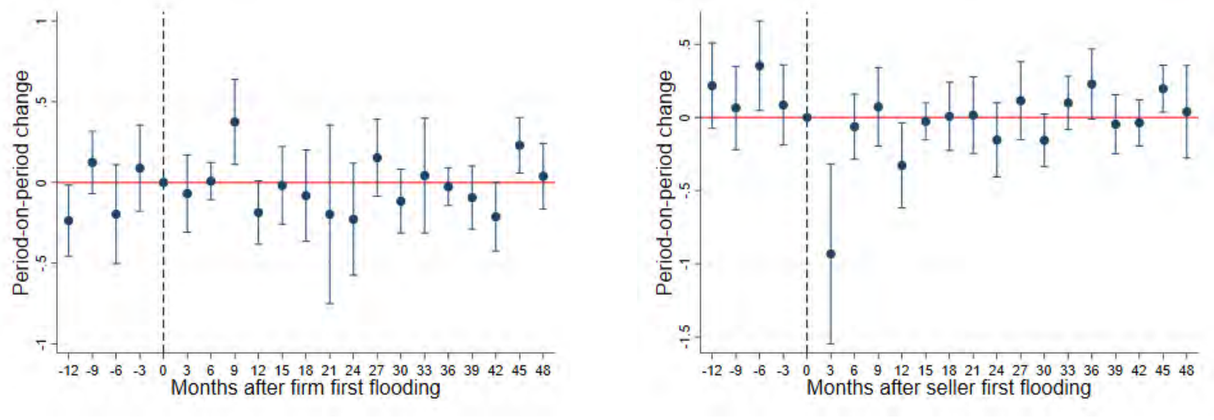
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.12. Impact of supplier flooding on flood risk of non-flooded suppliers (coinciding reports)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	5.704	2.727	6.565
	(7.195)	(10.09)	(8.143)
Suppliers' max flood extent	-44.41***	-41.80***	-40.35***
	(11.75)	(11.85)	(12.06)
Average effect of mean flooded supplier buffer in cm	-0.627	-0.590	-0.570
Average effect of 10% flooded supplier buffer in cm	-4.441	-4.180	-4.035
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0081	0.0273	0.0579
N	86,648	86,061	83,544

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 that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

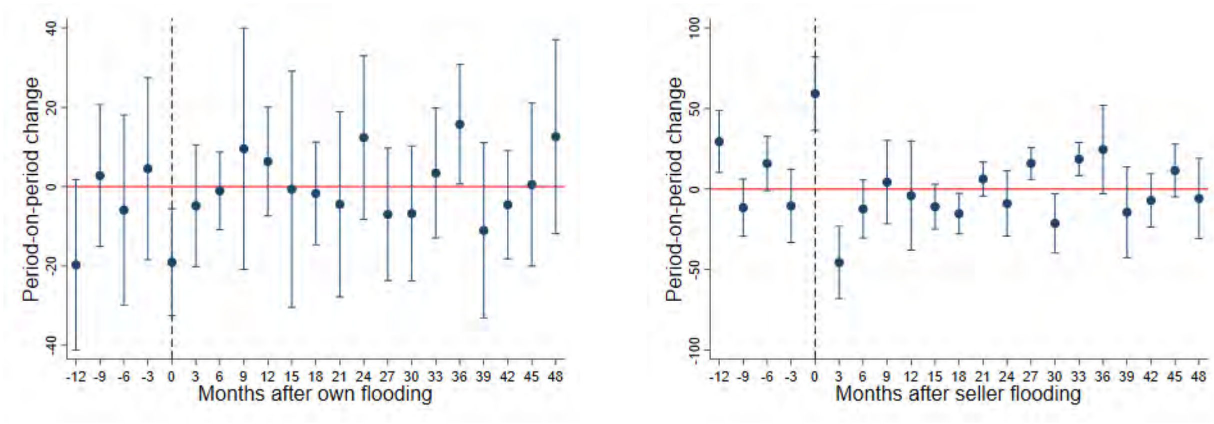
Figure F.31. Dynamic impact of supplier flooding on flood risk of all suppliers (coinciding reports)



(a) Own flooding (b) Supplier flooding

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). We restrict attention to transactions for which buyer and seller reports coincide precisely. Observations are firm-year-month pairs 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 × district level.

Figure F.32. Dynamic impact of supplier and own flooding on flood risk of ≤ 5% flooded suppliers (coinciding reports)



(a) Own flooding

(b) Supplier flooding

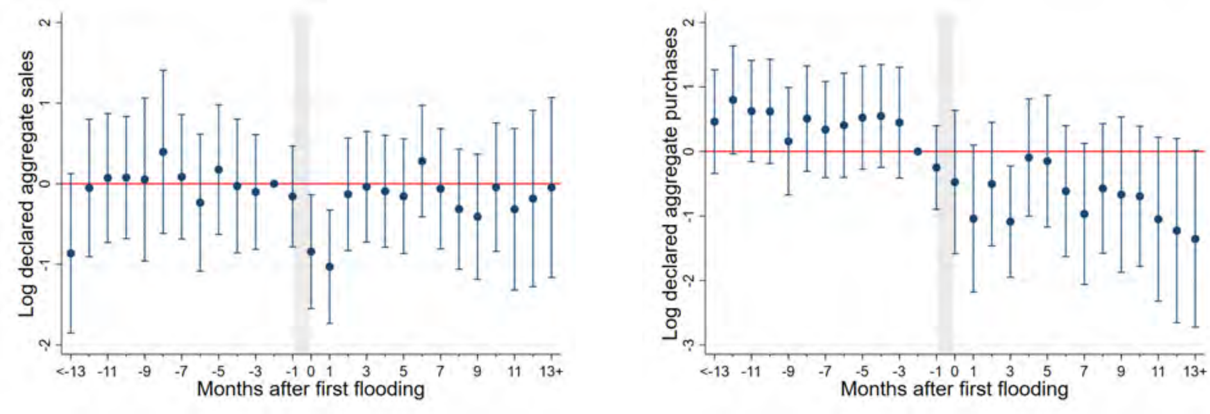
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by ≤ 5% following equation (23). We restrict attention to transactions for which buyer and seller reports coincide precisely. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10km apart. The 95% confidence intervals rely on standard errors clustered at the time × district level.

F.6 Firm buffers with 1km and 3km radii

Our main specifications define firm-level or supplier-level flooding (flood risk) based on the share of a circular buffer with two-kilometer radius around the firm or supplier that intersects the flood layer (average flood risk within the buffer). Here, we show that results are robust to instead constructing circular buffers with radii of one or three kilometers.

F.6.1 Impact of flooding on firm sales and purchases

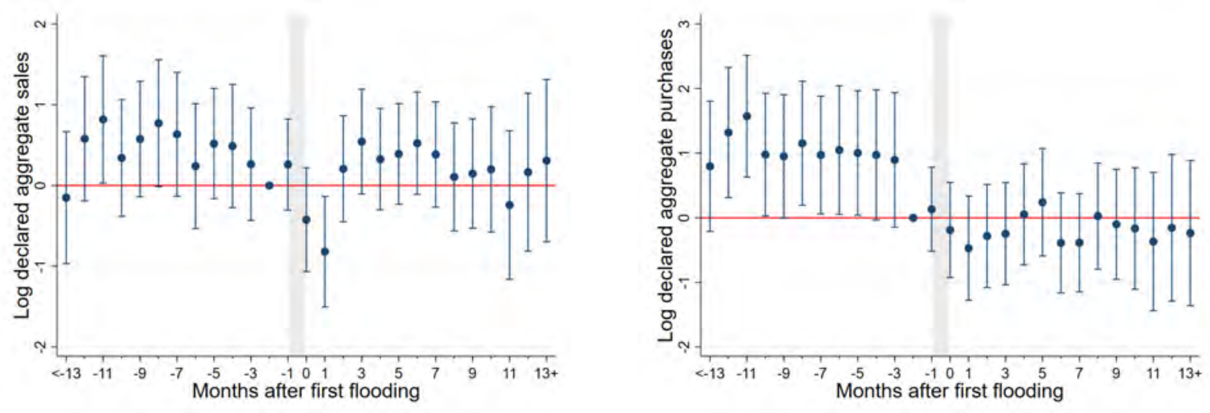
Figure F.33. Impact of flooding on firm sales and purchases (1km buffer)



(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). Here, we use a 1km buffer around the firm to define the treatment (share of firm buffer flooded) instead of the standard 2km buffer. The unit of observation is a firm-month-year. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure F.34. Impact of flooding on firm sales and purchases (3km buffer)



(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). Here, we use a 3km buffer around the firm to define the treatment (share of firm buffer flooded) instead of the standard 2km buffer. The unit of observation is a firm-month-year. The 95% confidence intervals rely on standard errors clustered at the firm-level.

F.6.2 Firm location

Table F.13. Impact of flooding on firm relocation and location flood risk (1km buffer)

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 1km buffer flooded	2.274***	3.036***	-122.9***	-56.28**
	(0.717)	(0.765)	(38.65)	(26.51)
District FE	Yes		Yes	
District × Fathom 1 in 100 FE		Yes		Yes
R^2	0.046	0.067	0.103	0.469
N	43,848	43,260	5,737	5,599

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on a 10km-relocation indicator 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. 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 F.14. Impact of destination flood history on relocation flows (1km buffer)

	Number of Firms Moved
Dest. flooded 12mo prior	-0.943***
	(0.360)
Origin × Destination FE	Yes
Origin × Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10km
N	924

Notes: The table reports Poisson pseudo-maximum-likelihood estimates of the effect of destination flood history on relocation flows following equation (5). Standard errors (given in parentheses) are clustered at the origin-destination level. The sample is restricted to firms whose 2011 and 2019 locations are known and >10km apart. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.15. Impact of flooding on firm relocation and location flood risk (3km buffer)

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 3km buffer flooded	2.036**	3.048***	-254.4*	-41.27
	(0.843)	(0.908)	(128.8)	(38.96)
District FE	Yes		Yes	
District × Fathom 1 in 100 FE		Yes		Yes
R^2	0.046	0.068	0.130	0.493
N	43,848	43,499	5,737	5,607

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on a 10km-relocation indicator 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. 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

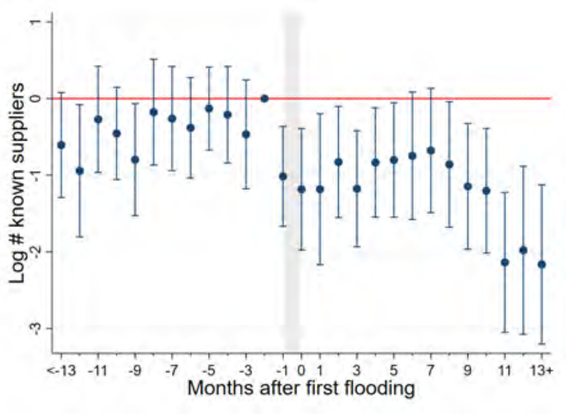
Table F.16. Impact of destination flood history on relocation flows (3km buffer)

	Number of Firms Moved
Dest. flooded 12mo prior	-0.693***
	(0.244)
Origin × Destination FE	Yes
Origin × Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10km
N	1,879

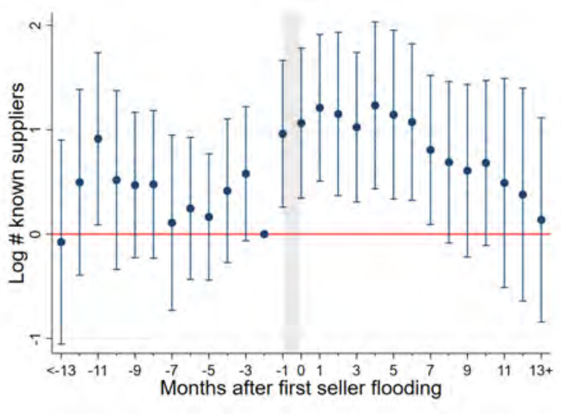
Notes: The table reports Poisson pseudo-maximum-likelihood estimates of the effect of destination flood history on relocation flows following equation (5). Standard errors (given in parentheses) are clustered at the origin-destination level. The sample is restricted to firms whose 2011 and 2019 locations are known and >10km apart. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

F.6.3 Supplier diversification

Figure F.35. Supplier Diversification: Impact of flooding on log number of suppliers (1km buffer)



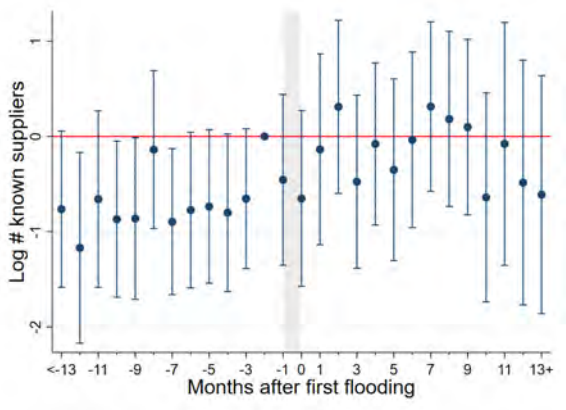
(a) Own flooding



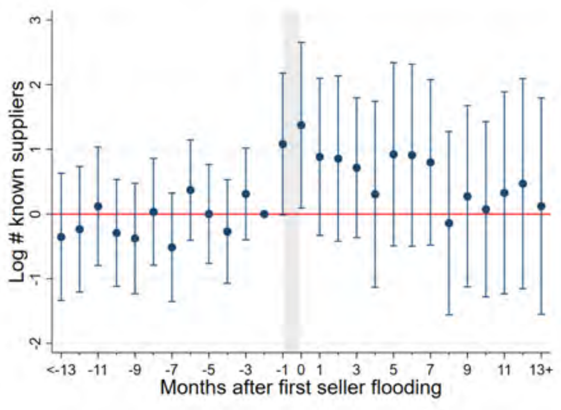
(b) Supplier flooding

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. Here, we use a 1km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. 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 F.36. Supplier Diversification: Impact of flooding on log number of suppliers (3km buffer)



(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. Here, we use a 3km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. 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.

F.6.4 Supplier choice

Table F.17. Impact of supplier flooding on supplier flood risk (1km buffer)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-1.904	-1.971	-2.016
	(6.293)	(7.063)	(6.120)
Suppliers' max flood extent	-32.49***	-35.15***	-40.91***
	(6.763)	(6.059)	(6.029)
Average effect of mean flooded supplier buffer in cm	-0.616	-0.666	-0.776
Average effect of 10% flooded supplier buffer in cm	-3.249	-3.515	-4.091
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0114	0.0336	0.0655
N	144,566	143,805	139,302

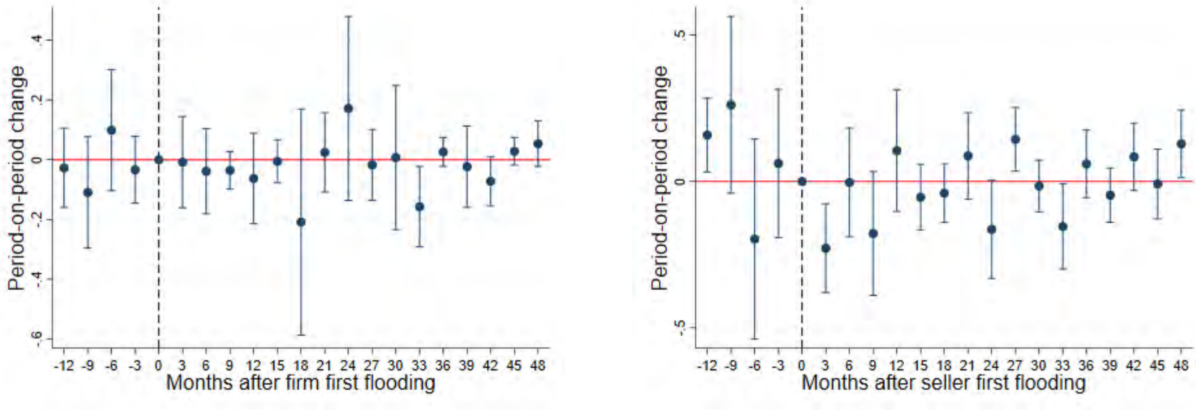
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.18. Impact of supplier flooding on flood risk of non-flooded suppliers (1km buffer)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-5.492	-6.850	-5.186
	(7.193)	(7.903)	(6.472)
Suppliers' max flood extent	-10.99	-13.16*	-9.002
	(6.978)	(7.132)	(7.350)
Average effect of mean flooded supplier buffer in cm	-0.208	-0.249	-0.171
Average effect of 10% flooded supplier buffer in cm	-1.099	-1.316	-0.900
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0100	0.0330	0.0626
N	144,483	143,722	139,224

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 that are not flooded (defined as $\leq$ 5% overlap of the 1km buffer and the flood polygon). 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

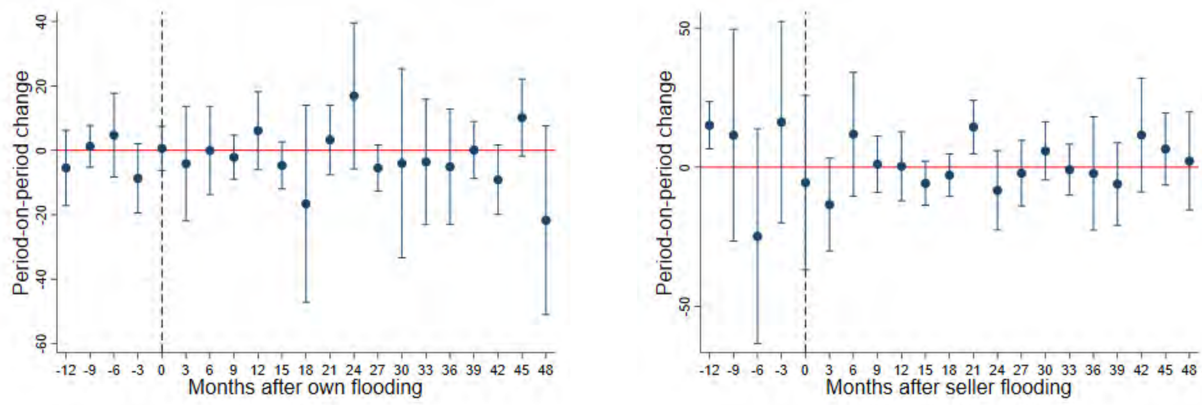
Figure F.37. Dynamic impact of supplier flooding on supplier flood risk (1km buffer)



(a) Own flooding (b) Supplier flooding

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). Here, we use a 1km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. 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 F.38. Dynamic impact of supplier and own flooding on flood risk of $\leq$ 5% flooded suppliers (1km buffer)



(a) Own flooding (b) Supplier flooding

Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq$ 5% following equation (23). Here, we use a 1km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. Observations are firm-by-flood-year-month pairs 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.

Table F.19. Impact of supplier flooding on supplier flood risk (3km buffer)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-1.122	-7.011	0.0913
	(10.05)	(10.09)	(12.03)
Suppliers' max flood extent	-75.88***	-77.11***	-89.46***
	(24.64)	(25.54)	(28.41)
Average effect of mean flooded supplier buffer in cm	-0.825	-0.838	-0.973
Average effect of 10% flooded supplier buffer in cm	-7.588	-7.711	-8.946
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0113	0.0267	0.0575
N	144,566	143,883	139,302

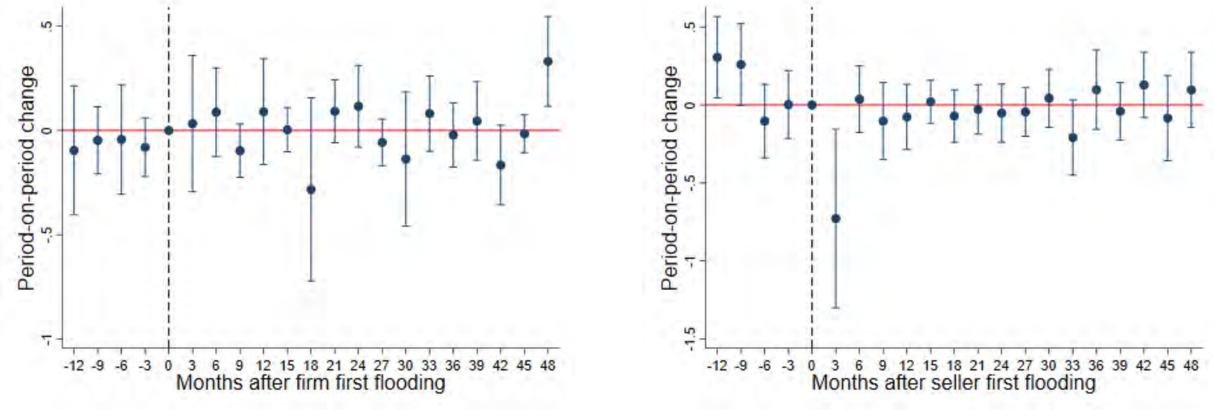
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.20. Impact of supplier flooding on flood risk of non-flooded suppliers (3km buffer)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-6.679	-11.26	-5.805
	(9.250)	(10.25)	(10.61)
Suppliers' max flood extent	-44.25***	-42.91***	-45.31***
	(10.69)	(10.58)	(11.89)
Average effect of mean flooded supplier buffer in cm	-0.481	-0.467	-0.493
Average effect of 10% flooded supplier buffer in cm	-4.425	-4.291	-4.531
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0087	0.0260	0.0550
N	144,320	143,633	139,063

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 that are not flooded (defined as ≤ 5% overlap of the 3km buffer and the flood polygon). 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

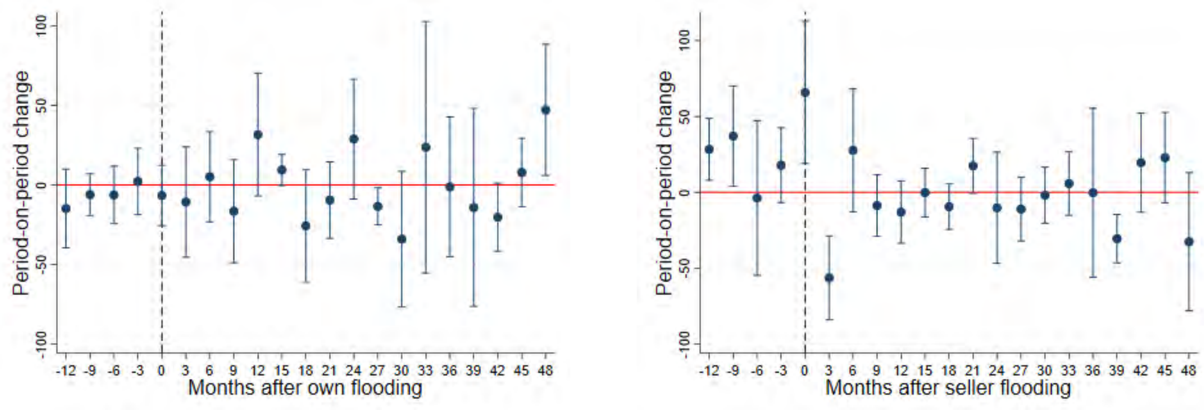
Figure F.39. Dynamic impact of supplier flooding on supplier flood risk (3km buffer)



(a) Own flooding (b) Supplier flooding

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). Here, we use a 3km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. 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 F.40. Dynamic impact of supplier and own flooding on flood risk of $\leq$ 5% flooded suppliers (3km buffer)



(a) Own flooding (b) Supplier flooding

Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq$ 5% following equation (23). Here, we use a 3km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. Observations are firm-by-flood-year-month pairs 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.

F.7 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.3. In this section we demonstrate the robustness of results to measuring flood risk in relation to 1 in 10 year floods or 1 in 50 year floods.

F.7.1 Firm location

Table F.21. Impact of flooding on firm relocation and location flood risk (1 in 10 year return period)

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	2.081***	2.168***	-123.1	-20.14
	(0.798)	(0.820)	(76.47)	(48.06)
District FE	Yes		Yes	
District × Fathom 1 in 10 FE		Yes		Yes
R^2	0.046	0.067	0.073	0.407
N	43,848	43,665	5,737	5,676

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on a 10km-relocation indicator 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. 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 F.22. Impact of flooding on firm relocation and location flood risk (1 in 50 year return period)

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	2.081***	2.567**	-164.6*	-34.64
	(0.798)	(1.004)	(87.91)	(48.88)
District FE	Yes		Yes	
District × Fathom 1 in 50 FE		Yes		Yes
R^2	0.046	0.068	0.111	0.459
N	43,848	43,522	5,737	5,605

Notes: Columns (1) and (2) display logit estimates of the effect of flooding on a 10km-relocation indicator 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. 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

F.7.2 Supplier choice

Table F.23. Impact of supplier flooding on supplier flood risk (1 in 10 year return period)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-4.420	-5.961	-4.585
	(5.733)	(5.768)	(6.935)
Suppliers' max flood extent	-41.09***	-43.02***	-48.99***
	(14.89)	(15.40)	(17.54)
Average effect of mean flooded supplier buffer in cm	-0.608	-0.636	-0.725
Average effect of 10% flooded supplier buffer in cm	-4.109	-4.302	-4.899
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0074	0.0167	0.0551
N	144,566	144,236	139,302

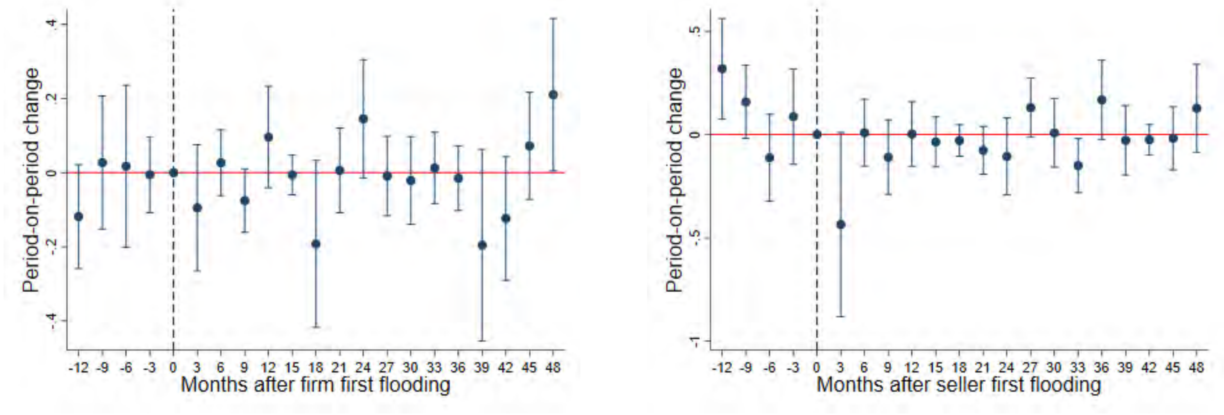
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 10 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.24. Impact of supplier flooding on flood risk of non-flooded suppliers (1 in 10 year return period)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-7.446	-7.190	-7.923
	(5.383)	(5.363)	(6.344)
Suppliers' max flood extent	-24.49***	-25.05***	-25.65***
	(7.536)	(7.338)	(8.093)
Average effect of mean flooded supplier buffer in cm	-0.362	-0.371	-0.379
Average effect of 10% flooded supplier buffer in cm	-2.449	-2.505	-2.565
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0061	0.0162	0.0546
N	144,423	144,090	139,164

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 that are not flooded (defined as $\leq$ 5% overlap of the 2km buffer and the flood polygon). 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 10 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

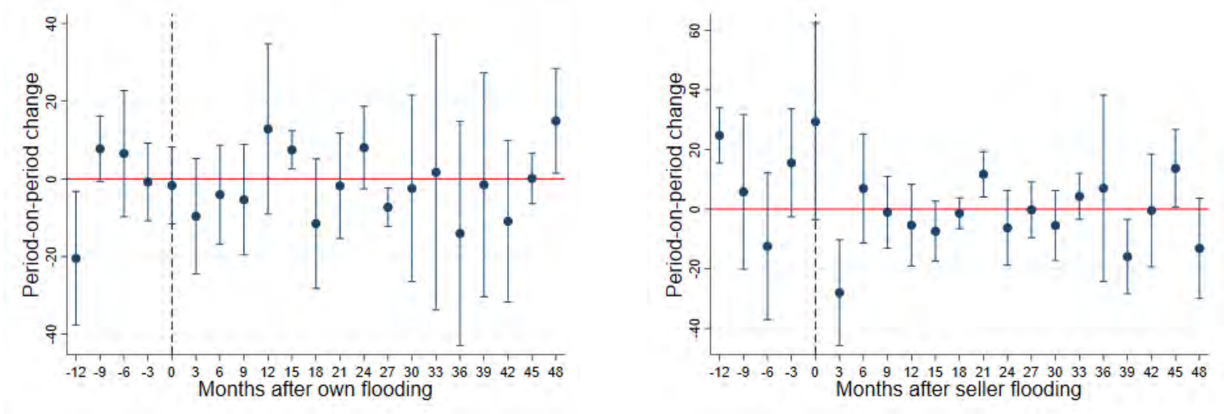
Figure F.41. Dynamic impact of supplier flooding on flood risk of all suppliers (1 in 10 year return period)



(a) Own flooding (b) Supplier flooding

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). 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. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure F.42. Dynamic impact of supplier and own flooding on flood risk of $\leq$ 5% flooded suppliers (1 in 10 return period)



(a) Own flooding (b) Supplier flooding

Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq$ 5% following equation (23). 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 $\leq$ 10km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Table F.25. Impact of supplier flooding on supplier flood risk (1 in 50 year return period)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-4.742	-3.913	-6.162
	(8.730)	(7.641)	(10.28)
Suppliers' max flood extent	-55.66***	-58.00***	-65.96***
	(15.90)	(16.54)	(18.33)
Average effect of mean flooded supplier buffer in cm	-0.823	-0.858	-0.975
Average effect of 10% flooded supplier buffer in cm	-5.566	-5.800	-6.596
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0101	0.0295	0.0582
N	144,566	143,840	139,302

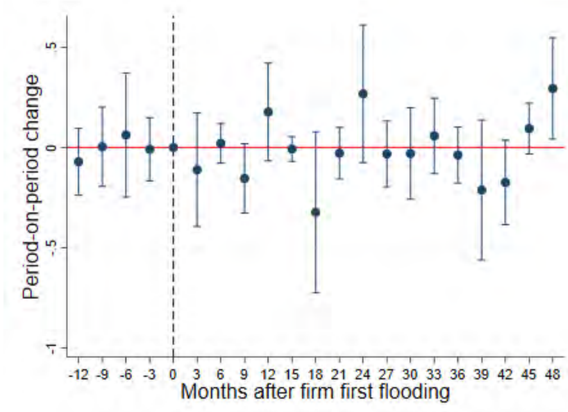
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 50 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.26. Impact of supplier flooding on flood risk of non-flooded suppliers (1 in 50 year return period)

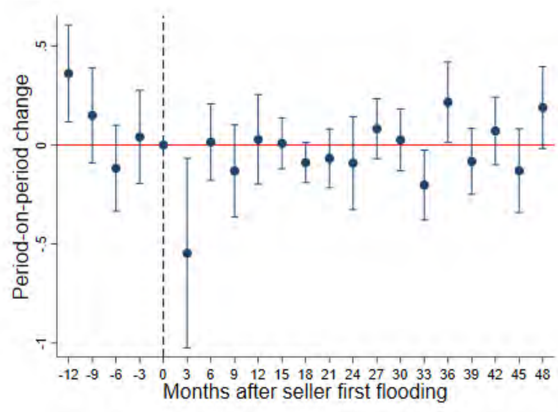
	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-9.010	-5.380	-11.01
	(8.811)	(7.466)	(10.47)
Suppliers' max flood extent	-26.85***	-27.36***	-26.12***
	(8.973)	(8.549)	(9.719)
Average effect of mean flooded supplier buffer in cm	-0.397	-0.405	-0.386
Average effect of 10% flooded supplier buffer in cm	-2.685	-2.736	-2.612
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0079	0.0288	0.0563
N	144,423	143,698	139,164

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 that are not flooded (defined as $\leq$ 5% overlap of the 2km buffer and the flood polygon). 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 50 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure F.43. Dynamic impact of supplier flooding on flood risk of all suppliers (1 in 50 year return period)



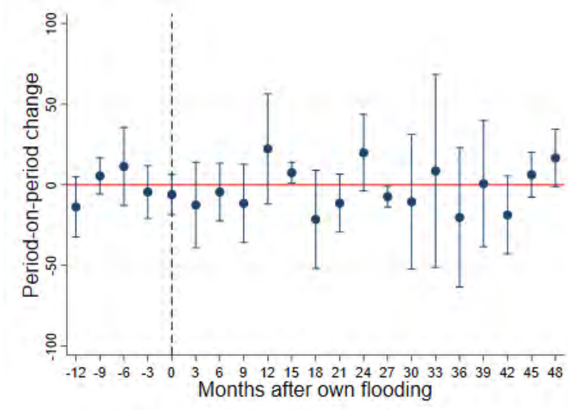
(a) Own flooding



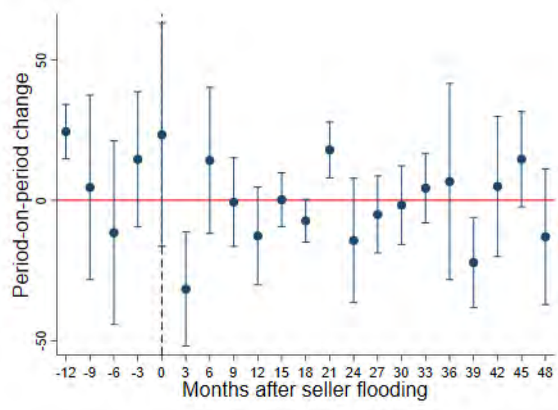
(b) Supplier flooding

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). 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. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure F.44. Dynamic impact of supplier and own flooding on flood risk of $\leq$ 5% flooded suppliers (1 in 50 return period)



(a) Own flooding



(b) Supplier flooding

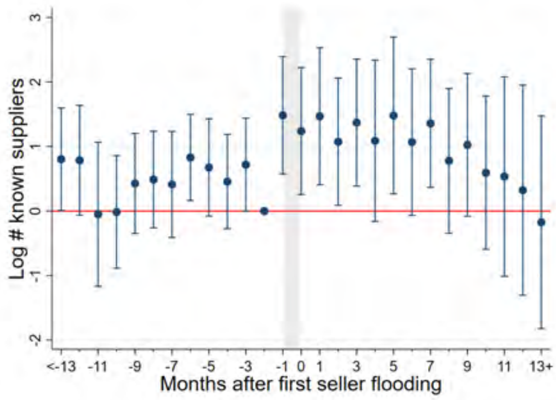
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq$ 5% following equation (23). Here, flood risk is measured for a 1 in 50 instead of a 1 in 100 year return period. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

F.8 6-month or 12-month partner window for indirect treatment specifications

The central results define a buyer firm's suppliers as those firms from which the buyer firm has made purchases in the prior three months. This section considers the robustness of results to instead using a 6-month or 12-month window to define a buyer firm's suppliers.

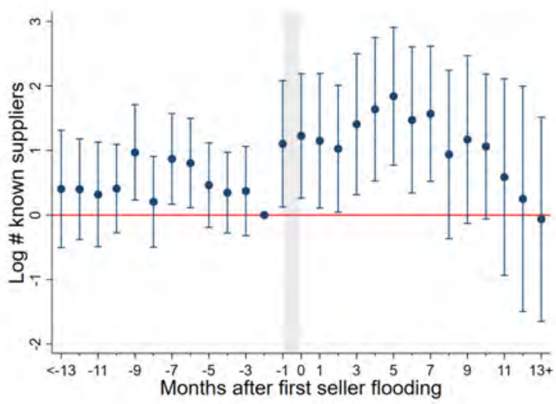
F.8.1 Supplier diversification

Figure F.45. 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 ≤ 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 F.46. 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 ≤ 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.

F.8.2 Supplier choice

Table F.27. Impact of supplier flooding on supplier flood risk (6-month window)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	1.024	-10.67	0.208
	(8.508)	(8.889)	(10.00)
Suppliers' max flood extent	-63.11***	-65.40***	-72.23***
	(13.00)	(13.30)	(14.43)
Average effect of mean flooded supplier buffer in cm	-0.946	-0.980	-1.083
Average effect of 10% flooded supplier buffer in cm	-6.311	-6.540	-7.223
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0108	0.0308	0.0553
N	155,182	154,467	149,598

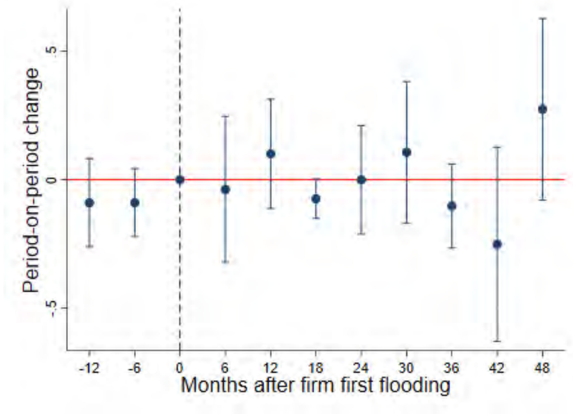
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq$ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.28. Impact of supplier flooding on flood risk of non-flooded suppliers (6-month window)

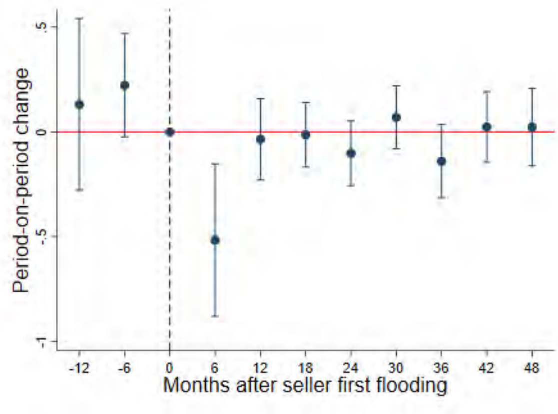
	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-4.727	-8.541	-4.731
	(8.839)	(10.07)	(10.82)
Suppliers' max flood extent	-31.00***	-31.62***	-31.94***
	(9.159)	(8.921)	(9.433)
Average effect of mean flooded supplier buffer in cm	-0.465	-0.474	-0.479
Average effect of 10% flooded supplier buffer in cm	-3.100	-3.162	-3.194
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0086	0.0304	0.0536
N	155,051	154,336	149,473

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 that are not flooded (defined as $\leq$ 5% overlap of the 2km buffer and the flood polygon). 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. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure F.47. Dynamic impact of supplier flooding on flood risk of all suppliers (6-month window)



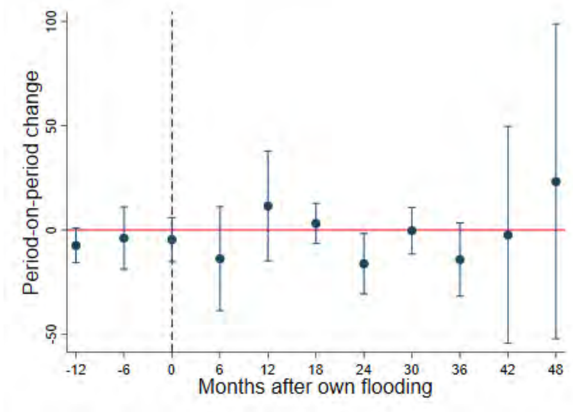
(a) Own flooding



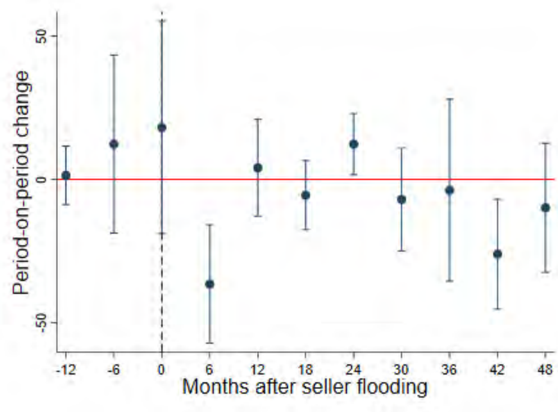
(b) Supplier flooding

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). 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. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure F.48. Dynamic impact of supplier and own flooding on flood risk of $\leq$ 5% flooded suppliers (6-month window)



(a) Own flooding



(b) Supplier flooding

Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq$ 5% following equation (23). 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 $\leq$ 10km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Table F.29. Impact of supplier flooding on supplier flood risk (12-month window)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	3.640	-8.949	4.606
	(7.246)	(6.351)	(7.781)
Suppliers' max flood extent	-61.41***	-64.89***	-72.00***
	(11.47)	(11.73)	(12.97)
Average effect of mean flooded supplier buffer in cm	-0.899	-0.950	-1.054
Average effect of 10% flooded supplier buffer in cm	-6.141	-6.489	-7.200
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0107	0.0285	0.0548
N	164,681	163,971	158,820

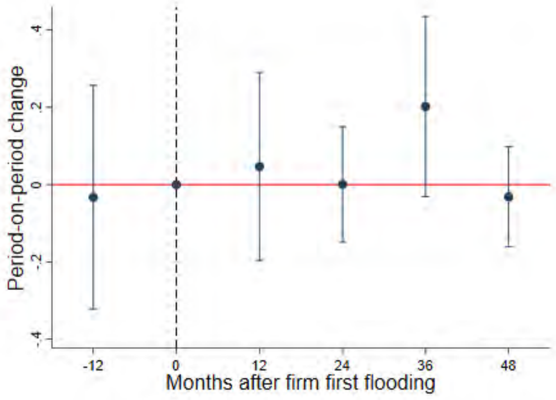
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.30. Impact of supplier flooding on flood risk of non-flooded suppliers (12-month window)

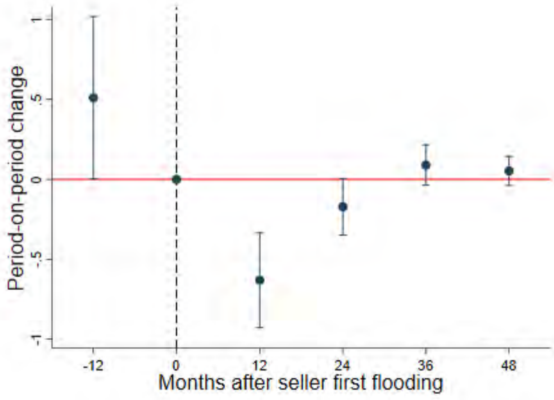
	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-13.56	-23.98**	-12.47
	(8.235)	(10.19)	(9.675)
Suppliers' max flood extent	-43.74***	-45.38***	-46.06***
	(8.472)	(8.649)	(8.701)
Average effect of mean flooded supplier buffer in cm	-0.615	-0.638	-0.647
Average effect of 10% flooded supplier buffer in cm	-4.374	-4.538	-4.606
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0084	0.0281	0.0548
N	130,928	130,231	125,729

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 that are not flooded (defined as ≤ 5% overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10km apart.We exclude all firms which are flooded or have any supplier flooded in a different event during the flood risk windows. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure F.49. Dynamic impact of supplier flooding on flood risk of all suppliers (12-month window)



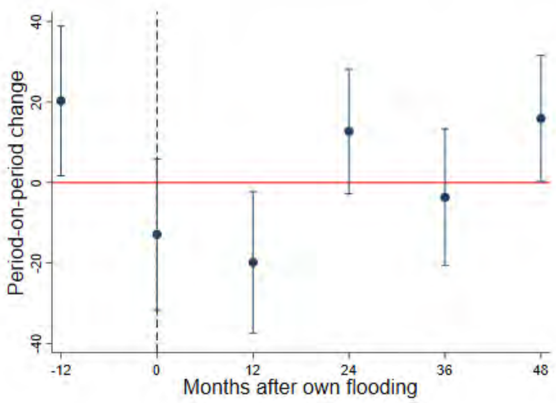
(a) Own flooding



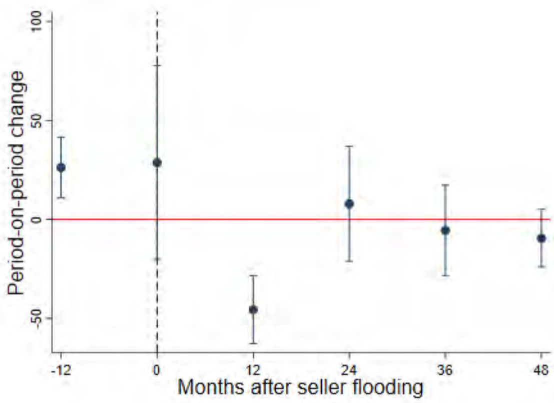
(b) Supplier flooding

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). 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. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure F.50. Dynamic impact of supplier and own flooding on flood risk of $\leq 5\%$ flooded suppliers (12-month window)



(a) Own flooding



(b) Supplier flooding

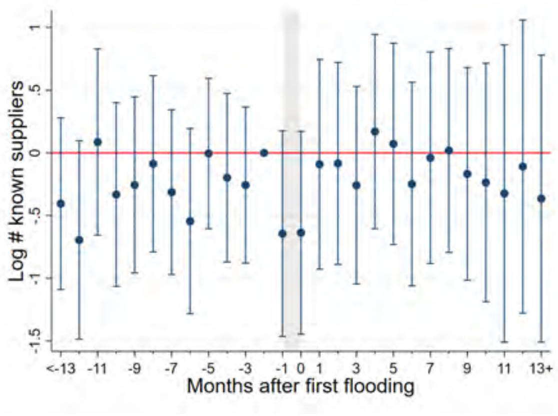
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (23). Here, we use a 12 instead of a 3-month window to define suppliers. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq$ 10km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

F.9 Results including moving firms

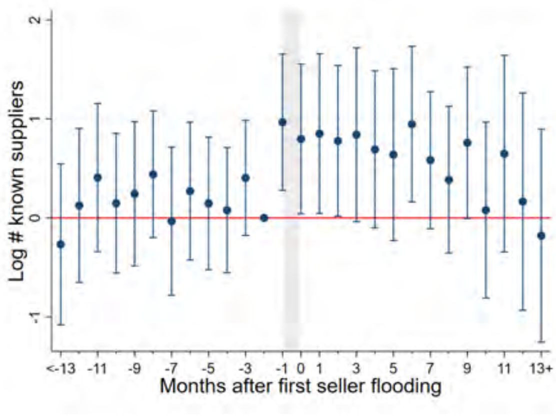
The central results investigating supplier choice restrict attention to firms that did not relocate more than 10km over the sample period in order to shut down mechanical shifts in the supplier base due to a new firm location. This section considers the robustness of results to including relocating firms. Geographic variables (firm flood exposure, district, risk decile) used in the specifications below are taken from the firm's 2011 (baseline) address.

F.9.1 Supplier diversification

Figure F.51. 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.

F.9.2 Supplier choice

Table F.31. Impact of supplier flooding on supplier flood risk (incl. movers)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-4.493	-7.114*	-3.351
	(4.378)	(4.097)	(4.668)
Suppliers' max flood extent	-49.81***	-50.83***	-62.39***
	(14.01)	(14.29)	(15.20)
Average effect of mean flooded supplier buffer in cm	-0.748	-0.763	-0.936
Average effect of 10% flooded supplier buffer in cm	-4.981	-5.083	-6.239
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0096	0.0276	0.0545
N	217,289	216,535	208,992

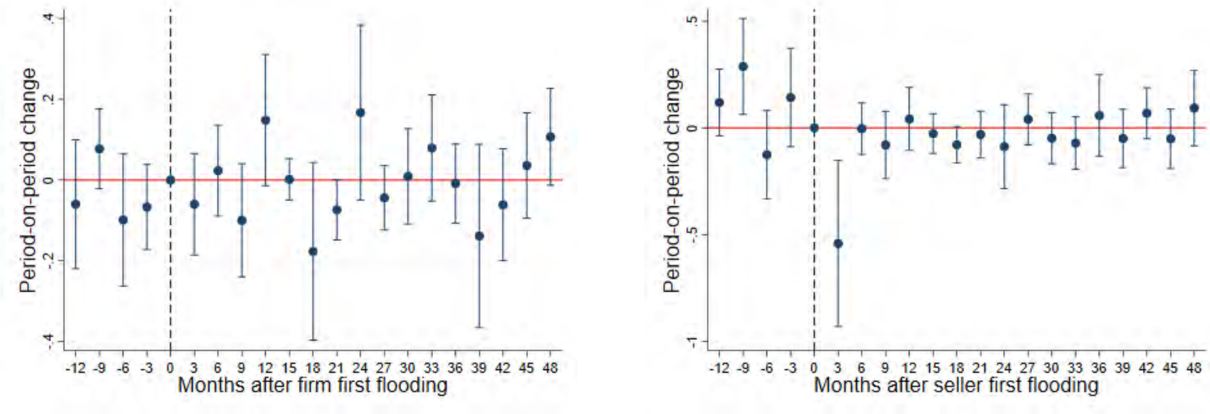
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.32. Impact of supplier flooding on flood risk of non-flooded suppliers (incl. movers)

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-5.224	-7.205*	-4.394
	(4.615)	(4.259)	(4.917)
Suppliers' max flood extent	-22.00***	-21.93***	-24.48***
	(7.562)	(7.265)	(7.610)
Average effect of mean flooded supplier buffer in cm	-0.330	-0.329	-0.367
Average effect of 10% flooded supplier buffer in cm	-2.200	-2.193	-2.448
Time × District FE	Yes		
Time × District × Risk decile FE		Yes	
Time × District × Industry FE			Yes
R^2	0.0079	0.0278	0.0538
N	217,017	216,270	208,725

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 that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known. Standard errors (in parentheses) are clustered at the time × district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

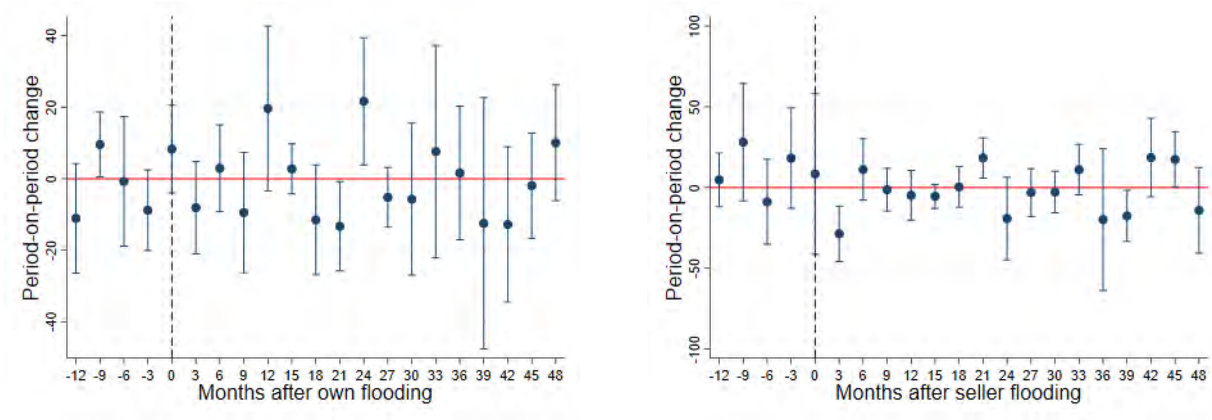
Figure F.52. Dynamic impact of supplier flooding on flood risk of all suppliers (incl. movers)



(a) Own flooding (b) Supplier flooding

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-month pairs. Here, this includes relocating firms. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure F.53. Dynamic impact of supplier and own flooding on flood risk of $\leq 5\%$ flooded suppliers (incl. movers)



(a) Own flooding (b) Supplier flooding

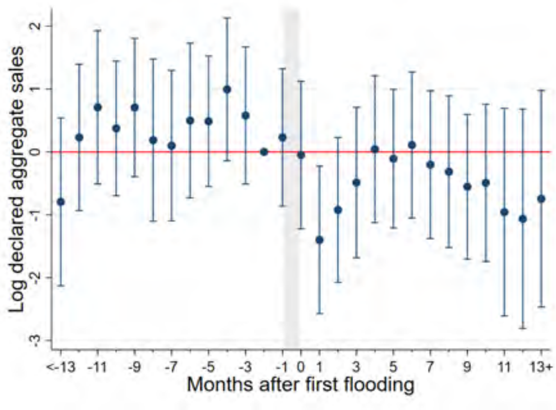
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (23). Observations are firm-by-flood-year-month pairs. Here, this includes relocating firms. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

F.10 Results excluding repeated exposures

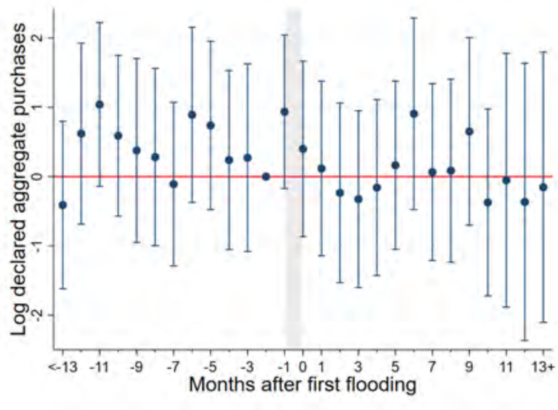
In the standard event studies, we consider a firm treated at the intensity of its first treatment in all periods following this first treatment. Given that treatment in a subsequent flood event could affect estimates for later treatment lags, in this section we present event study results restricting 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.

F.10.1 Impact of flooding on firm sales and purchases

Figure F.54. Impact of flooding on firm sales and purchases (excl. repeated exposures)



(a) Log sales

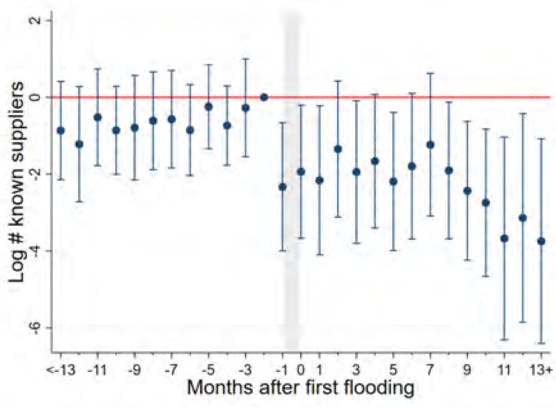


(b) Log purchases

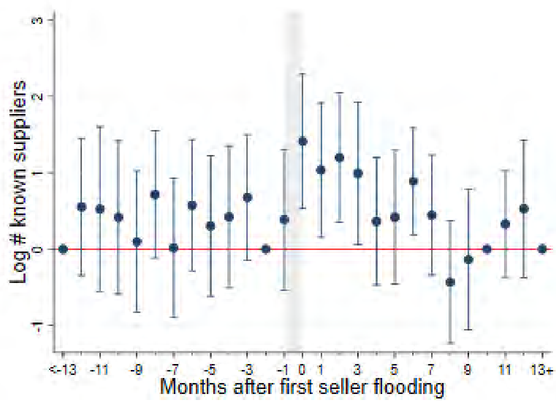
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observations are firm-month-years which are flooded in no or one flood event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

F.10.2 Supplier diversification

Figure F.55. Supplier Diversification: Impact of flooding on log number of suppliers (excl. repeated exposures)



(a) Own flooding

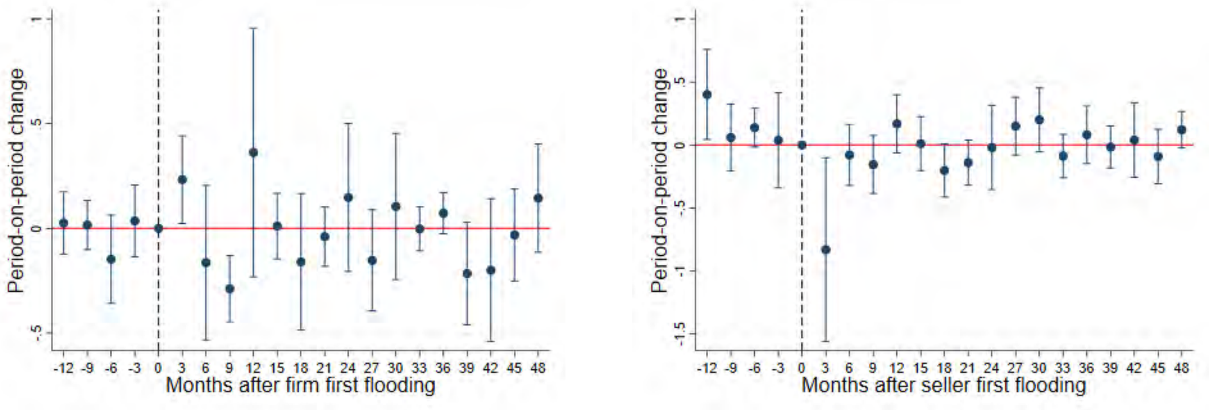


(b) Supplier flooding

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.

F.10.3 Supplier choice

Figure F.56. Dynamic impact of supplier flooding on flood risk of all suppliers (excl. repeated exposures)



(a) Own flooding

(b) Supplier flooding

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.

F.11 Robustness of route-level flooding impacts

Table F.33. 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)
$(\text{Shortest Path Flooded}_{bst^*}) \times \text{Post}_t$	-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 binary 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.