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

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PRELIMINARY DRAFT - MOST RECENT VERSION HERE

Abstract

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

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

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

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1 Introduction

Climate change presents a global threat to human populations and economic growth. Despite growing policy and research focus on mitigating the drivers of 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. This paper considers how firms—the central locus for the location of economic activity and of first-order importance for the welfare of populations—anticipate and adapt to climate-related shocks.

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

Our empirical analysis provides evidence that firms affected by natural disasters undertake adaptive production and sourcing decisions along *all* of the margins of location, supplier and supply route choice in the aftermath of major floods. We use detailed data on transactions between firms, and a robust identification strategy permitted by measurement of both firm- and supply route-level exposure to natural disasters, to attribute these adjustments to forward-looking decisions over future risk exposure rather than the direct disruptive impacts of flooding. This finding has crucial implications for our understanding of the role of climate risk in firm decision-making and how resilient firm production networks will be as the climate changes. While a worsening trajectory of natural disaster risk will have damaging impacts for firms, our results suggest that these will be mediated by firms responding adaptively as more information becomes available. More broadly, the complex adaptive behavior we identify is informative about the forward-looking behavior of firms in the presence of risk, an aspect of economic decision-making that plays a central role in a large range of economic and policy questions.

The context of our study is Pakistan, one of the countries most exposed to extreme weather worldwide (Eckstein et al., 2021) and where rapid industrialization is proceeding alongside increasing vulnerability to the effects of climate change. Floods are preeminent among these: the country frequently ranks in the top deciles for per capita flood losses globally (see Figure A.1), with major floods involving severe disruption to firms and infrastructure. The 2022 floods alone are estimated to have resulted in damages of $40 billion (PMO, 2022) (roughly 11.5% of 2021 GDP), 30% of which are accounted for by damages to infrastructure and non-residential structures (World Bank, 2022). Transportation infrastructure is especially affected by flooding: the 2022 floods damaged over 8000 miles of roads and 392 bridges (Congressional Research Service, 2022), while the 2010 floods are reported to have damaged 10% of the country's road network (World Bank, 2010).

We study firm and production network adaptation in Pakistan from 2011 to 2018 at a highly granular spatial and temporal scale using a series of novel datasets. We leverage georeferenced monthly microdata on the near-universe of formal firm-to-firm sales transactions of Pakistani firms to capture the key adaptation margins available to firms at a high frequency and level of precision. We complement the transaction records with data on over six billion observations from GPS trackers installed on more than 15,000 commercial trucks over the same period to measure the extent to which supply routes are affected by natural disasters. Flood disruptions to firm activities and the road network are measured by intersecting these with satellite-derived data on major flood events. In order to capture how far responses to flood events may be adaptive in reducing vulnerability to future such events, we supplement this data with high-resolution measures of flood risk derived from a global flood hazard model that uses detailed terrain and hydrography data.

We first document severe but short-lived disruption of firm activities and traffic induced by flooding of firm premises and roads. Sales and purchases of the mean flooded firm decline by 1.48% and 0.51% respectively in the month of recorded flooding, though both recover within six months. Pronounced increases in the probability of exit are observed in the direct aftermath of particularly severe flood events. Network linkages play an important role in the transmission of these shocks, with transaction-level specifications suggesting that negative effects of flooding affecting one firm are also felt by those firms connected via vertical linkages. Flooding of roads also leads to large but brief disruptions to traffic flows: mean truck speeds decline by 0.8km/hr and truck-day counts by 16-20% immediately following floods, with reversion of both outcomes to pre-exposure levels within a month. These estimates are in line with a small but growing literature on the direct disruptive impacts of floods for firms in other low and middle income contexts (Rentschler et al., 2021, Hu et al., 2019). The significant but apparently transient nature of these impacts raises the question of whether firm responses in the aftermath of such events may persist in the longer term, and how far these may help firms to adapt to a worsening trajectory of climate risk. The core of our analysis therefore turns to the question of whether these temporary flooding disruptions induce firms to undertake long-term adaptive changes in order to reduce their vulnerability to future flooding.

We provide the first micro-level evidence of firm-level adaptive relocation by using georeferenced data on firm locations at the beginning and end of the study period to consider whether firms relocate towards areas less prone to flooding in the aftermath of flood events. The results suggest that the average flooded firm sees a 2.1% increase in the odds of relocating more than 10km away over the ten-year study period relative to those that are not flooded. Importantly, this relocation is adaptive in the sense that flooding induces firms to relocate systematically towards less flood-prone locations: the average flooded firm that relocates more than 10km sees a 3.8cm reduction in the expected flood depth it would experience during a 1-in-100 year flood. District-level gravity specifications also suggest that relocating firms respond to recent flooding in deciding on a destination location, substantively avoiding locations that have recently been flooded within origin-destination district pair moves. These 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), aggregate economic activity as proxied by night lights (Kocornik-Mina et al., 2020, Elliott et al., 2015), and employment (Indaco et al., 2021), by considering evidence for firm-level relocation.

Given that firms may be exposed to climate risk via vertical linkages as well as directly, we use transaction-level data to examine adaptation margins involving supplier choice that are more difficult to identify. The results suggest that flooded firms adjust their choice of supply partners to lower their indirect flood exposure, both via diversification of their supplier base and by shifting towards less flood-prone suppliers. Diversification may be expected to ameliorate expected flood losses by reducing dependence on individual suppliers or customers, and spreading risk across suppliers with uncorrelated shocks (Cole et al., 2013, Meltzer et al., 2021, Boehm and Sonntag, 2022, Castro-Vincenzi, 2022). Consistent with this, we find that firms increase the number of suppliers from which they source following flooding of their suppliers. Combining transaction-level data with data on underlying flood risk at firm locations reveals that flood-exposed firms also 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 effects of no longer being able to source from flood-affected sellers, and persists for at least four years after flood exposure.[1] These results suggest that accounting for network-based adaptation margins is important and demonstrate the sophisticated nature of firms' adaptive responses beyond the direct flood exposure of production sites.

The vulnerability of the firm network is predicated not only on the flood risk of firms, but also on the riskiness of the trading links that connect them: even if firms are sited in low risk locations and source from low risk suppliers, they remain exposed if the roads they use to trade with supply partners are prone to flooding. 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 to control for any direct effects of floods on firms themselves and rule out potentially confounding shocks that may affect flooded firms even after their sales and purchases have recovered, for instance local labor market disruptions or correlated cost shocks. The results suggest that firms respond to very short-lived flood-induced disruptions to road transportation by reducing their dependence on supply partners reached via flood-prone routes. Despite pre-flood traffic flows being restored within a month, firms do not switch back to sourcing from these suppliers once access is restored. This provides our most cleanly-identified evidence of firms undertaking long-term adaptation in response to transient shocks, and highlights the importance of accounting for route- as well as firm-level adaptation margins.

Taken together, these results provide evidence that firms anticipate future flood risk and undertake adaptive actions following exposure to major flood events. The implications of these responses for firms' vulnerability to future shocks, and the policies that might best support effective long-term adaptation, will depend on the mechanisms underlying firm responses. If adaptation reflects rational updating as flood events change firm priors over flood risk, responses may be expected to be long-lived, and flood risk information might prove an effective means of inducing welfare-enhancing adaptation. Conversely, if flood events increase the salience of flood risk without changing underlying firm expectations, adaptive responses may be more likely to subside in the medium term. While a growing empirical literature considers such effects in individual decision-making relating to climate risks (Ortega and Taspınar, 2018, Bernstein et al., 2019, Bakkensen and Barrage, 2017, Gallagher, 2014, Deryugina, 2013, Kala, 2017), the evidence on firm beliefs is much more limited. The persistence of the adaptive responses we identify is more consistent with experience-based rational updating, suggesting that projecting the impacts of future flooding based on current disruptions may lead to incorrect conclusions (for instance as discussed in Carleton and Hsiang, 2016).

We quantify the economy-wide implications of the adaptive behaviors identified for the aggregate vulnerability of firm production networks and welfare using a structural model of endogenous production network formation. These effects are difficult to estimate directly by comparing the outcomes of firms that adapt versus those that do not in the aftermath of future flood events without time-series data over very long horizons. Flood events occur infrequently, and the impact of adaptation on future vulnerability is relevant with respect to the full distribution of potential future floods rather than a particular flood event. Aggregating the firm-level adaptation estimates across firms in the network is also likely to be misleading in estimating aggregate impacts given spillover effects across firms and the importance of general equilibrium responses. We therefore quantify aggregate

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

impacts of adaptive responses using a quantitative spatial model that captures firm-to-firm linkages and general equilibrium forces, and can be simulated over the full distribution of potential future flood events.

The model considers endogenous production network formation among firms that are subject to both idiosyncratic and aggregate flood risk. Firms are imperfectly informed about the (joint) distribution of these risks, but learn about flood risk from realized flood events, in response to which they can update their beliefs. 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 across different locations. Once shocks have been realized, firms make production and sourcing decisions conditional on these draws in order to minimize costs.

This modeling framework builds on recent advances in modeling production network formation under uncertainty (Kopytov et al., 2022) to incorporate imperfect information among firms, who learn about flood risk from flood events. We augment this framework to 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 identify adaptive flood-induced changes in firms' supplier search decisions from observed changes in sourcing shares, without imposing parametric assumptions about the belief-updating process. The structure of the model therefore allows us to estimate the aggregate impacts of adaptive changes in firms' supplier choice and simulate policy counterfactuals. Preliminary results suggest that adaptation following individual flood events ameliorates damages from future floods in similar locations, but may accentuate losses from future floods affecting very different areas.

The paper's findings suggest that natural disaster risk plays an important role in firm decision-making and that the realization of climate shocks influences firm expectations in a meaningful way. This manifests via adaptation along location, supplier and route choice margins, with complex system-wide effects as a result of manifold inter-linkages in production networks. A significantly worsening trajectory of flood events is predicted in Pakistan (World Bank Group and Asian Development Bank, 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 and are first order in informing our understanding of how costly climate change will be and designing appropriate policy responses.

The remainder of the paper proceeds as follows. Section 2 describes the datasets used in the analysis. Section 3 provides evidence for the disruptive impacts of flood events on firm production and road transportation in Pakistan. Section 4 examines firm and supply chain adaptation in the aftermath of flood events. Section 5 provides a quantitative model of production network formation and adaptation under supply chain uncertainty, which we bring to our empirical setting in Section 6 to understand the importance of adaptive decisions for the distribution of aggregate outcomes. Section 7 concludes.

2 Data

The analysis draws on four novel georeferenced micro-datasets relating to firm networks and their vulnerability to flooding in Pakistan from 2011 to 2018, described in this section.

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

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

We take a number of steps to exclude incomplete or potentially misreported transaction data. We exclude firms that have been identified as - or transact exclusively with - 'invoice mills', firms that exploit breaks in the supply chain to purchase and sell VAT invoices without conducting any real business (Waseem, 2019, Keen and Smith, 2006). This removes 4% of firms in the sample. Also excluded are 29% of firms for which there is insufficient address information to geocode the firm's location and therefore for which we cannot identify flood exposure. A large fraction of the remaining firms report very infrequently or not at all (the latter appearing in the dataset only by virtue of having transactions reported upon by their VAT-registered transaction partners): 66% report sales at most once, and 70% report purchases at most once. Given that measurement for such firms is likely to be poor and that these will not be informative for studying the effects of flooding, we also exclude firms that report at most twice in any transaction measure.[3] The full set of sample restrictions reduces the firm count considerably to 73,336, but excludes firms that account for only a very small share of economic activity, 2.9% of aggregate sales and 3.4% of aggregate purchases.

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

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

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

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

Table 1. Firm-level summary statistics

# Buyers = # Sellers	73,336			
Share of firms with 2011 and 2019 geocodes	60%			
Share of firms whose 2km buffer ever flooded	28%			
Share of firms whose 2km buffer flooded more than once	4%			
Share of firms whose partners' 2km buffer ever flooded	78%			
Share of firms whose partners' 2km buffer flooded more than once	54%			
Median firm age at the end of sample period	32.48			
Average probability of firm exit in given month	0.43%			
	Monthly		Annually	
	Mean	SD	Mean	SD
Log total sales declared	14.74	2.07	16.73	2.15
Log all aggregated sales	14.77	2.15	16.77	2.26
Log self-reported sales	14.84	2.08	16.99	2.12
Log total purchases declared	14.45	2.15	16.35	2.20
Log all aggregated purchases	14.26	2.38	16.23	2.43
Log self-reported purchases	14.45	2.22	16.36	2.30
Number of unique suppliers	4.60	18.30	13.06	46.24
Number of unique buyers	5.09	47.71	17.38	120.39
Share of months with positive declared sales or purchases	49%	31%		
Share of months with positive self-reported sales or purchases	53%	30%		
Share of months with positive self/reverse sales or purchases	56%	31%		
Firm panel observations (nonzero)	3,736,834		413,190	

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 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. All sales and purchases are denominated in Pakistani Rupee (PKR) before logging. Annual statistics are calculated for the fiscal year. Firm age is measured in years.

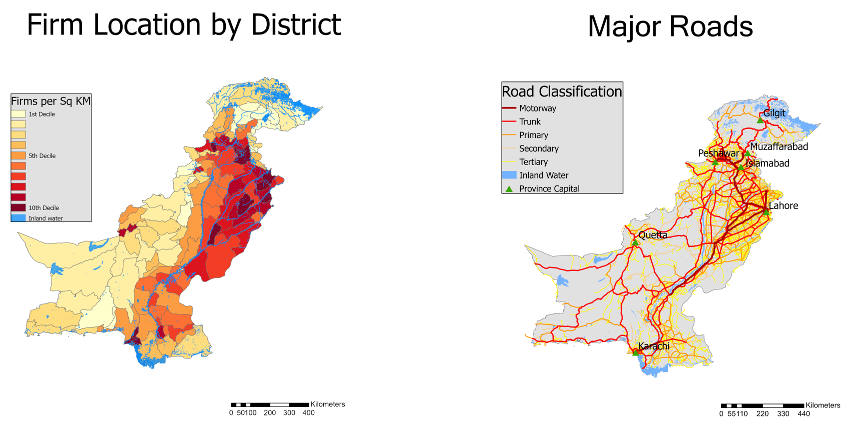
Table 2. Transaction-level summary statistics

	Mean	SD
Log Transaction size	12.43	2.27
Transaction(s) per pair in years with ≥ 1	4.27	3.81
Transaction(s) per pair per year over sample period	1.25	2.12
Time between transactions (months) for pairs with > 1 transaction	2.13	4.10
Share of B purchases accounted for by average S	35%	36%
Share of S sales accounted for by average B	24%	31%
Transaction panel observations (non-zero)	15,514,145	
Firm pairs ever reported	1,660,006	
Share of active firm-pairs out of all possible combinations	.034%	

All sales and purchases are denominated in Pakistani Rupee (PKR) before logging. Transactions between a buyer and seller are only counted if the transaction value is greater than zero.

Address information for firms in the sample was used to geocode firm locations using the Google

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



(a) Firms

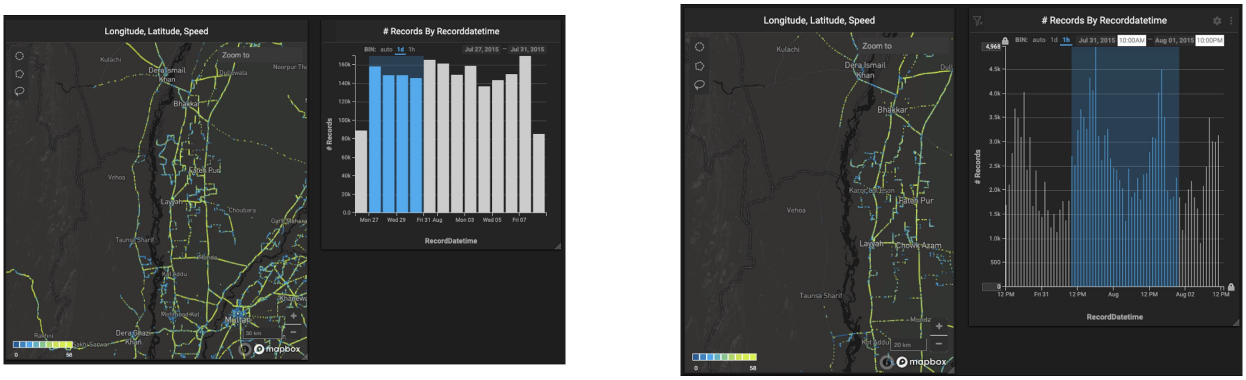
(b) Roads

Figure 1. Locations of firms and roads

2.2 GPS tracker data from commercial trucks

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

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



(a) Jul 27-30, 2015

(b) Jul 31-Aug 1, 2015

Figure 2. N-55 Indus Highway flooding disruption

We validate the tracker data by comparing it to documented flood-related road disruptions. Figure 2 displays the capacity of this data to capture flood-induced disruption to roads at an extremely fine spatial and temporal resolution. The Figure shows the area surrounding the N55 highway near Vehova in Punjab Province, which at 09:15 on 31 July 2015 was reported by Pakistan's National Disaster Management Authority to have been hit by "floodwater coming from Koh-e-Suleman Range" which "swept away a 300-foot portion of the highway". The left hand panel shows normal traffic running along the highway running north-south directly to the left of the Indus River in the four days leading up to the flood from 27-30 July. The right hand panel shows the abrupt cessation of traffic along the route in the direct aftermath of the flooding from 10:00 on 31 July to 10:00 on 1 August. In Section 3.3, we use weekly road edge level regressions to document a systematic pattern of such flood-induced disruptions to road traffic in our sample.

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

Figures A.4 and A.5 suggest that the resulting edge-time level dataset captures travel speeds well. Figure A.4 compares calculated speeds in the full sample to speeds reported by the trackers themselves at the time of each observation, for each road type in 2012. This comparison demonstrates that calculating travel speeds using the method described above overcomes selection bias in the reported speeds arising from the fact that GPS trackers are disproportionately likely to report when vehicles are starting, stopping, braking, or turning, which accounts for the mass of observations at very low reported travel speeds. In contrast, calculated speeds follow a smooth distribution

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

with a sensible distribution by road type. Figure A.5 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 2010-2019 are obtained from the United Nations Satellite Centre (UNOSAT) flood portal.[7] This service provides satellite imagery of major flood events generated in response to requests from organizations such as UN entities, member states, government offices and NGOs, most often to aid disaster response efforts.[8] These images allow us to map the exact location of floods as detected from satellites, from which we extract a reference water layer.[9] Flood-affected firms and roads are identified by intersecting the resulting flood areas with georeferenced firm and road locations.

For firm-level specifications, we aggregate satellite images to the monthly level, which yields a total of 14 monthly flood events over 2010-2019. The aggregate extent of flooding during years in which we observe flood events during our sample is shown in Figure A.6. We capture flooding of firm locations using the maximum share of a 2km buffer surrounding the firm's geocoded location that is flooded during a given flood event. As described in Table 1, using this definition 28% of firms in the sample are ever flooded during the sample period and 4% are flooded more than once.

Given that roads are often disrupted by floods for shorter durations, we consider flood-induced road disruption at the weekly level. Satellite images are grouped at the weekly level, yielding a total of eleven 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. Among geocoded ordinary-time shortest routes between firm pairs, 0.7% of buyer-seller-week observations see any flooding along the route across the entire sample period. This figure rises to 25% during weeks for which any flooding is observed. At the buyer-seller level, 46% of ordinary-time shortest routes experience flooding at least once during the sample period.

2.4 Flood risk data

Given our focus on adaptation to flood risk, we supplement our data on flood exposure with data on flood risk. These data come from Fathom-Global, which uses a global flood hazard model combined with detailed terrain and hydrography data. The resulting datasets comprise rasters at a resolution of 90 meters representing fluvial and pluvial flood risk (measured as the expected flood depth in meters) with return periods of 1 in 10 years, 1 in 50 years and 1 in 100 years.[10] For each return

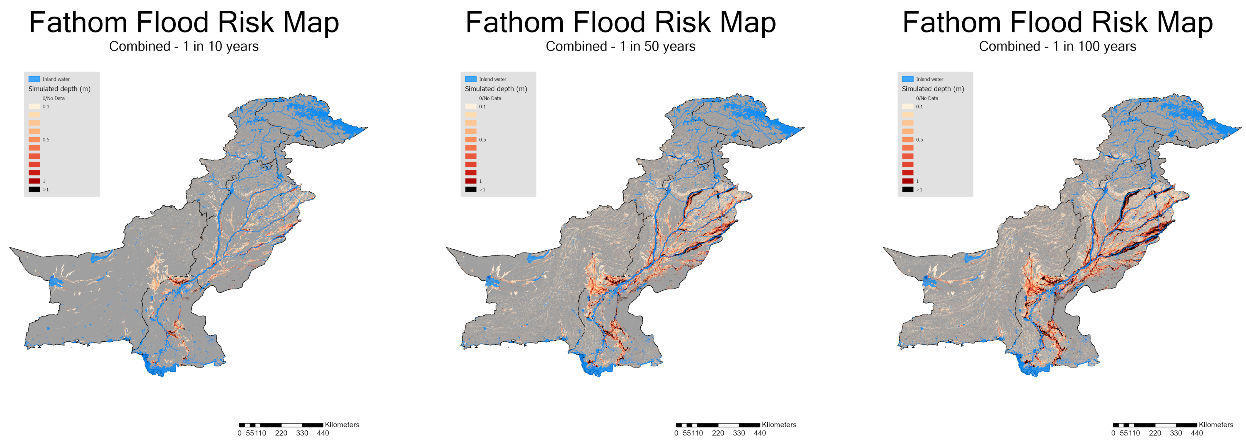
[7]http://floods.unosat.org/geoportal/catalog/main/home.page.

[8]We cross-reference the floods identified from this source with major flood events identified in other key natural disaster datasets (the EM-DAT dataset of the Centre for Research on the Epidemiology of Disasters, the Dartmouth Flood Observatory and Sentinel Asia) to confirm that major flood events described in these sources are captured in our data. Relative to these sources, the UNOSAT data provides the advantage of exact flood locations and extents as observed from satellites during our study period.

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

[10]Fathom-Global 2.0 is based on LISFLOOD-FP, a two-dimensional hydrodynamic model designed to simulate floodplain inundation over complex topography (Bates (2010). The key datasets used are the MERIT-Hydro global

period, we take the maximum of the projected fluvial and pluvial flood risk. Figure 3 maps the Fathom flood risk for each return period across Pakistan, and demonstrates a significant degree of overlap between flood-prone locations and areas with a high density of firms as shown in Figure 1.



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

Figure 3. Fathom flood risk maps of Pakistan for return periods of 10, 50 and 100 years

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.2. 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. Table A.1 presents summary statistics of the flood risk characteristics of firms in the sample, broken down according to those that are never flooded, flooded once, or flooded multiple times. 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.3 and Table A.2.

3 Floods and supply chain disruption

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

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.

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

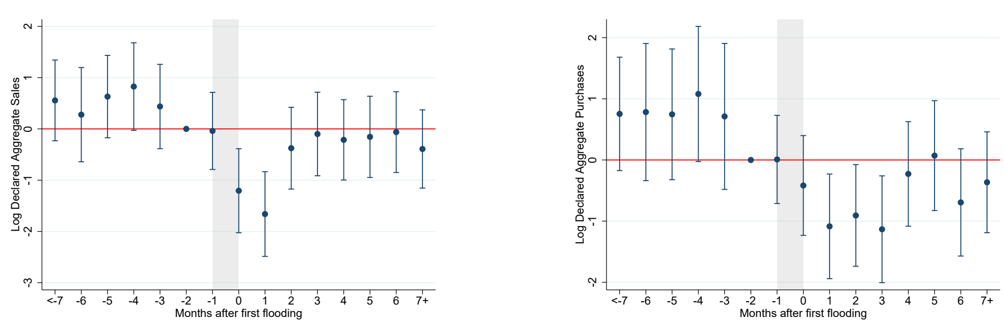
3.1 Impacts of firm flooding

We first consider the direct impact of firm flooding on their operations as measured by sales and purchases using the following specification:

$$y_{it} = \sum_{\substack{\tau=-6 \\ \tau\neq-2}}^{6} \beta_\tau \text{FloodExtent}_{i,t-\tau} + \alpha_{im(t)} + \alpha_{iy(t)} + \alpha_t + \varepsilon_{it} \tag{1}$$

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

The results of estimating this specification, shown in Figure 4, display intuitive reductions in both the sales and purchases of flood-hit firms in the direct aftermath of flooding events. The immediate impacts are statistically significant and economically large: during the month of impact, sales decline by 1.48% and purchases by 0.51% for the mean treated firm, which sees 1.2% of its 2km buffer flooded. These impacts are, however, relatively short-lived, with recovery of both sales and purchases to their pre-flooding levels within six months. 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.



(a) Log sales

(b) Log purchases

Figure 4. Impact of flooding on firm sales and purchases

[12] Results are robust to replacing month-year fixed effects with district-month-year fixed effects or Fathom flood risk decile-month-year fixed effects.

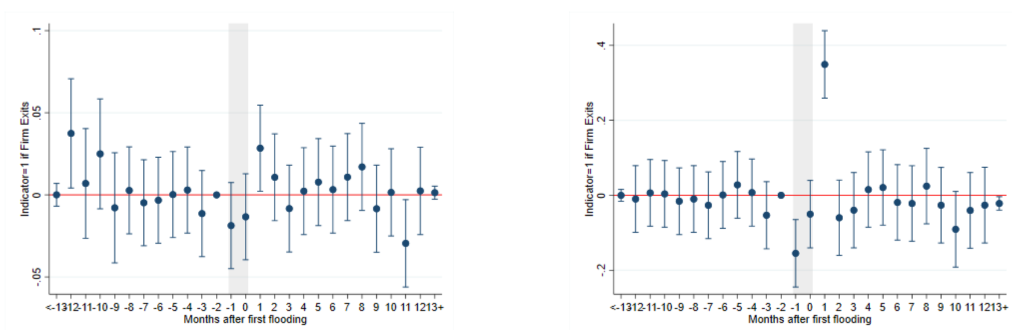
[13] In Appendix C.1, we consider the robustness of results to using the estimator proposed in Sun and Abraham (2021) to address potential challenges associated with two-way fixed effects regressions including treatment lags and leads with variation in treatment timing.

Given the sizeable impacts of flooding on firm operations shown in Figure 4, it seems possible that large floods might be sufficiently disruptive as to result in the exit of the worst-affected firms. We consider the impact of firm flooding on firm exit using the following specification:

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

where y_{it} is an indicator variable equal to one if firm i exits in month-year t and α_{dt} are district-month-year fixed effects.

The estimates of this model using the full sample are shown in the first panel of Figure 5. This demonstrates a marginally significant increase in firm exit in the month following recorded flooding. The magnitude of the effect corresponds to a 0.04 percentage point increase in the probability of exit for the mean treated firm. For reference, the probability of exit of firms over the entire study period is 16.5%. Considering separate results by flood event, however, reveals that this masks significant heterogeneity. As can be seen in the second panel of Figure 5, the severe floods in 2014 demonstrate much stronger evidence for sizeable and statistically significant impacts of flooding on firm exit: the mean firm first treated in 2014 sees a 0.4 percentage point increase in the probability of exit.[14]



(a) All floods (b) September 2014 flood

Figure 5. Impact of flooding on firm exit

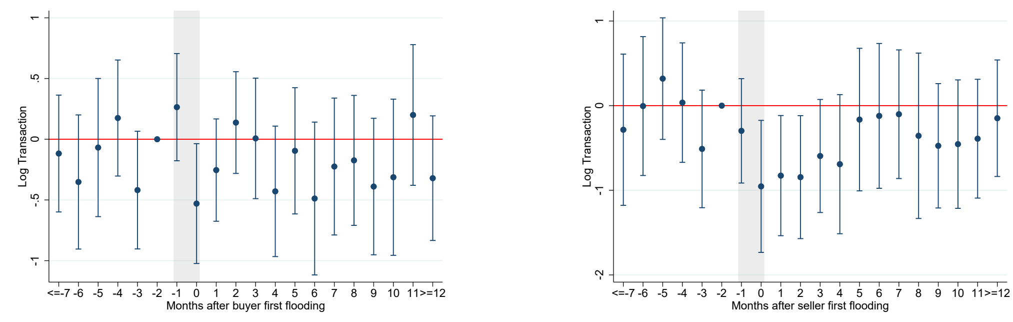
3.2 Propagation of flood shocks through supply chain networks

This section considers whether flood shocks propagate through supply chain networks in Pakistan, consistent with evidence that trade networks can transmit natural disaster shocks in the United States (Barrot and Sauvagnat, 2016) and earthquake shocks in Japan (Boehm et al., 2019, Carvalho et al., 2021). The following specification is used to consider the impact of buyer flooding (and symmetrically for seller flooding) on buyer-seller transactions when either party is flooded:

$$y_{bst} = \sum_{\substack{\tau=-6 \\ \tau\neq-2}}^{12} \beta_\tau \text{BuyerFlood}_{b,t-\tau} + \alpha_{bs} + \alpha_{st} + \eta_{\text{age}(b,s),t} + \varepsilon_{bst} \tag{3}$$

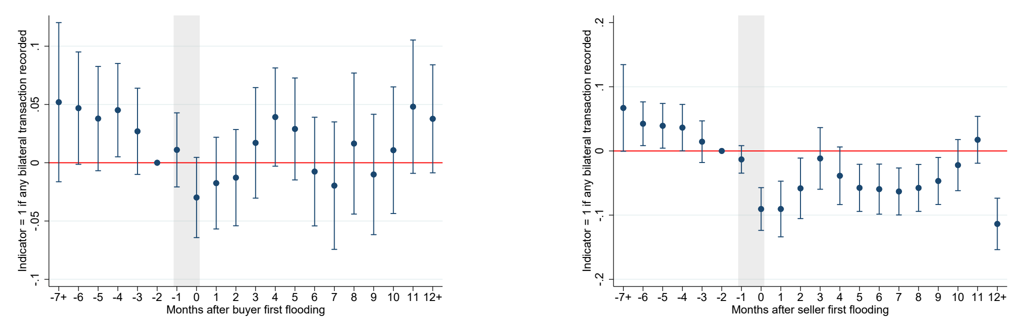
[14] Conditional on firm survival, we see muted effects on the extensive margin as shown in Figure A.7. While this suggests that surviving firms do not stop selling or buying altogether in the aftermath of floods, this may also be partly accountable to the infrequency of firm reporting as shown in the firm-level summary statistics in Table 1.

where BuyerFlood_{bt} is the maximum share of buyer b's 2km buffer that is flooded during month-year t; and α_{bs} and α_{st} are buyer-seller and seller-time fixed effects respectively. 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.8). Standard errors are clustered at the level of the flooded firm. In intensive margin specifications that consider the impact of buyer or seller flooding on transactions conditional on the buyer-seller relationship continuing to exist, the dependent variable y_{bst} denotes the log transaction values between buyer b and seller s during month-year t. In extensive margin specifications, y_{bst} is instead an indicator variable denoting whether or not there were positive sales between buyer b and seller s during month-year t.



(a) Buyer flood (b) Seller flood

Figure 6. Impact of flooding on buyer-seller transactions: intensive margin



(a) Buyer flood (b) Seller flood

Figure 7. Impact of flooding on buyer-seller transactions: extensive margin

The results of the intensive margin specifications are shown in Figure 6 and the extensive margin specifications in Figure 7. For both sets of outcomes, buyer-seller transactions appear to be more significantly disrupted when the seller in the relationship is flooded. The intensive margin results show substantial but short-lived declines in transaction values for those buyer-seller relationships that continue to exist: flooding of the mean treated seller firm (which sees 1.1% of its buffer flooded) reduces transactions by 1.04%, with full recovery to pre-flooding levels within six months of the flood. Flooding of the mean treated buyer firm (which sees 1.3% of its buffer flooded) results in a marginally significant reduction in transactions by 0.04% in the month during which flooding occurs, with reversion in the next period. The results in Figure 7 suggest more persistent extensive margin impacts of seller flooding, with limited evidence for effects of buyer flooding. There is a significant decrease in the probability of any transactions occurring between a buyer-seller pair for up to one year after the seller is flooded, with the probability of any bilateral sale decreasing by 0.1% immediately following seller flooding for the mean treated buyer-seller pair.

While these results suggest that transactions are disrupted when either the buyer or seller in the relationship is flooded, firms may be able to smooth such shocks by substituting towards other supply chain partners. Figure A.9 examines how far flooding of a supplier (buyer) affects the *aggregate* purchases (sales) of its supply partner. The results are insignificant at conventional levels, suggesting that while flooding of an individual seller will see buyer purchases from that seller decline, buyers are to some extent able to substitute towards other sellers such that the impacts on their aggregate purchases are muted.

3.3 Impacts of road flooding

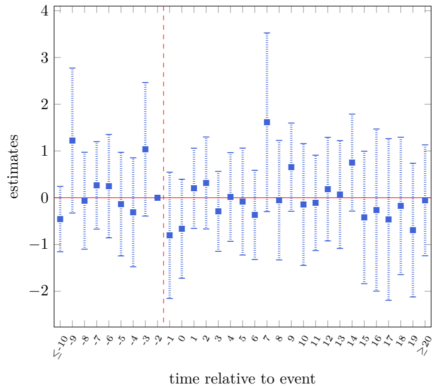
Flooding may disrupt firm and supply chain network activity not only via direct damage to firm buildings, equipment and stocks, but also as a result of disruptions to the road network. Such effects may be substantial: for instance, the World Bank estimates that the devastating floods of 2010 damaged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

$$y_{iw} = \sum_{\substack{\tau=-10 \\ \tau\neq-2}}^{20} \beta_\tau \cdot \mathbb{1}(i \text{ flooded at } w-\tau \text{ and } w-\tau \in y(w)) \cdot \text{FloodExtent}_{i,y(w)} + \alpha_i + \alpha_{dw} + \varepsilon_{iw} \quad (4)$$

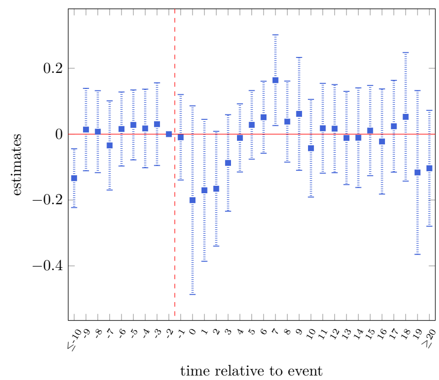
where y_{iw} is an outcome for road edge i during week w; $y(w)$ is the year of week w; $\text{FloodExtent}_{i,y(w)}$ is the share of the total road length of i that is flooded in the first week of flooding during $y(w)$; α_i are road edge fixed effects; and α_{dw} are district-week fixed effects.

To capture alternative measures of road disruption, we consider several outcome variables. Panel (a) of Figure 8 shows the impact on the mean speed of trucks traveling on the edge, and panel (b) on the log day-truck count. Panels (c) and (d) display effects 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 first or fifth percentile respectively for the relevant edge across all weeks.[15]

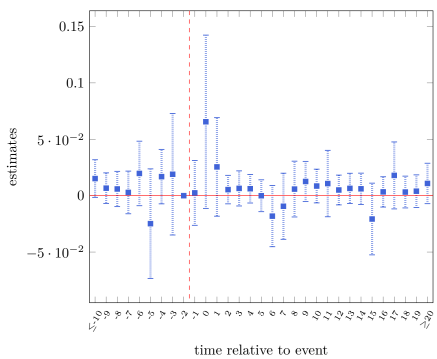
[15] The day-truck count is the number of different trucks travelling on that edge in that week, counting each truck more than once if they travel on the edge on different days of the week. For the specifications examining mean speed in panel (a), we consider the set of edge-week observations for which we have at least 10 day-truck observations with valid speed since mean speed is poorly measured when trucks pass very infrequently. The regressions (b), (c), and (d) 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.



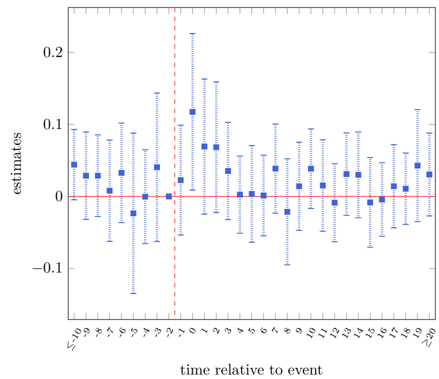
(a) Mean truck speed



(b) Day-truck count



(c) Disruption (< 1st percentile)



(d) Disruption (< 5th percentile)

Figure 8. Impact of flooding on road traffic

The results of all of these specifications paint a consistent picture of sizeable but brief disruptions to traffic induced by flooding of roads. Mean truck speeds at the road edge-week level decline by 0.8km/hr in the week in which flooding is recorded, but return to pre-flooding levels by the following week. The point estimates of effects on day-truck counts shown in panel (b) show a more persistent decline in the range of 16-20%, with reversion to pre-flooding levels within a month of flooding. Disruption indicators based on thresholds of the first or fifth percentile of edge-level day-truck counts show increases of 6.6pp and 11.7pp respectively in the week in which flooding is recorded, with reversion within a fortnight.

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

4 Evidence for firm and supply chain adaptation

In this section, we turn to the key question of whether firms undertake adaptive actions following flood events that may reduce their vulnerability to future such events. 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.

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 are interested both in whether flooding induces firms to relocate, and in how far flooding may prompt 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. To address this, we present all firm relocation specifications where the threshold for defining a firm 'move' varies from 0km to a 20km distance between the 2011 and 2019 address coordinates. Summary statistics in Appendix Table A.3 reveal that there is a non-zero difference between the 2011 and 2019 location of 68% of firms, an implausibly high relocation rate over an eight-year horizon which is likely predominantly accountable to these small discrepancies in address information leading to local discrepancies in geocode locations. Consistent with this, defining firm relocations based on thresholds of 5km, 10km or 20km give more plausible relocation rates of 24%, 13% and 7% respectively, which are therefore the preferred specifications on which we focus the discussion.

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

$$Pr\left(\text{Move}_i\right) = F\left(\beta \text{FloodExtent}_i + \alpha_{zd}\right) \tag{5}$$

where $Move_i$ is an indicator denoting whether firm i moved during the sample period; and $FloodExtent_i$ is the maximum share of firm i's 2km buffer that is flooded during the firm's first experienced flood during the study period. We consider specifications including district-level fixed effects α_d and fixed effects α_{zd} at the level of district $\times$ decile of Fathom flood risk (with a 1 in 100 year return period) in order to restrict attention to within-district variation among firms with similar levels of underlying flood risk, parsimoniously specified to avoid imposing excessive structure on the manner in which flood risk should enter. The latter accounts for the fact that firms located in areas of higher versus lower underlying flood risk may have differential propensities to relocate. Standard errors are clustered at the district level.

The results, shown in Table 3, suggest that firm flooding increases the probability that firms relocate during the sample period. The results are significant, and the point estimates largest, where relocations are defined based on a change in the firm's geocoded location of at least 5km which, as described above, most plausibly capture real firm moves. Across both specifications with district fixed effects and district $\times$ Fathom flood risk decile fixed effects, the magnitudes suggest that flooding results in a consistent 2% increase in the odds of relocating more than 10km for the mean flooded firm. This is a significant effect relative to the 1 in 15 mean odds of relocating more than 10km among non-flooded firms.

Table 3. Impact of flooding on firm relocation

	Dependent Variable: Move Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Max Share of 2km Buffer Flooded	-0.0704	1.840**	1.752**	-0.297	1.604*	1.848**
	(0.742)	(0.751)	(0.803)	(0.726)	(0.952)	(0.834)
District FE	Yes	Yes	Yes			
District × Fathom 1in100 FE				Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km	0km	5km	10km
R^2	0.005	0.021	0.046	0.017	0.041	0.067
N	43,831	43,841	43,848	43,515	43,487	43,395

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Firm relocations 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:

$$\triangle \text{FloodRisk}_i = \beta \text{FloodExtent}_i + \alpha_{zd} + \varepsilon_i \tag{6}$$

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 Table 4, suggest that flooding indeed induces firms to relocate to less flood-prone locations. Using within-district variation, the mean treated firm that moved more than 10km, which has 1.9% of its buffer flooded, sees a 3.8cm reduction in expected 1 in 100 year flood depth. Table 4 also displays negative effects in specifications that restrict to within district-risk decile variation, with an intuitive reduction in magnitude and statistical significance.

Table 4. Impact of flooding on Fathom flood risk of firm's location

	Dependent Variable: Change in Flood Risk				
	(1)	(2)	(3)	(4)	(5)
Max Share of 2km Buffer Flooded in Flood Month	-1.407	-1.998	-2.475	-2.063*	-2.100**
	(0.849)	(1.239)	(1.543)	(1.173)	(0.998)
District FE	Yes	Yes	Yes	Yes	Yes
District × Fathom 1in100 FE					
R^2	0.028	0.039	0.086	0.126	0.189
N	43,866	29,684	10,623	5,737	2,912
Max Share of 2km Buffer Flooded in Flood Month	-0.533*	-0.770	-0.665	-0.516	-0.510
	(0.304)	(0.466)	(0.672)	(0.616)	(0.457)
District FE					
District × Fathom 1in100 FE	Yes	Yes	Yes	Yes	Yes
R^2	0.190	0.268	0.424	0.449	0.492
N	43,754	29,569	10,481	5,596	2,789
Move Distance Restriction		>0km	>5km	>10km	>20km
Pr(Move=1)		0.68	0.24	0.13	0.07
Average 1in100 Flood Risk		0.28	0.29	0.30	0.32

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results in this section suggest that flooded firms are differentially likely to relocate during the study period, and that they relocate systematically towards less flood-prone locations. 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.[16] This is illustrated in Figure 9: 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?

[16] 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. For locations in destination districts that are not flooded during the sample period, t_d is set to a time period beyond the end of the sample. Firms whose origin address is not flooded during the study period are dropped from the estimation.

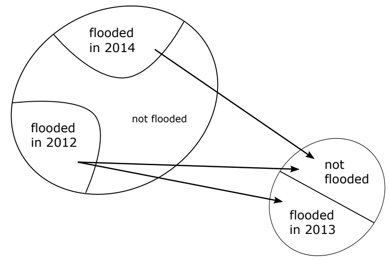


Figure 9. Illustration of differential relocation based on destination flood history

We examine this using the following gravity Poisson specification:

$$X_{ot_odt_d} = \alpha_{od} + \alpha_{ot_o} + \alpha_{t_d} + \beta \mathbb{1}\left(t_o - t_d > 12\right) + \varepsilon_{ot_odt_d} \tag{7}$$

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

The results of this analysis are shown in Table 5. These 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.

Table 5. Impact of destination flood history on relocation flows

	Dependent Variable: Number of Firms Moved			
	(1)	(2)	(3)	(4)
Dest. flooded 12mo prior	-1.857***	-0.781***	-0.730***	-0.904***
	(0.267)	(0.214)	(0.224)	(0.281)
Origin $\times$ Destination FE	Yes	Yes	Yes	Yes
Origin $\times$ Flood Event (month) FE	Yes	Yes	Yes	Yes
Flood Event of Destination FE	Yes	Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km	20km
N	2,596	2,288	2,135	1,704

Poisson Pseudo-maximum-likelihood estimator. Standard errors in parentheses, clustered at the origin-destination level. Sample is restricted to firms fully geocoded in 2011 and 2019.

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

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 consider evidence for adaptation via diversification of suppliers in response to both flooding of a firm's own premises and flooding of their suppliers. To investigate evidence for the former, we use the following specification:

$$y_{it} = \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_\tau \text{FloodExtent}_{i,t-\tau} + \alpha_{im(t)} + \alpha_{iy(t)} + \alpha_t + \varepsilon_{it} \tag{8}$$

where y_{it} denotes firm i's log number of suppliers in month-year t; FloodExtent_{it} is the maximum share of firm i's 2km buffer that is flooded during month-year t; and $\alpha_{im(t)}$, $\alpha_{iy(t)}$, and α_t are firm-month, firm-year and month-year fixed effects respectively. Standard errors are clustered at the firm level.[18]

To test whether firms diversify their supplier base in response to flooding of their *suppliers*, we consider the following specification, where the coefficients of interest are the $\beta_{1,\tau}$ terms, including controls for the firm's own flood status:

$$y_{bt} = \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_{1,\tau} \text{SellerFlood}_{b,t-\tau} + \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_{2,\tau} \text{OwnFlood}_{b,t-\tau} + \alpha_{bm(t)} + \alpha_{by(t)} + \alpha_t + \varepsilon_{bt} \tag{9}$$

where y_{bt} denotes the log number of suppliers of buyer firm b during month-year t. SellerFlood_{bt} are the treatment terms, based on the firm's first observed supplier flooding event. Given that many firm-pairs transact only infrequently (see Section 2.1), a buyer may be affected by flooding of those suppliers from which it sources but with which it happens not to transact in the single month under consideration. We therefore define here a buyer firm's suppliers as those firms from which the buyer firm has made any purchases in the prior three months.[19] The treatment terms are constructed as the maximum share of the 2km buffer flooded across all suppliers that account for more than 10% of firm b's purchases within the three-month window. OwnFlood_{bt} are controls for the firm's own flood status during the first observed supplier flooding event and using 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 buyer firm-month, buyer firm-year, and month-year fixed effects, respectively. Standard errors are clustered at the firm level.

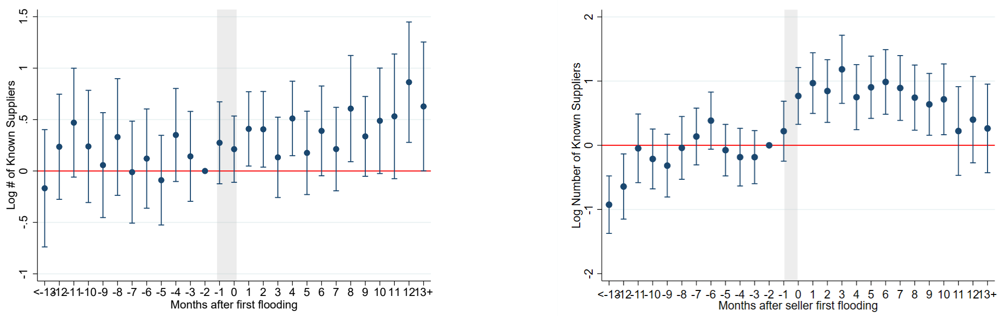
The results of both specifications examining the impacts of direct and indirect flood exposure are shown in Figure 10. These do not suggest that there is strong evidence for diversification in response to flooding of a firm's own premises (panel A), but suggest that firms do diversify their

[17] All specifications investigating supplier choice restrict attention to firms that did not relocate over the sample period, in order to remove the potential effects of relocating firms switching suppliers to those based in their new location. A firm is defined as not having relocated over the sample period if its geocoded locations in 2010 and 2019 are less than 10km apart. All results are robust to including relocating firms, as shown in Appendix C.8.1.

[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 number of total suppliers, as shown in Figure A.12.

[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 C.7.

supplier base in response to supplier flooding (panel B). In the case of the latter, for the mean treated firm, which sees 1.3% of its seller's buffer flooded, the number of suppliers increases by 1.56% by three months after supplier flooding was recorded, with no evidence of pre-trends. This response is relatively short-lived, with a reversion to pre-exposure levels within a year, though more persistent results are obtained where suppliers are defined based on firms from which the buyer firm has made any purchases in the prior twelve or six months (see Appendix C.7).



(a) Impact of flooding on log number of suppliers

(b) Impact of supplier flooding on log number of suppliers

Figure 10. Supplier Diversification

4.3 Choice of suppliers

The results in the previous subsection suggest that firms affected by floods are differentially likely to see subsequent increases in the *number* of their suppliers, consistent with adapting to flood risk via diversification. Another potential margin of adaptation is to change the *characteristics* of their suppliers by shifting towards a portfolio of suppliers less prone to flooding. We consider two dimensions of such a decision. In this section, we examine how far flood-affected firms shift the composition of their suppliers towards less-flood prone suppliers. In the next section, we consider whether floods affecting transportation infrastructure also induce firms to reduce dependence on suppliers reached via flood-prone routes.

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

$$\Delta y_{bt^*} = \beta_1 OwnFlood_{bt^*} + \beta_2 SellerFlood_{bt^*} + \alpha_{d(b)t^*} + \epsilon_{bt^*} \tag{10}$$

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 of all of the maximum shares of b's sellers' 2km buffers that are flooded at t^*; and $\alpha_{d(b)t^*}$ are buyer district $\times$ event fixed effects. The set of observations consists of all firm-flood pairs (b, t^*). The dependent variable, Δy_{bt^*}, is the three month period-on-period change in weighted flood risk of b's suppliers before and after t^*. This captures the change in the risk profile of all of b's suppliers in the three months before versus after flood exposure, and is given by:

$$\Delta y_{bt^*} = \frac{\sum_{(s,t)\in(S_b(t^*,t^*+3],(t^*,t^*+3])} Risk_s x_{bst}}{\sum_{(s,t)\in(S_b(t^*,t^*+3],(t^*,t^*+3])} x_{bst}} - \frac{\sum_{(s,t)\in(S_b[t^*,t^*-3),[t^*,t^*-3))} Risk_s x_{bst}}{\sum_{(s,t)\in(S_b[t^*,t^*-3),[t^*,t^*-3))} x_{bst}} \tag{11}$$

The results are shown in Table 6. The results in the second row suggest that buyers respond to supply chain disruptions caused by flooding of their suppliers by shifting towards less flood-prone suppliers. In the central specification including district × time fixed effects, the magnitudes suggest that the mean treated firm (which sees a maximum flood extent among its sellers' buffers of 2.9%) experiences a 0.9cm reduction in the sales-weighted average supplier flood risk for a 1 in 100 year flood event. There is no significant evidence that buyers adjust the flood-risk composition of their suppliers in response to flooding of their own premises.

Table 6. Impact of flooding on suppliers' weighted average Fathom flood risk

	Dependent Variable: Change in Supplier Risk	
	(1)	(2)
Own Max Flood Ext.	0.0100	-0.0725
	(0.0347)	(0.0980)
3m Suppliers Max Flood Ext.	-0.529***	-0.570***
	(0.0326)	(0.167)
Time FE	Yes	
District × Time FE		Yes
Suppliers from pre-flood Window		
R^2	0.0021	0.0109
N	133,974	133,870

Standard errors in parentheses, clustered at the district-event (month) level. Sample includes only firms whose 2019 address is less than 10km from their 2011 address, given they have both.
Supplier risk is measured as a sales-weighted average of supplier flood risk in terms of expected flood depth in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

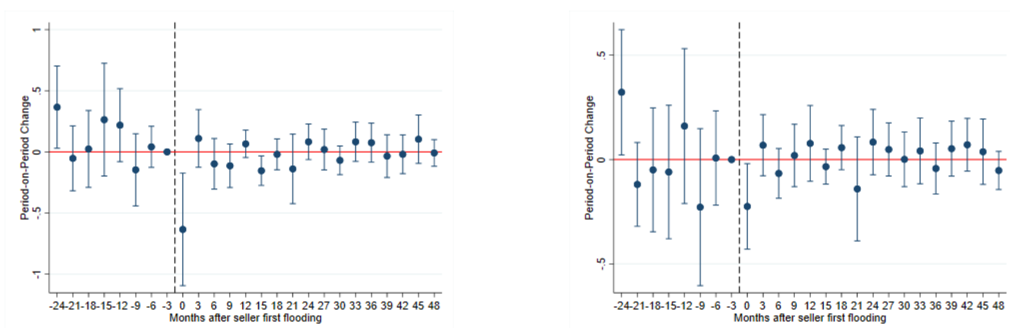
The shift towards less flood-prone suppliers may be driven by forward-looking adaptation, but is also consistent with the mechanical effect of being forced to source less from flood-hit suppliers while their operations are disrupted. To disentangle these effects, Table 7 restricts attention to the flood risk of buyers' *non-flooded* suppliers only.[20] In this case, the significant negative coefficients suggest that, when a buyer experiences flooding of any of their suppliers, this induces them to shift towards safer suppliers even among the subset of suppliers that were not affected by the floods. The mean treated firm in our sample sees a 0.4cm decrease in sales-weighted flood risk among its *non-flooded* suppliers. There is again weaker evidence in the first row that own firm flooding also induces a shift towards safer suppliers among the subset of non-flooded suppliers.

[20] In contrast to the specifications from Table 6, in this specification we restrict attention to the first instance of flooding among a firm's suppliers.

Table 7. Impact of flooding on non-flooded suppliers' weighted average Fathom flood risk

	Dependent Variable: Change in Supplier Risk	
	(1)	(2)
Own Max Flood Ext.	-0.0744***	-0.112
	(0.0283)	(0.0949)
3m Suppliers Max Flood Ext.	-0.251***	-0.285**
	(0.0360)	(0.111)
Time FE	Yes	
District × Time FE		Yes
Suppliers from pre-flood Window		
R^2	0.0006	0.0125
N	130,461	130,353

Standard errors in parentheses, clustered at the district-event (month) level. Sample includes only firms whose 2019 address is less than 10km from their 2011 address, given they have both.
Supplier risk is measured as a sales-weighted average of supplier flood risk in terms of expected flood depth in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



(a) Suppliers' weighted average Fathom flood risk

(b) Non-flooded suppliers' weighted average Fathom flood risk

Figure 11. Dynamic impact of supplier flooding on suppliers' weighted average Fathom flood risk

The persistence of this shift is examined in Figure 11, which displays quarter-on-quarter changes in supplier flood risk for periods extending to four years after, and back to two years before, the flood event. The results show that firms with flooded suppliers shift their supplier mix towards less flood-prone suppliers in the subsequent three months, consistent with the results of Table 6. Importantly, there is no reversion towards higher flood risk suppliers up to four years after the firm's exposure to a flooded supplier, suggesting that the flood-induced shift towards safer suppliers is very persistent. As shown in Figure 11b, this is also the case when restricting attention to non-flooded suppliers.[21]

[21] Figure C.33 presents results excluding firms that source from suppliers that are flooded multiple times, which

4.4 Evidence from route-level flooding

Given the evidence in Section 3.3 that floods may affect firm activities via transportation disruption as well as flooding of firm premises, we consider whether firms also adapt following flood events by reducing their dependence on supply partners reached via flood-prone routes. Our interest here is in whether the short-term disruption to traffic flows caused by floods (which as seen in Figure 8 persist for a matter of weeks at most) induces firms to switch away from suppliers reached via those routes permanently. If firms do not switch back to sourcing from these suppliers once access along the road is restored, this is indicative of longer-term adaptation in response to transient shocks.

The route-level specifications leverage the bilateral nature of transaction-level data to fully isolate adaptive behavior from potentially confounding shocks that may affect flooded firms. In particular, using variation from pairwise route-level flooding allows us to include buyer-time and seller-time fixed effects, thereby absorbing any shocks to buyers and sellers, including those that may persist even after flooded firms' sales and purchases have recovered.[22] We estimate event study regressions of the form:

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

where y_{bst} is an outcome at the buyer-seller-time level (sales in the (b, s) relationship at time 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. $\eta_{\text{age}(b,s),t}$ are indicator variables for the age of the buyer-seller relationship, and α_{bs}, α_{bt}, and α_{st} are, respectively, buyer-seller, buyer-time, and seller-time fixed effects. As such, we identify outcomes from variation within buyer-seller relationships, controlling for time-varying buyer and seller characteristics. In the extensive margin specifications, the set of observations consists of all triples (b, s, t) where b and s transact at least twice, and b and s have both entered by time t. In the intensive margin specifications, the set of observations (b, s, t) is all triples where s has positive sales to b at t.

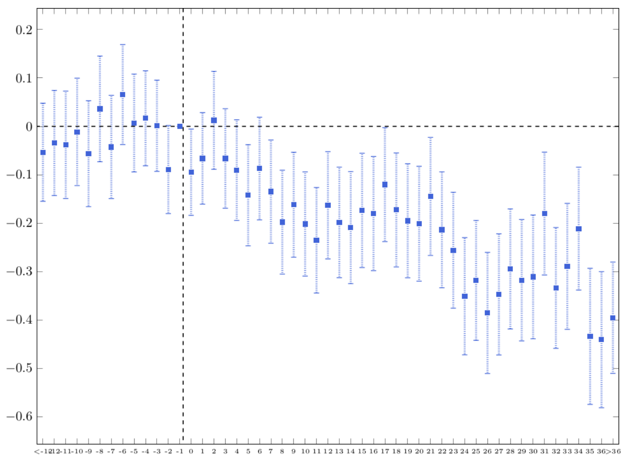
Figure 12 shows the baseline extensive margin results. After a flood hits the route between a buyer-seller pair bs, the likelihood of the buyer-seller relationship remaining active declines markedly compared to non-flooded relationships (and controlling for the average life cycle of a relationship through $\eta_{\text{age}(b,s),t}$). Trends are flat in the year-long window prior to flood exposure, increasing confidence that this effect is attributable to the impact of flooding. To illustrate the magnitude of the estimates, a point estimate of -0.2 five months after treatment implies that the transaction probability in that period declines by 0.1 percentage points for the median flooded route (which sees 0.5% of its length being flooded).[23] The figure shows that the decline is persistent for at least three years, and notably that it extends beyond the duration of road disruptions, which typically last less than one month (see Section 3.3). Conditional on a transaction occurring, we do not find

with a 10% purchase share threshold account for 12% of treated firms and 2.2% of aggregate sales. The robustness of the results to this restriction indicates that the persistence of the effect is not driven by repeated exposures.

[22]For instance, it is possible that, even once flooded firms' sales and purchases have recovered, local labor market or correlated cost shocks might continue to affect their operations and contribute to persistent changes in outcomes at the firm level.

[23]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%.

any adjustment in the transaction magnitude following a flood (Figure A.10). This suggests that substitution away from supply partners reached by flooded routes is driven entirely by transactions ceasing, rather than intensive margin reductions in transaction volumes.



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). 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.

Figure 12. Impact of road flooding on extensive margin sales in buyer-seller relationship

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

4.5 Mechanisms underlying adaptive responses

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

Rational learning would suggest that firms affected by floods change their beliefs over the underlying distribution of flood risk and adaptive actions reflect a rational response to this. Such channels have been studied in a recent literature examining individual decision-making in relation to climate risks (Lybbert et al., 2007, Moore, 2017, Kala, 2017), though evidence from firm behavior remains scarce (Kremer et al., 2019). A second mechanism posits that floods instead change the *importance* of flood risk in firm decision-making, for instance by increasing the salience of climate risk. Such 'availability bias' might induce flood-hit firms to infer erroneously that they are subject to higher flood risk relative to a firm with identical statistical information, simply by virtue of recent experience (Tversky and Kahneman, 1973, Kahneman, 2011, Bordalo et al., 2021), behaviors that have been documented in individuals' decisions to purchase weather insurance and responses to surveys about climate change (Gallagher, 2014, Turner et al., 2014, Karlan et al., 2014, Deryugina, 2013).[24]

While mechanisms predicated on experience-based updating should imply persistent responses, availability heuristics would predict larger impacts from more recent floods, with 'forgetting' as flood events recede into the more distant past. We observe firm and network behavior over eight years, a relatively long timespan relative to the frequency of flooding, and along all adaptive margins observe persistence for as long as responses are measurable in our data. The evidence in Section 4.1 suggesting that floods undertake adaptive relocation is consistent with a permanent response following a temporary shock. Flood-induced adaptive shifts in supplier mix persist for at least five years (Figure 11), and shifts away from suppliers reached via flooded routes for at least three years (Figure 8), without evidence of attenuation in either case. Table A.6 considers the results of the firm move gravity specification (Equation 7) where the treatment defined based on flooding of an origin area post-dating that of a destination area by more than 12 months is extended to time periods of 24 and 36 months, and demonstrates that effects remain robust without any significant reduction in coefficient magnitude.[25] While it is possible that behavior may revert over longer timescales, taken together this evidence is inconsistent with salience effects being first-order in the medium-run.

4.6 Robustness

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

5 Model

In this Section, we consider how far the post-flood adaptation identified in Section 4 affects the economy's aggregate vulnerability to future floods. This is difficult to identify from the regression results alone: while these do contain quantitative information about adaptation, the fact that general equilibrium forces and indirect exposure (via multi-step linkages) are not identified prevents us from interpreting aggregates of these estimates as economy-wide effects. Assessing the impact of observed adaptation on outcomes following subsequent flood events will also yield estimates that are difficult to interpret given that, in the long run, the relevance of adaptation lies not necessarily in reducing the exposure of the economy to any *realized* flood event, but to the full *distribution* of flood events. In fact, adaptation could worsen the impact of any particular flood event—for instance where idiosyncratic floods afflict areas that are not especially flood-prone—even though it reduces the impact of floods on average.

[24] A third possible alternative is that floods lower the fixed cost of making changes that the firm may already have wished to make. Such a mechanism is potentially consistent with the adaptive relocation results in Section 4.1: firms that wished to relocate to safer areas but previously found the fixed cost of doing so too high may use the 'opportunity' afforded by the need to rebuild to do so in a less flood-prone location. It is possible, though arguably less intuitive, to apply a similar logic to the shift towards safer suppliers described in Table 6 if there are large human capital or systems costs to switching suppliers. Such a mechanism cannot, however, account for flood-induced supplier diversification (Section 4.2) and the finding in Table 7 that supplier flooding induces buyers to shift their *non-flooded* supplier mix towards less flood-prone firms.

[25] These results use the preferred specification which defines a firm move based on firms whose 2011 and 2019 geocodes are more than 10km apart, but results are robust to using other thresholds.

We therefore estimate the aggregate impacts of adaptation by constructing a quantitative spatial model which overcomes these challenges by incorporating general equilibrium and indirect effects explicitly, and permitting estimation of the impacts of adaptation over the full distribution of potential flood events. The model features firms that are subject to idiosyncratic and aggregate flood risk and—while imperfectly informed about these risks—update their beliefs in response to the realization of floods. Firms search for suppliers taking into account their beliefs over the flood risk of potential partner firms before the realization of flood shocks. Conditional on search outcomes and the realization of flood shocks, firms then choose suppliers to minimize costs. This setup yields sourcing shares that are described by a gravity equation which can be inverted to yield adaptive changes in supplier search decisions from observed changes in sourcing shares. The advantage of this simple and transparent procedure is that we can estimate the benefits of adaptive changes without having to impose assumptions about the nature of the belief updating process.

This setup builds on recent models of production network formation under uncertainty (Kopytov et al., 2022) but allowing for imperfectly informed firms that learn about underlying flood risk from flood shock realizations. Following Oberfield, 2018 and Boehm and Oberfield, 2020, 2022, we also incorporate extreme value distribution assumptions in this framework in order to yield tractable empirical estimates of discrete sourcing decisions that are informative about firm beliefs over flood risk.[26]

5.1 Model setup

The economy consists of N locations indexed by n. The number of firms in location n is exogenously given as 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.

5.2 Households

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

$$u(q) = \frac{1}{1-\rho} q^{1-\rho}, \qquad \rho > 0$$

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

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

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

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

$$\lambda = \frac{u'(q)}{p} = \frac{q^{-\rho}}{p}$$

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

5.3 Production

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

5.3.1 Second stage: Sourcing and production

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

$$y_j(\phi) = a_{n(j)}b_{n(j)}\xi_j l_j^{1-\alpha}(z(\phi)x_j)^{\alpha} \tag{13}$$

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

We assume that 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: for each unit to be used as an input in production, $\tau_{n(j)n(s)} \geq 1$ units need to be purchased and shipped. Denoting the cost of one unit of equipped labor by w, the marginal cost of production using technique ϕ is:

$$c_j\left(\phi\right) = \frac{1}{a_{n(j)}b_{n(j)}\xi_j} w^{1-\alpha}\left(\tau_{n(j)n(s)}\frac{c_s(\phi)}{z\left(\phi\right)}\right)^{\alpha} \tag{14}$$

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 be able to characterize the aggregate equilibrium, we impose a number of functional form assumptions. Following methods developed by Kortum (1997) and Oberfield (2018), we assume that the distribution of match-specific productivity draws z is such that the number of technique draws where the supplier is in location n' and that yield a match-specific productivity z greater than a threshold $\bar{z}$ is Poisson distribution with mean $m_{nn'}\bar{z}^{-\zeta}$. The parameters $m_{nn'}$ describe search effort and result from search choices in the first stage: higher search effort leads, on average, to better draws. The parameter ζ governs the tail of the distribution of match-specific productivity draws. Higher ζ implies a thinner tail and therefore on average more similar draws, such that a buyer will be more willing to substitute to a different supplier when a supplier experiences an idiosyncratic cost shock. Second, we place a functional form assumption on the distribution of the idiosyncratic flood shock by assuming that $\xi_j^{\zeta/\alpha}$ follows a positive one-sided stable distribution characterized by its Laplace transform:

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

These functional form assumptions allow us to characterize the distribution of firms' production costs in each location:

Lemma 1. *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:

$$\bar{c}_n^{-\zeta} = \left(a_{n(j)}b_{n(j)}\right)^{\zeta}\left(w^{1-\alpha}\right)^{-\zeta}\left(\sum_{n'} m_{nn'}\tau_{nn'}^{-\zeta}\bar{c}_{n'}^{-\zeta}\right)^{\alpha}\Gamma\left(1-\frac{\alpha}{\beta}\right) \tag{15}$$

The expression for sourcing shares follows immediately:

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

$$\frac{X_{nn'}}{X_n} = \frac{m_{nn'}\tau_{nn'}^{-\zeta}\bar{c}_{n'}^{-\zeta}}{\sum_{\tilde{n}} m_{n\tilde{n}}\tau_{n\tilde{n}}^{-\zeta}\bar{c}_{\tilde{n}}^{-\zeta}}. \tag{16}$$

5.3.2 First stage: Search

Before the location-specific flood shocks b_n have been realized, firms have beliefs over the distribution of these shocks described by the information set $\mathcal{I}$. We assume that all firms in a location n have the same beliefs.

Firms are owned by the representative household and maximize profits π discounted by the households' stochastic discount factor λ, subject to a resource constraint. A firm j in location n solves:

$$\begin{aligned} &\max_{m_{nn'}} \mathbb{E}\left(\lambda\pi_j(m_{n1},\ldots,m_{nN})|\mathcal{I}\right) \\ \text{s.t.}\quad & g(m_{n1},\ldots,m_{nN}) = \bar{m} \\ & m_{nn'} \geq 0 \quad \text{for all } n' \end{aligned} \tag{17}$$

where g is such that the solution to this problem is unique for each n.

5.4 Equilibrium

An equilibrium of the economy is a matrix of search efforts $m_{nn'}(\mathcal{I})$ and cost indices $\bar{c}_n$ such that (i) the matrix of search efforts $m_{nn'}(\mathcal{I})$ solves the firms' optimal search problem (17); (ii) conditional on the realization of shocks, the 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.*

6 Quantitative Implementation

We quantify the welfare consequences of firms' adaptive changes following each flood event by taking the model described in Section 5 to the data in our empirical setting. The results in Section 4 demonstrated that firms persistently change their sourcing shares to source relatively more from less flood-prone areas following flood events. In this Section, we use the model-implied gravity equation to identify adaptation as persistent changes in sourcing shares and estimate the consequences of this adaptation for the network's aggregate vulnerability to future flooding.

We assume that the static economy described in Section 5 is played out in each time period, where time periods are linked by the dynamics of firms' beliefs over the distribution of floods, $\mathcal{I}$. For each flood event, we define a pre-flood period where no flood is present ($b_n = 1$ for all locations n); a flooded period during which the flood has direct adverse effects on TFP in affected locations; and a post-flood period where 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. Based on the dynamics of direct flooding impacts in Section 3, the flooded period is assumed to run from $t = -1$ to $t = +6$ around each recorded flood event. We assume that technological productivity levels a_n, elasticity parameters and trade costs $\tau_{nn'}$ are constant over the three periods of each flood event. Flood shocks b and ξ are realized independently across flood events.

To aid computational tractability, estimation of the model is at the level of spatial units (hereafter 'locations') that aggregate firm observations within particular regions. These units are defined by three characteristics of the location of firms, chosen to reflect the model's key assumption that all firms in a location n have the same beliefs. The first is the quartile of the Fathom flood risk distribution across all firm locations in Pakistan in which the firm lies[27], which determines whether changes in sourcing decisions are towards more or less flood-prone suppliers. Given the evidence in Table 7 that firms whose suppliers are affected by a given flood update their beliefs differentially, the spatial units are also determined according to whether or not any of the firm's suppliers is flooded in the particular flood event under consideration. Finally, spatial units account for the district in which the firm is located to permit heterogeneity in adaptation according to the proximity of flooding. We aggregate sales transactions between firms in these spatial units.

In Section 6.1, we describe how the sourcing shares gravity equations are used to identify adaptive changes in firms' search decisions over potential suppliers in response to each of the flood events in our sample period. In Section 6.2, we then use the model to estimate how these changes affect firms' vulnerability to subsequent floods and aggregate flood risk.

6.1 Estimating changes in search decisions

In order to identify changes in search decisions $\hat{m}_{nn'}$ of firms in location n over potential suppliers in location n' between the pre- and post-flood periods, we express the gravity equation in changes:

$$\widehat{\left(\frac{X_{nn't}}{X_{nt}}\right)} = \exp\left(\log \hat{m}_{nn'} - \zeta \log \hat{\bar{c}}_{n'} + \frac{\zeta}{\alpha} \log \hat{\bar{c}}_n\right) \tag{18}$$

where variables with a hat denote changes from pre- to post-flood periods, i.e. $\hat{x} = x_{post}/x_{pre}$ and changes in the scale parameters of the cost distributions are given by:

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

Motivated by the empirical result in Section 4.2 that flood-induced diversification of suppliers is not persistent, we impose the restriction that, for all n, the sum of each firm's log search efforts across upstream locations remains constant between pre- and post-flood periods:[28]

[27] A firm's flood risk is based on the average Fathom flood risk in the 2km radius circle surrounding the firm's point geocode location.

[28] This assumption corresponds to a constraint of $\sum_{n'} \log m_{nn'} = \log \bar{m}$ in the firm's search problem described in equation (17). An example of a microfoundation for this constraint could be that the manager needs to spend $\log m$

$$\sum_{n'} \log \hat{m}_{nn'} = 0$$

Given parameters α and ζ and data on changes in sourcing shares $\widehat{X}_{nn'}$ between the pre- and post-flood periods, this system of equations can be solved directly for changes in search decisions $\hat{m}_{nn'}$ across each flood event, which characterize adaptation in the model. We set the input share α to equal the average annual share of reported purchases to sales, which is 0.77.[29] The trade elasticity ζ is calibrated to be 4 following Simonovska and Waugh (2014) and Bartelme et al. (2019).

6.2 Counterfactual simulations

With estimates of flood-induced changes in search decisions $\hat{m}_{nn'}$ in hand, we next consider the implications of these adaptive changes for (i) the response of the economy to subsequent floods; and (ii) the distribution of welfare as determined by the overall distribution of flood risk.

Evaluating the role of adaptation for the impact of subsequent floods

To quantify the consequences of flood-induced adaptive changes in search decisions $\hat{m}_{nn'}$ for the impacts of subsequent floods, we use a parameterization of productivity shocks in terms of observed location-level flood exposure, and the model's gravity structure, to estimate the magnitude of realized flood shocks and simulate responses to these shocks under counterfactual scenarios in which the adaptive changes in $\hat{m}_{nn'}$ had not occurred.

We assume that productivity shocks in each location are related to the average flood exposure of the 2-kilometer buffer of firms in a location n in a log-linear way:

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

We estimate the coefficient η by substituting this expression into the equation for changes in sourcing shares from the period before to *during* each flood (during which time search decisions $m_{nn'}$ are assumed unchanged):

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

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

$$\hat{\bar{c}}_n = \hat{b}_n^{-1} \left[\sum_{n'} \frac{X_{nn'}}{X_n} \hat{\bar{c}}_{n'}^{-\zeta}\right]^{-\alpha/\zeta} \tag{20}$$

Estimation of this equation using observed sourcing shares $X_{nn'}$ yields an estimate of the coefficient η, which can in turn be used together with observed average flood exposures of the 2-kilometer buffers of firms in a location n to obtain the productivity cost of flooding b_n in each location from equation (19).

units of time to search for m suppliers in a location, and the total time available to the manager in which to search for suppliers is constant.

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

Conditional on a realization of aggregate flood shocks b_n across locations, welfare is:

$$u = \frac{1}{1-\rho} \left(\frac{\varepsilon}{\varepsilon - 1} \right)^{1-\rho} \left(\prod_n c_n^{-\beta_n} \right)^{1-\rho} \tag{21}$$

and hence the change in welfare is:

$$\hat{u} = \left(\prod_n \hat{c}_n^{-\beta_n} \right)^{1-\rho}$$

We calculate the welfare change from flooding using the estimated $\hat{b}_n$, once using the realized pre-flood sourcing shares, and once in the counterfactual scenario with sourcing shares that would have prevailed if adaptation following a previous flood (as identified in Section 6.1) had not happened. Comparing these two welfare impacts tells us how much prior adaptation has improved (or worsened) the damages imposed by a subsequent flood. Finally, we calibrate the final demand shares β_n to the share of each location's sales to out-of-network buyers.

Evaluating the role of adaptation for aggregate flood risk

Equation (21) gives the expression for the household's utility *conditional* on a realization of the flood shocks b_n. To evaluate the aggregate impact of adaptation on the distribution of households' welfare, we need to parameterize the joint distribution of flood shocks across locations and consider how adaptation affects outcomes across this distribution. The Fathom flood risk data described in Section 2.4 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.[30] We therefore augment the Fathom flood risk data with additional data from the Global Flood Database[31] and EM-DAT[32], which report the centroid and total area of 51 historical floods in Pakistan dating back to 1979.[33]

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.[34] To aggregate to the level of summer monsoon seasons, we take the union of all simulated floods in a given summer.[35]

This procedure yields a distribution for the spatial extent and depth of flood shocks. We translate these into economic shocks using equation (19) with the value for η estimated above, and simulate

[30] Simulating the joint distribution of floods across locations would require a catastrophe model, which is not currently available for Pakistan.

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

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

[33] 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.

[34] 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.

[35] This parameterization of aggregate flood risk is based on historical flood realizations and time-invariant Fathom flood risk data, and therefore does not project a worsening future trajectory of flood risk due to climate change.

the response of household welfare to 10,000 summer monsoon draws using equations (20) and (21) in scenarios where adaptation to floods observed during our sample period had and had not taken place. This allows us to quantify the aggregate implications of adaptation in the aftermath of floods during our study period for aggregate welfare across the distribution of future flood risk. Given that there will be heterogeneity across space in the extent to which post-flood adaptation improves welfare, we can also use the estimated $\hat{\hat{c}}_n$ to examine these distributional implications.

[Counterfactual simulation results here]

7 Conclusion

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

The fact that firms learn from flood experience, and respond by undertaking adaptive actions to reduce their vulnerability, raises the optimistic prospect that private adaptation may go some way to mitigating the projected impacts of a rapidly changing climate. But recent experience and significant remaining uncertainty about future climate impacts are cause to sound a note of caution: in the last 12 years, Pakistan has experienced two '1 in 100 year' floods, and average annual flood losses continue to reach catastrophic levels. In this context, the paper's findings raise important policy questions about whether additional complementary approaches might effectively induce adaptation – for instance, could providing accurate information to firms on flood risk be sufficient to induce meaningful adaptation, or do firms only respond to costly flood experience?

The interdependent nature of firm supply chains and the central role of vertical linkages in adaptation suggest that firm adjustments may have important general equilibrium implications for other firms and the resilience of the aggregate firm network. We use the estimates of firm- and network-level adaptive responses to calibrate a spatial equilibrium model of firm production and sourcing decisions to capture such spillovers and estimate general equilibrium effects. This sheds light on the aggregate quantitative implications of the adaptation margins studied in reducing the vulnerability of the firm network to future flood events.

The finding that firms anticipate and adapt to flood risk also opens up an exciting research agenda on firm expectations about long-range climate change trajectories. Dynamic effects may be especially interesting if, for instance, belief updating and adaptive behaviors attenuate over time as major flood events become more common, consistent with evidence for shorter-lived employment impacts of natural disasters in contexts where they are experienced more often (Belasen and Polachek, 2008). Given sharply deteriorating projections of natural disaster incidence as climate change proceeds, understanding such dynamics will be crucial in anticipating future adaptation and damages.

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A Supplementary Tables and Figures

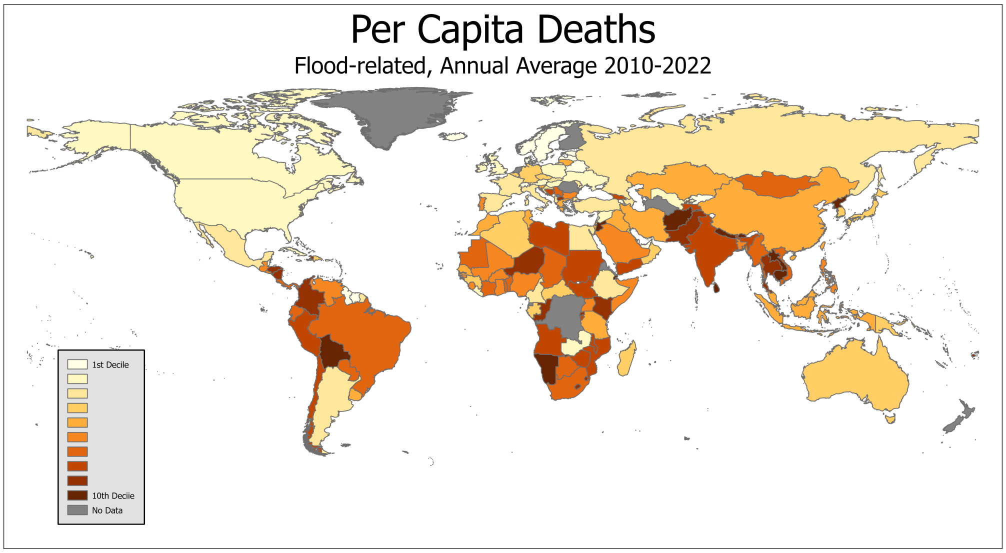


Figure A.1. Per capita deaths from flooding worldwide, 2010-2022 (EM-DAT, 2022)

Table A.1. Fathom flood risk of firms

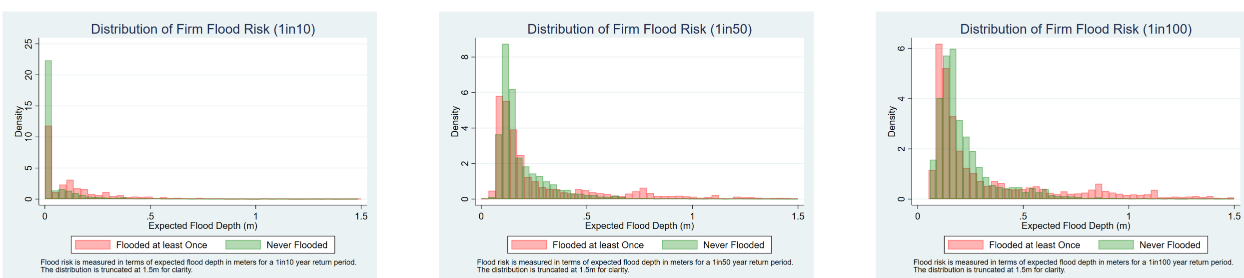
	# Firms	Mean	SD	Min	Max
Flooded Once in Sample					
Fathom (1in10) Flood Risk	21,883	0.16	0.24	0.00	3.71
Fathom (1in50) Flood Risk	21,883	0.30	0.31	0.00	2.52
Fathom (1in100) Flood Risk	21,883	0.33	0.35	0.05	2.73
Flooded more than Once in Sample					
Fathom (1in10) Flood Risk	4,556	0.42	0.59	0.00	2.14
Fathom (1in50) Flood Risk	4,556	0.53	0.60	0.00	2.41
Fathom (1in100) Flood Risk	4,556	0.57	0.60	0.07	2.54
Never Flooded in Sample					
Fathom (1in10) Flood Risk	46,897	0.06	0.15	0.00	3.30
Fathom (1in50) Flood Risk	46,897	0.20	0.18	0.00	3.55
Fathom (1in100) Flood Risk	46,897	0.24	0.20	0.06	4.24
Total					
Fathom (1in10) Flood Risk	73,336	0.11	0.25	0.00	3.71
Fathom (1in50) Flood Risk	73,336	0.25	0.28	0.00	3.55
Fathom (1in100) Flood Risk	73,336	0.29	0.30	0.05	4.24

Flood risk is measured in terms of expected flood depth in meters for a given return period.

Table A.2. Fathom flood risk of shortest ordinary-time routes between firm pairs

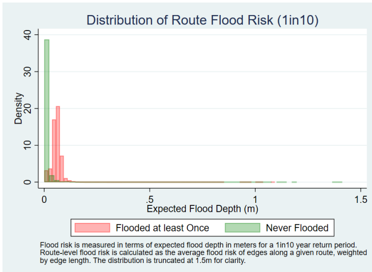
	# Routes	Mean	SD	Min	Max
Flooded Once in Sample					
Fathom (1in10) Flood Risk	120,232	0.04	0.05	0.00	1.09
Fathom (1in50) Flood Risk	120,232	0.13	0.11	0.00	1.65
Fathom (1in100) Flood Risk	120,232	0.18	0.14	0.00	2.37
Flooded more than Once in Sample					
Fathom (1in10) Flood Risk	697,514	0.06	0.02	0.00	1.01
Fathom (1in50) Flood Risk	697,514	0.18	0.04	0.00	2.18
Fathom (1in100) Flood Risk	697,514	0.25	0.06	0.00	2.54
Never Flooded in Sample					
Fathom (1in10) Flood Risk	808,615	0.01	0.03	0.00	2.07
Fathom (1in50) Flood Risk	808,615	0.04	0.07	0.00	4.40
Fathom (1in100) Flood Risk	808,615	0.06	0.10	0.00	5.53
Total					
Fathom (1in10) Flood Risk	1,626,361	0.03	0.04	0.00	2.07
Fathom (1in50) Flood Risk	1,626,361	0.11	0.09	0.00	4.40
Fathom (1in100) Flood Risk	1,626,361	0.15	0.13	0.00	5.53

Flood risk is measured in terms of expected flood depth in meters for a given return period. Route-level flood risk is calculated as the average flood risk of edges along a given route, weighted by edge length.

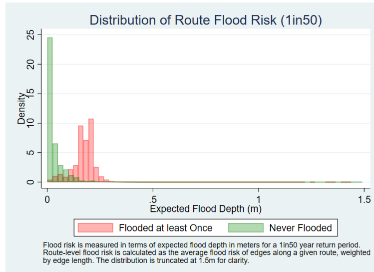


(a) 1 in 10 years return period (b) 1 in 50 years return period (c) 1 in 100 years return period

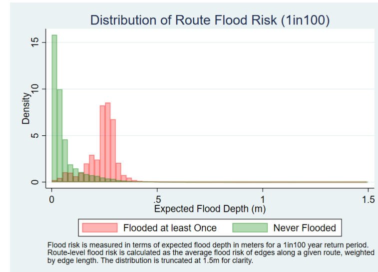
Figure A.2. Distribution of firms by Fathom flood risk



(a) 1 in 10 years return period



(b) 1 in 50 years return period



(c) 1 in 100 years return period

Figure A.3. Distribution of firm-pair routes by Fathom flood risk

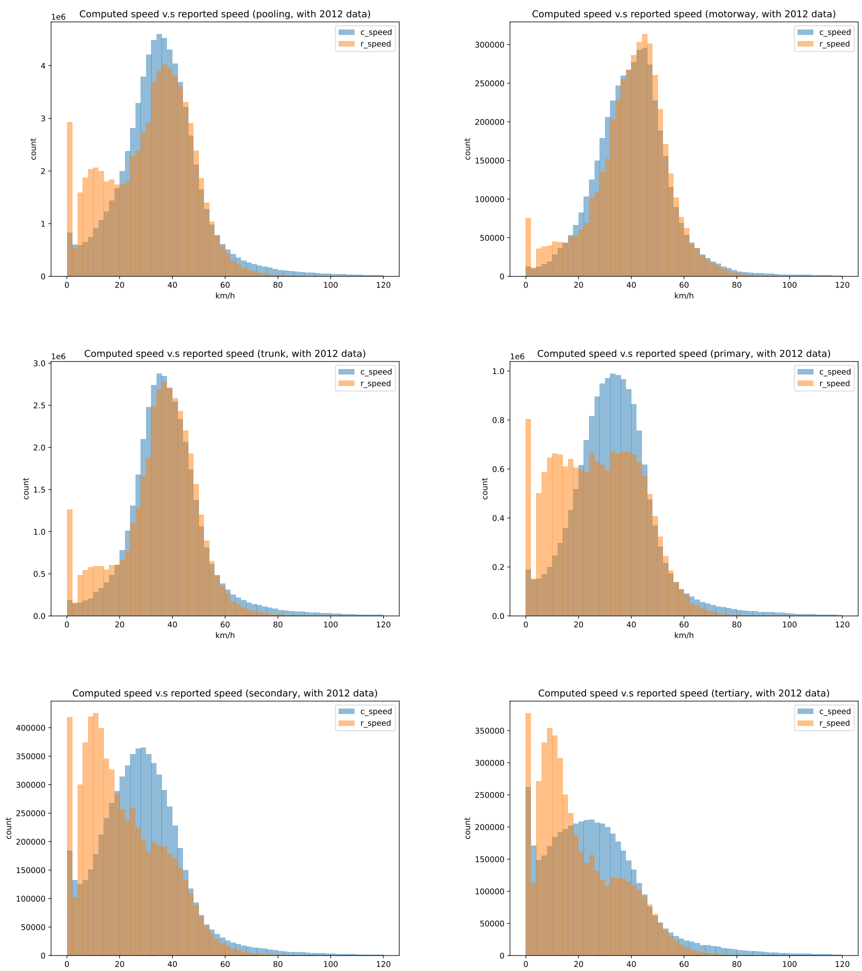
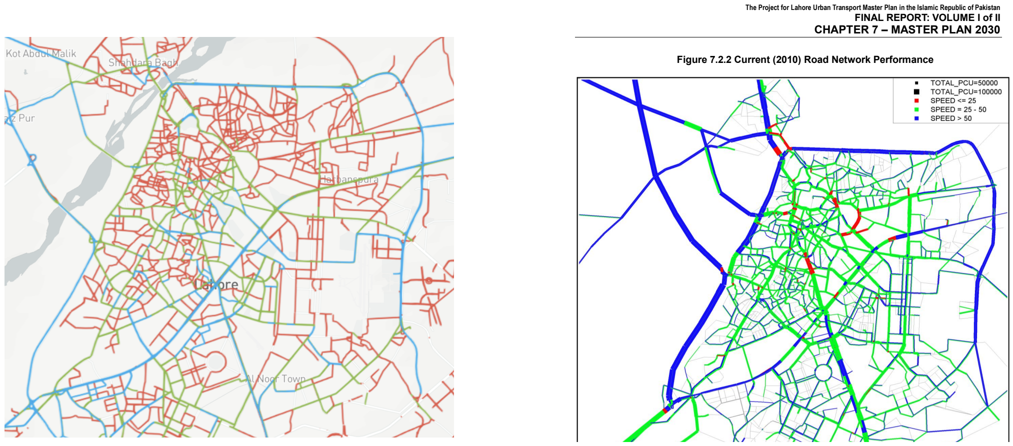


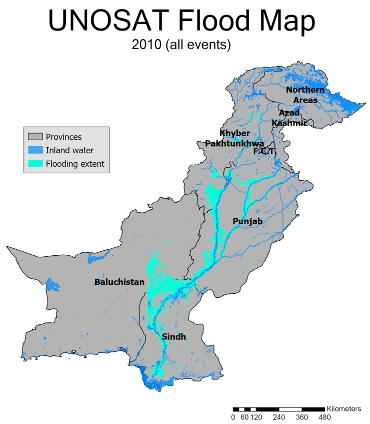
Figure A.4. Histograms of calculated speed and reported speed using 2012 data



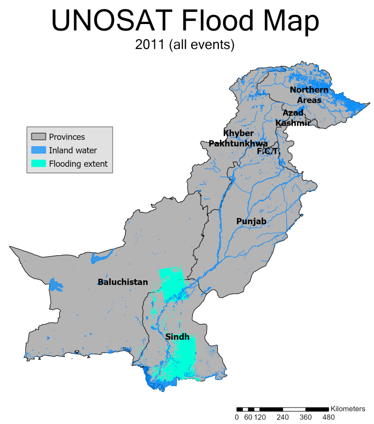
(a) Calculated speeds, 2015

(b) 2010 speeds reported in Japan International Cooperation Agency (2012)

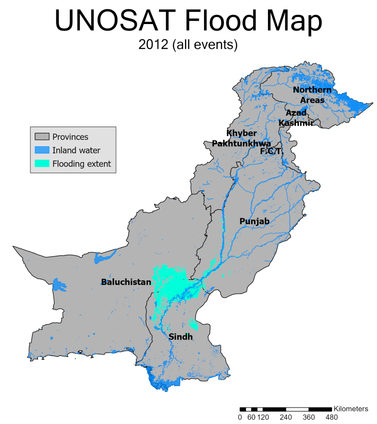
Figure A.5. Comparison of calculated and reported truck speeds in Lahore



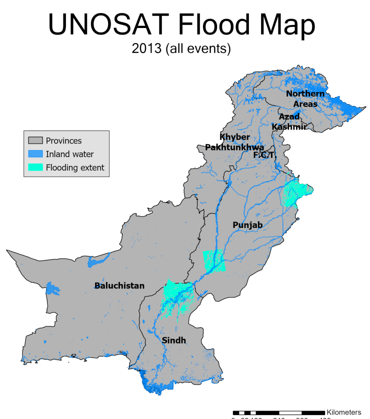
(a) 2010



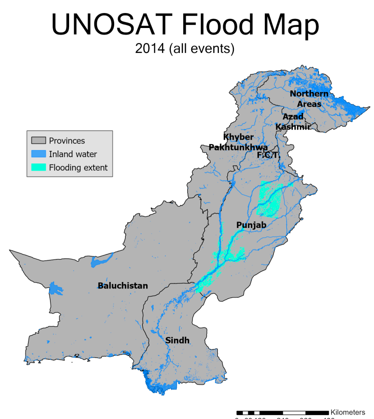
(b) 2011



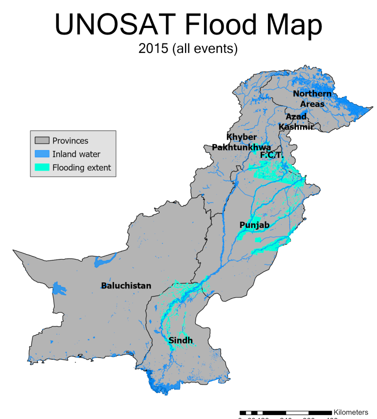
(c) 2012



(d) 2013

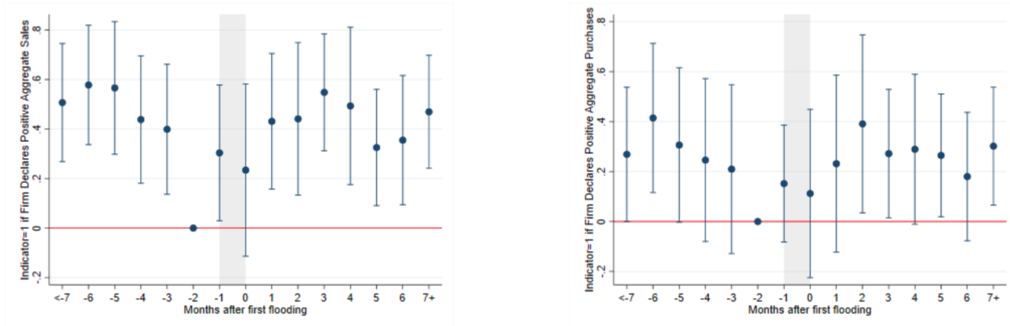


(e) 2014



(f) 2015

Figure A.6. Flood extent maps during sample period



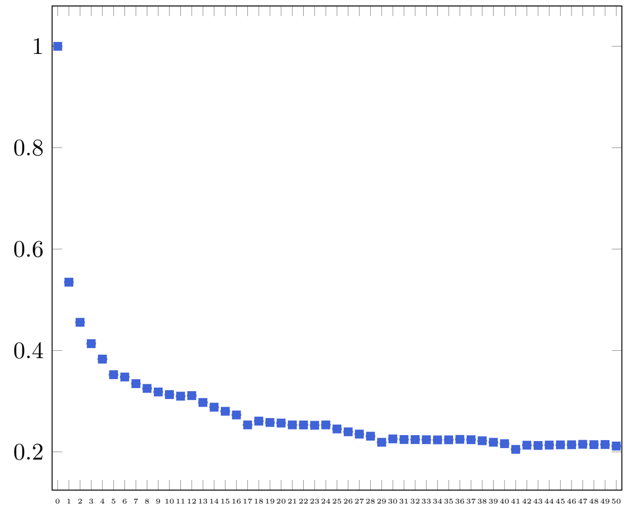
(a) Indicator for positive sales

(b) Indicator for positive purchases

Figure A.7. Impact of flooding on extensive margin sales and purchases

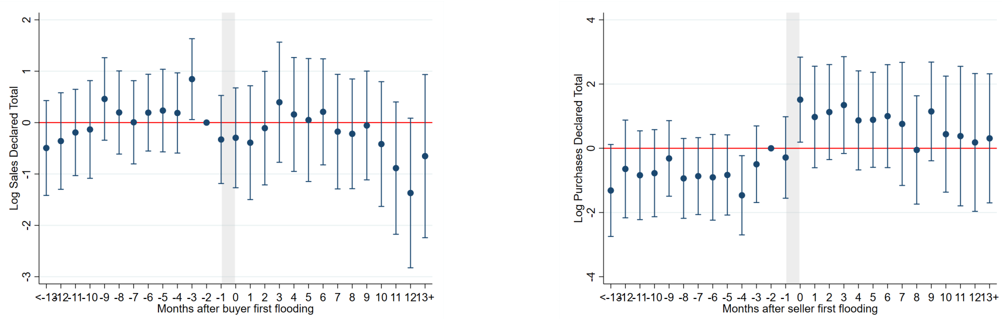
Table A.3. Firm relocation shares by distance moved threshold

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



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.8. Probability of having positive sales in the relationship, by month after first sale



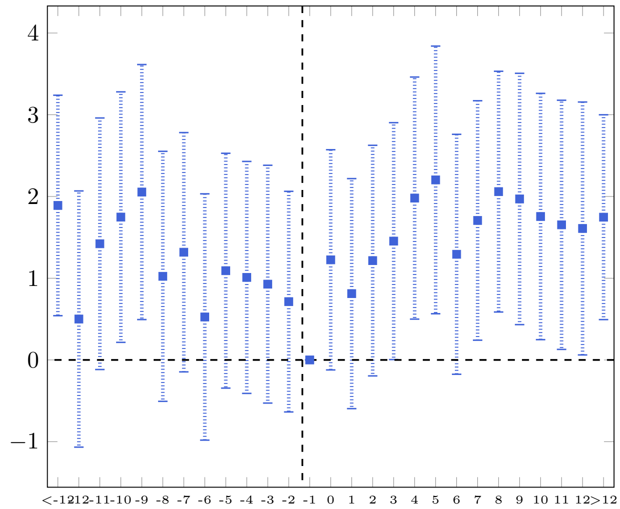
(a) Buyer flooded

(b) Seller flooded

Figure A.9. Impact of buyer flooding on seller's sales, and of supplier flooding on buyer's purchases. The empirical specification for considering impacts on a buyer firm's purchases of floods affecting its suppliers is as follows (and symmetrically for the impact on a seller firm's sales of floods affecting its buyers):

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

A buyer firm's suppliers are defined as those firms from which the buyer firm has made any purchases in the prior three months. The treatment terms are constructed as the maximum share of the 2km buffer flooded across all suppliers that account for more than 10% of firm i's purchases within the three-month window. The OwnFlood_{it} terms are controls for the firm's own flood status during the first observed supplier flooding event and using the maximum share of firm i's 2km buffer that is flooded during month-year t. Results are very similar if additional controls for the flooding status of the firm's buyers are included. Standard errors are clustered at the firm level.



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). 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.

Figure A.10. Impact of road flooding on intensive margin sales in buyer-seller relationship

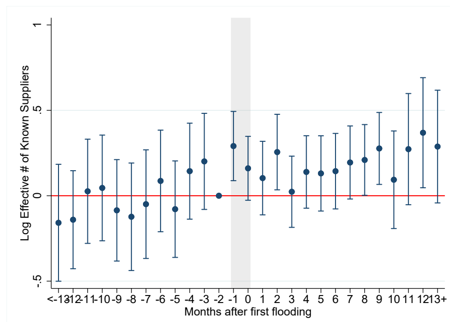


Figure A.11. Impact of flooding on log number of suppliers (Inverse HHI)

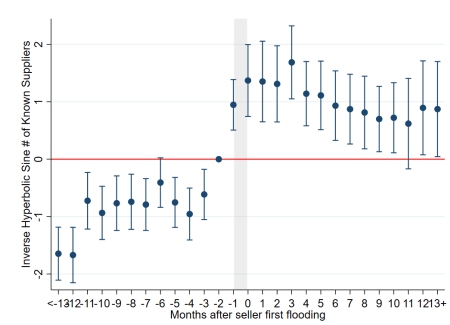


Figure A.12. Impact of supplier flooding on log number of suppliers (Inverse HHI)

Table A.4. Impact of flooding on firm relocation: 2011 address flooded in five years prior to sample

	Dependent Variable: Move Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Max Share of 2km Buffer Flooded	-0.0704	1.840**	1.752**	-0.297	1.604*	1.848**
	(0.742)	(0.751)	(0.803)	(0.726)	(0.952)	(0.834)
District FE	Yes	Yes	Yes			
District × Fathom 1in100 FE				Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km	0km	5km	10km
R^2	0.005	0.021	0.046	0.017	0.041	0.067
N	43,831	43,841	43,848	43,515	43,487	43,395

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5. Impact of flooding on Fathom flood risk of firm's location: 2011 address flooded in five years prior to sample

	Dependent Variable: Change in Flood Risk				
	(1)	(2)	(3)	(4)	(5)
Max Share of 2km Buffer Flooded in Flood Month	-1.407	-1.998	-2.475	-2.063*	-2.100**
	(0.849)	(1.239)	(1.543)	(1.173)	(0.998)
District FE	Yes	Yes	Yes	Yes	Yes
District × Fathom 1in100 FE					
R^2	0.028	0.039	0.086	0.126	0.189
N	43,866	29,684	10,623	5,737	2,912
Max Share of 2km Buffer Flooded in Flood Month	-0.533*	-0.770	-0.665	-0.516	-0.510
	(0.304)	(0.466)	(0.672)	(0.616)	(0.457)
District FE					
District × Fathom 1in100 FE	Yes	Yes	Yes	Yes	Yes
R^2	0.190	0.268	0.424	0.449	0.492
N	43,754	29,569	10,481	5,596	2,789
Move Distance Restriction		>0km	>5km	>10km	>20km
Pr(Move=1)		0.68	0.24	0.13	0.07
Average 1in100 Flood Risk		0.28	0.29	0.30	0.32

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6. Impact of destination flood history on relocation flows

	Dependent Variable: Number of Firms Moved		
	(1)	(2)	(3)
Dest. flooded 12mo prior	-0.730***		
	(0.224)		
Dest. flooded 24mo prior		-0.837**	
		(0.331)	
Dest. flooded 36mo prior			-0.729**
			(0.338)
Origin × Destination FE	Yes	Yes	Yes
Origin × Flood Event (month) FE	Yes	Yes	Yes
Flood Event of Destination FE	Yes	Yes	Yes
Move Dummy Threshold	10km	10km	10km
N	2,135	2,135	2,135

Poisson Pseudo-maximum-likelihood estimator. Standard errors in parentheses, clustered at the origin-destination level. Sample is restricted to firms fully geocoded in 2011 and 2019.

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

B Proofs

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

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

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

Proof.

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

□

Lemma 4. *Let X be Fréchet distributed with*

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

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

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

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

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

From the Shabhag-Sreehari lemma above we know that

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

Rearrange to get □

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

Lemma 5. *Let X be Frechet with*

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

Then $\log X$ has the characteristic function

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

Proof.

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

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

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

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

where:

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

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

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

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

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

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

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

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

is Weibull distributed. Hence

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

where we write shorthand n for $n(j)$. Conditional on b an ξ, the minimum cost is Weibull distributed. Apply now Lemma 4,

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

with

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

to get

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

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

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

□

C Robustness Specifications

C.1 Results using Sun and Abraham (2021) estimator

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. All key results are robust to using this estimator.

C.1.1 Supplier diversification

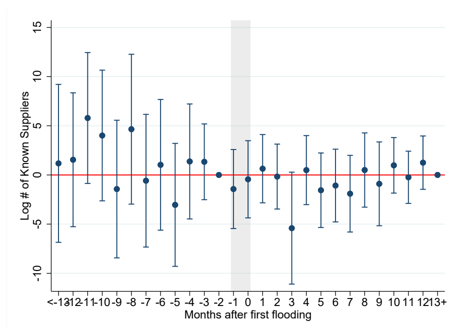


Figure C.1. Impact of flooding on log number of suppliers (Sun and Abraham estimator)

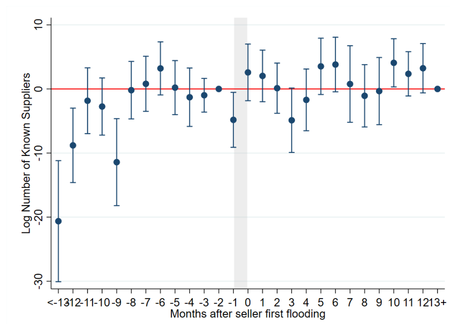
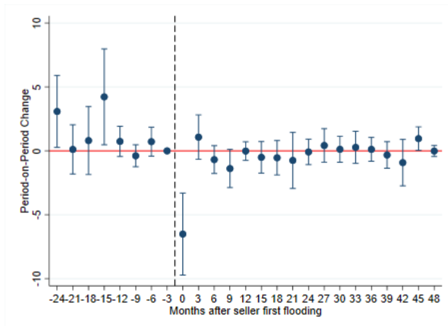
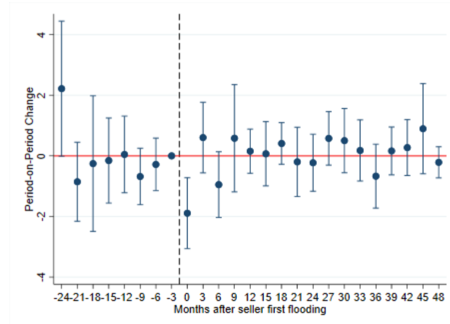


Figure C.2. Impact of supplier flooding on log number of suppliers (Sun and Abraham estimator)

C.1.2 Supplier choice



(a) All suppliers within 3 months



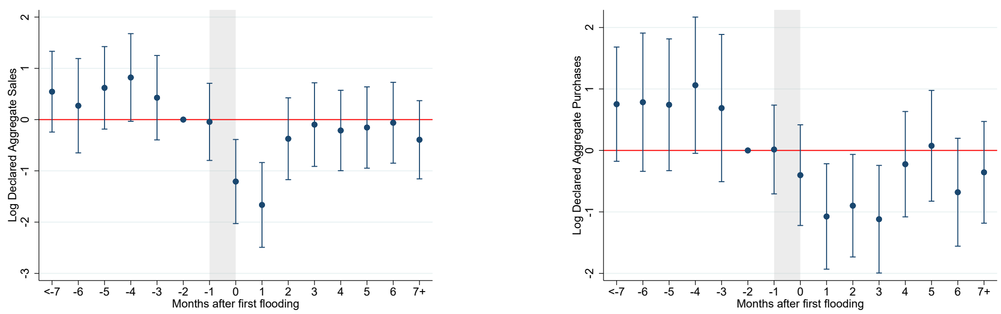
(b) Non-flooded suppliers within 3 months

Figure C.3. Dynamic impact of supplier flooding on suppliers' weighted average Fathom flood risk (Sun and Abraham estimator)

C.2 Results excluding electricity and gas producers

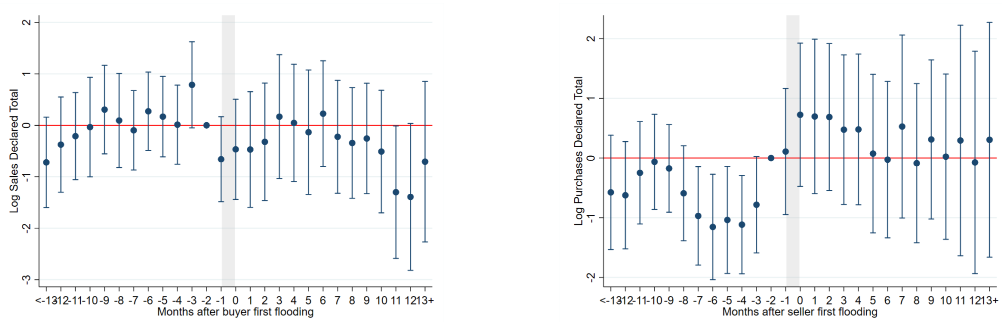
We examine how far the results are affected by industries for which supply disruptions of the nature considered in the analysis may not be pertinent. The first of these robustness checks excludes from the sample the 1% of firms, accounting for 14% of aggregate sales, with two-digit industry identifiers corresponding to electricity, gas and extraction of crude petroleum.[36] This accounts for the fact that, while firms purchase these inputs regularly, these are monopolies that firms are unable to substitute away from. The results in this case are very similar to the baseline results.

C.2.1 Intensive Margin



(a) Log Sales (b) Log Purchases

Figure C.4. Impact of flooding on firm sales and purchases

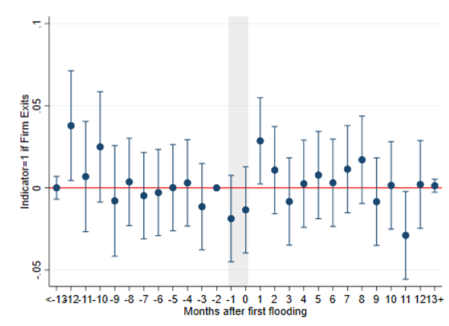


(a) Buyer flooded (b) Seller flooded

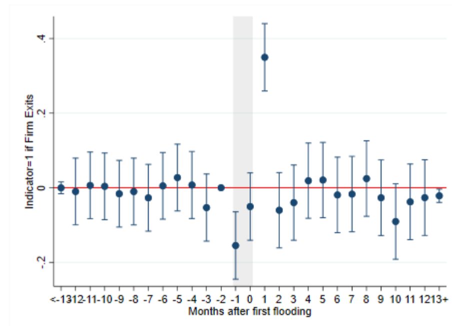
Figure C.5. Impact of buyer flooding on seller's sales, and of supplier flooding on buyer's purchases

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

C.2.2 Firm Exit



(a) All floods



(b) September 2014 flood

Figure C.6. Impact of flooding on firm exit

C.2.3 Firm Location

Table C.1. Impact of flooding on firm relocation

	Dependent Variable: Move Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Max Share of 2km Buffer Flooded	-0.109	1.835**	1.739**	-0.354	1.582*	1.929**
	(0.747)	(0.752)	(0.808)	(0.726)	(0.943)	(0.828)
District FE	Yes	Yes	Yes			
District × Fathom 1in100 FE				Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km	0km	5km	10km
R^2	0.005	0.021	0.045	0.017	0.042	0.068
N	43,516	43,520	43,525	43,190	43,169	43,074

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2. Impact of flooding on Fathom flood risk of firm's location

	Dependent Variable: Change in Flood Risk				
	(1)	(2)	(3)	(4)	(5)
Max Share of 2km Buffer Flooded in Flood Month	-1.404*	-1.992	-2.481	-2.066*	-2.109**
	(0.845)	(1.233)	(1.546)	(1.176)	(1.001)
District FE	Yes	Yes	Yes	Yes	Yes
District × Fathom 1in100 FE					
R^2	0.028	0.038	0.085	0.126	0.191
N	43,542	29,452	10,519	5,663	2,868
Max Share of 2km Buffer Flooded in Flood Month	-0.537*	-0.776*	-0.678	-0.519	-0.505
	(0.304)	(0.465)	(0.680)	(0.631)	(0.471)
District FE					
District × Fathom 1in100 FE	Yes	Yes	Yes	Yes	Yes
R^2	0.190	0.268	0.425	0.449	0.493
N	43,431	29,341	10,377	5,525	2,746
Move Distance Restriction		>0km	>5km	>10km	>20km
Pr(Move=1)		0.68	0.24	0.13	0.07
Average 1in100 Flood Risk		0.28	0.29	0.30	0.32

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3. Impact of destination flood history on relocation flows

	Dependent Variable: Number of Firms Moved			
	(1)	(2)	(3)	(4)
Dest. flooded 12mo prior	-1.854***	-0.786***	-0.737***	-0.898***
	(0.269)	(0.216)	(0.225)	(0.283)
Origin × Destination FE	Yes	Yes	Yes	Yes
Origin × Flood Event (month) FE	Yes	Yes	Yes	Yes
Flood Event of Destination FE	Yes	Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km	20km
N	2,578	2,268	2,101	1,674

Poisson Pseudo-maximum-likelihood estimator. Standard errors in parentheses, clustered at the origin-destination level. Sample is restricted to firms fully geocoded in 2011 and 2019.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.2.4 Supplier Diversification

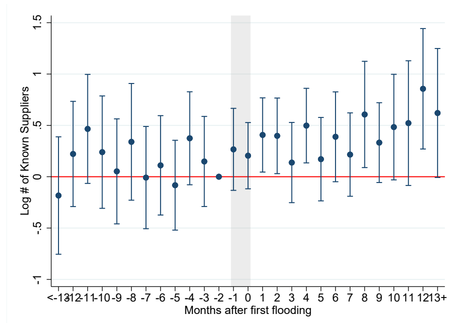


Figure C.7. Impact of flooding on log number of suppliers

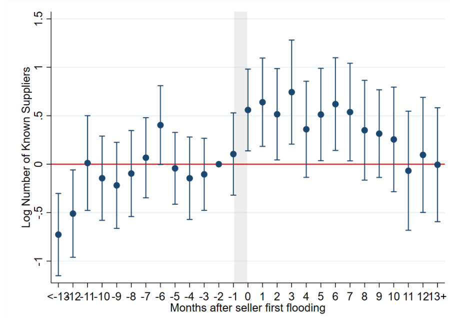


Figure C.8. Impact of supplier flooding on log number of suppliers

C.2.5 Supplier Choice

Table C.4. Impact of flooding on suppliers' weighted average Fathom flood risk

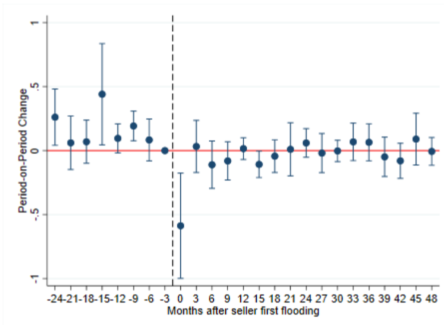
	Dependent Variable: Change in Supplier Risk	
	(1)	(2)
Own Max Flood Ext.	0.0572	0.0124
	(0.0359)	(0.0408)
3m Suppliers Max Flood Ext.	-0.527***	-0.557***
	(0.0317)	(0.153)
Time FE	Yes	
District × Time FE		Yes
Suppliers from pre-flood Window		
R^2	0.0023	0.0078
N	128,413	128,314

Standard errors in parentheses, clustered at the district-event (month) level. Sample includes only firms whose 2019 address is less than 10km from their 2011 address, given they have both.
Supplier risk is measured as a sales-weighted average of supplier flood risk in terms of expected flood depth in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

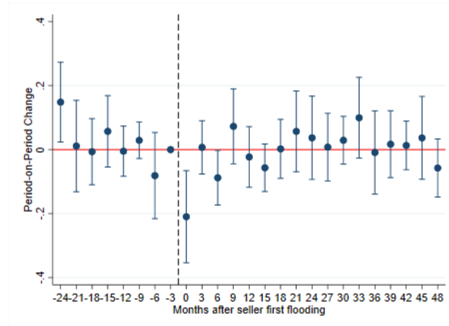
Table C.5. Impact of flooding on non-flooded suppliers' weighted average Fathom flood risk

	Dependent Variable: Change in Supplier Risk	
	(1)	(2)
Own Max Flood Ext.	-0.000346	-0.00697
	(0.0283)	(0.0190)
3m Suppliers Max Flood Ext.	-0.229***	-0.231***
	(0.0340)	(0.0714)
Time FE	Yes	
District × Time FE		Yes
Suppliers from pre-flood Window		
R^2	0.0005	0.0068
N	124,809	124,705

Standard errors in parentheses, clustered at the district-event (month) level. Sample includes only firms whose 2019 address is less than 10km from their 2011 address, given they have both.
Supplier risk is measured as a sales-weighted average of supplier flood risk in terms of expected flood depth in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



(a) All Suppliers within 3 months



(b) Non-Flooded Suppliers within 3 months

Figure C.9. Dynamic impact of supplier flooding on suppliers' weighted average flood risk

C.3 Results excluding capital purchases

We next consider the robustness of results to excluding transactions involving capital goods, given that lumpy capital purchases are likely to be infrequent and may be less prone to flood-induced supply disruptions. To do so, we remove all transactions in which either the buyer or the seller has a primary product code which maps to a capital good, identified using Part I of the Fifth Schedule of the Customs Act.[37] The central results showing evidence for firm-level adaptation are robust to this restriction.

C.3.1 Supplier Diversification

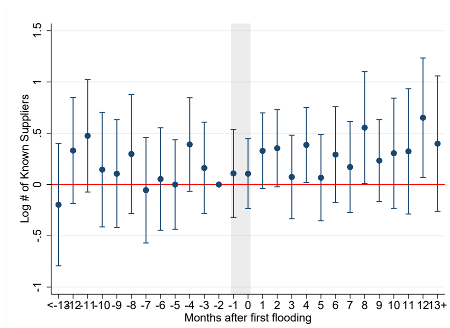


Figure C.10. Impact of flooding on log number of suppliers

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

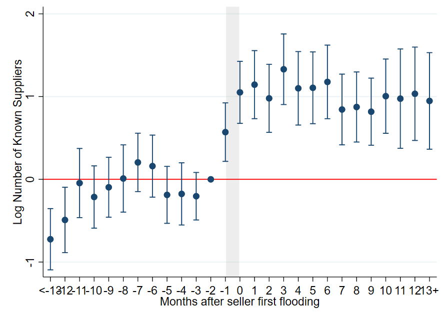
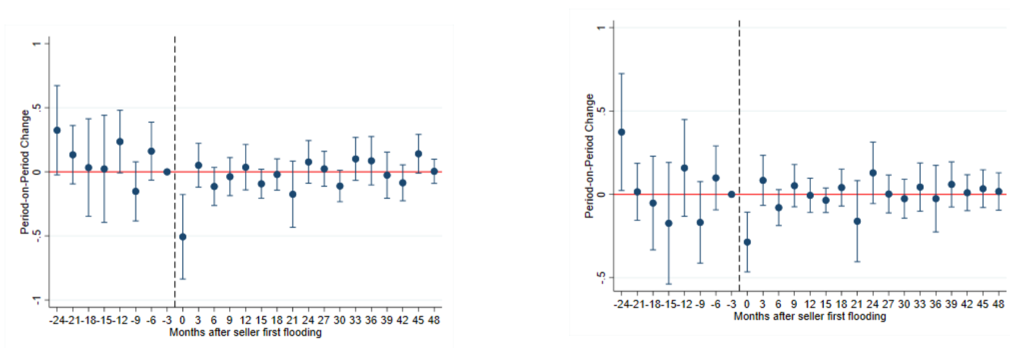


Figure C.11. Impact of supplier flooding on log number of suppliers

C.3.2 Supplier Choice



(a) All Suppliers within 3 months

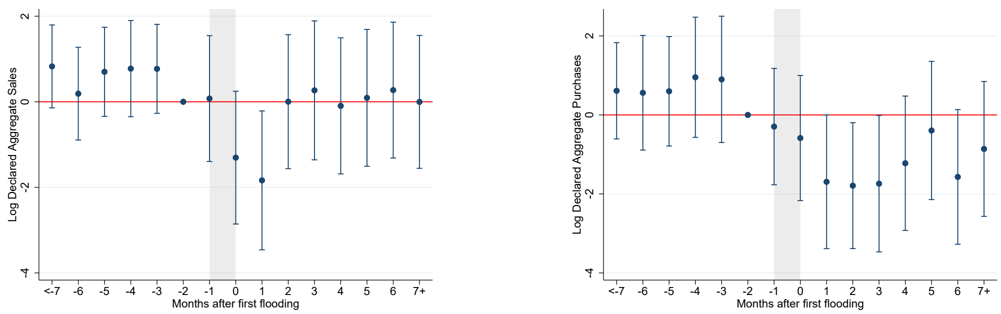
(b) Non-Flooded Suppliers within 3 months

Figure C.12. Dynamic impact of supplier flooding on suppliers' weighted average flood risk

C.4 Results using manufacturing firms

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

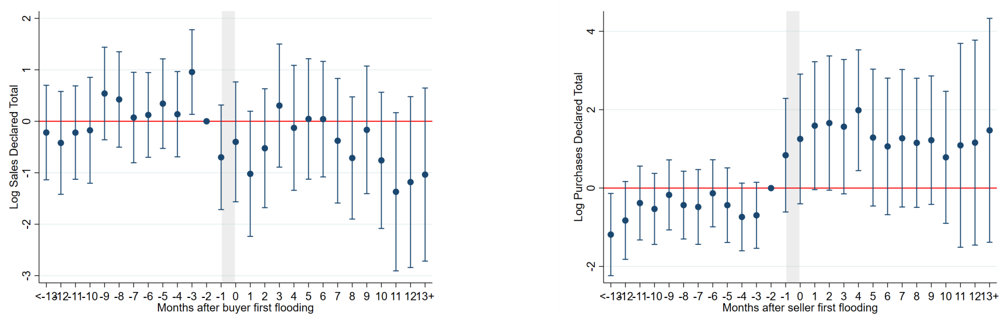
C.4.1 Intensive Margin



(a) Log Sales

(b) Log Purchases

Figure C.13. Impact of flooding on firm sales and purchases

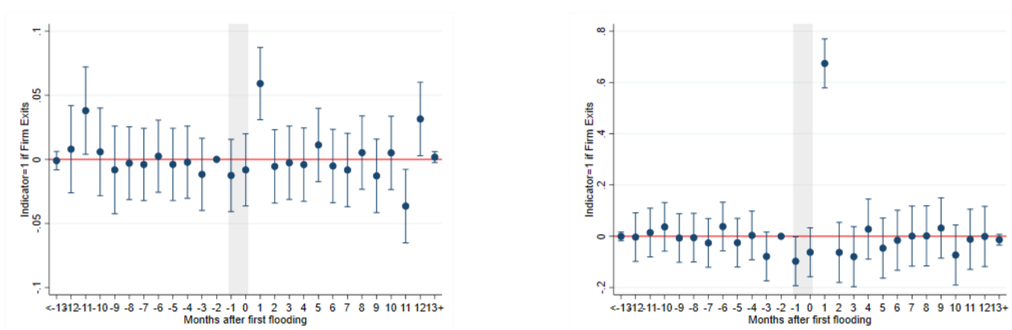


(a) Buyer flooded

(b) Seller flooded

Figure C.14. Impact of buyer flooding on seller's sales, and of supplier flooding on buyer's purchases

C.4.2 Firm Exit



(a) All floods

(b) September 2014 flood

Figure C.15. Impact of flooding on firm exit

C.4.3 Firm Location

Table C.6. Impact of flooding on firm relocation

	Dependent Variable: Move Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Max Share of 2km Buffer Flooded	0.288	1.445	1.291	0.346	1.346	1.473*
	(1.233)	(1.139)	(0.988)	(0.826)	(1.090)	(0.831)
District FE	Yes	Yes	Yes			
District × Fathom 1in100 FE				Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km	0km	5km	10km
R^2	0.007	0.028	0.052	0.024	0.047	0.072
N	17,384	17,429	17,422	17,068	17,114	17,070

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in100 year return period.

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

Table C.7. Impact of flooding on Fathom flood risk of firm's location

	Dependent Variable: Change in Flood Risk				
	(1)	(2)	(3)	(4)	(5)
Max Share of 2km Buffer Flooded in Flood Month	-1.019	-1.389	-1.616	-1.277	-1.477
	(0.719)	(1.010)	(1.221)	(0.985)	(1.141)
District FE	Yes	Yes	Yes	Yes	Yes
District × Fathom 1in100 FE					
R^2	0.034	0.043	0.089	0.146	0.227
N	17,447	12,339	4,872	2,752	1,396
Max Share of 2km Buffer Flooded in Flood Month	-0.286	-0.334	-0.153	-0.0410	-0.289
	(0.258)	(0.400)	(0.569)	(0.564)	(0.476)
District FE					
District × Fathom 1in100 FE	Yes	Yes	Yes	Yes	Yes
R^2	0.188	0.255	0.424	0.459	0.536
N	17,331	12,222	4,780	2,660	1,289
Move Distance Restriction		>0km	>5km	>10km	>20km
Pr(Move=1)		0.71	0.28	0.16	0.08
Average 1in100 Flood Risk		0.27	0.28	0.29	0.31

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in100 year return period.

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

Table C.8. Impact of destination flood history on relocation flows

	Dependent Variable: Number of Firms Moved			
	(1)	(2)	(3)	(4)
Dest. flooded 12mo prior	-1.482***	-0.684**	-0.894***	-0.963**
	(0.343)	(0.312)	(0.264)	(0.404)
Origin × Destination FE	Yes	Yes	Yes	Yes
Origin × Flood Event (month) FE	Yes	Yes	Yes	Yes
Flood Event of Destination FE	Yes	Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km	20km
N	1,343	1,174	1,057	905

Poisson Pseudo-maximum-likelihood estimator. Standard errors in parentheses, clustered at the origin-destination level. Sample is restricted to firms fully geocoded in 2011 and 2019.

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

C.4.4 Supplier Diversification

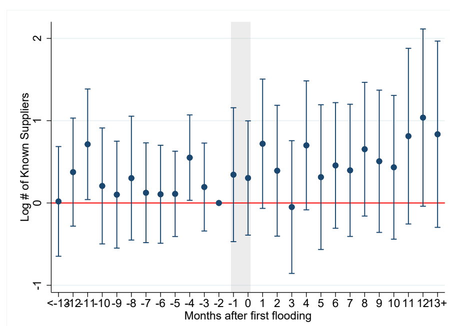


Figure C.16. Impact of flooding on log number of suppliers

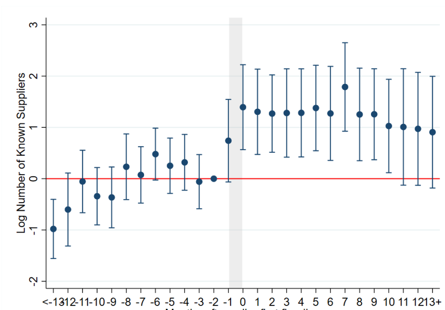


Figure C.17. Impact of supplier flooding on log number of suppliers

C.4.5 Supplier Choice

Table C.9. Impact of flooding on suppliers' weighted average Fathom flood risk

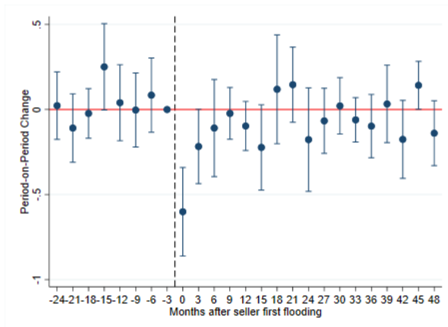
	Dependent Variable: Change in Supplier Risk	
	(1)	(2)
Own Max Flood Ext.	0.0950	0.203***
	(0.0642)	(0.0452)
3m Suppliers Max Flood Ext.	-0.571***	-0.549***
	(0.0496)	(0.0817)
Time FE	Yes	
District × Time FE		Yes
Suppliers from pre-flood Window		
R^2	0.0030	0.0192
N	46,213	46,109

Standard errors in parentheses, clustered at the district-event (month) level. Sample includes only firms whose 2019 address is less than 10km from their 2011 address, given they have both.
Supplier risk is measured as a sales-weighted average of supplier flood risk in terms of expected flood depth in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

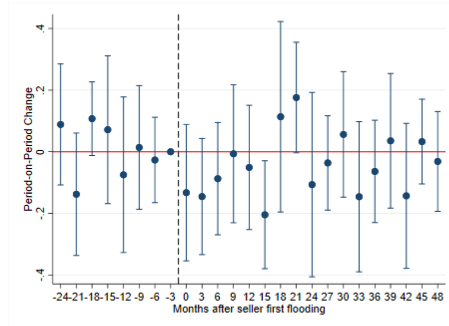
Table C.10. Impact of flooding on non-flooded suppliers' weighted average Fathom flood risk

	Dependent Variable: Change in Supplier Risk	
	(1)	(2)
Own Max Flood Ext.	0.0476	0.0437
	(0.0554)	(0.0482)
3m Suppliers Max Flood Ext.	-0.188***	-0.164
	(0.0597)	(0.125)
Time FE	Yes	
District × Time FE		Yes
Suppliers from pre-flood Window		
R^2	0.0007	0.0185
N	44,262	44,162

Standard errors in parentheses, clustered at the district-event (month) level. Sample includes only firms whose 2019 address is less than 10km from their 2011 address, given they have both.
Supplier risk is measured as a sales-weighted average of supplier flood risk in terms of expected flood depth in meters for a 1in100 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



(a) All Suppliers within 3 months



(b) Non-Flooded Suppliers within 3 months

Figure C.18. Dynamic impact of supplier flooding on suppliers' weighted average flood risk

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

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

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

C.5.1 Supplier diversification

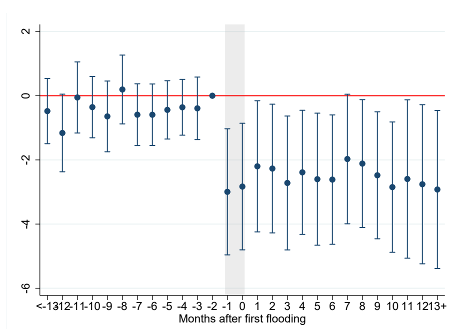


Figure C.19. Impact of flooding on log number of suppliers (cross-validated reports)

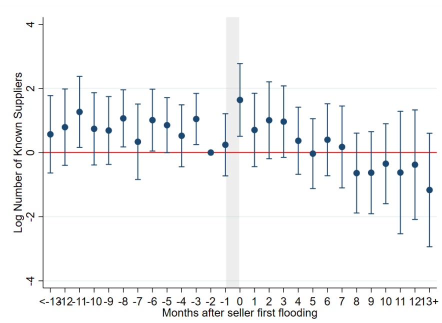
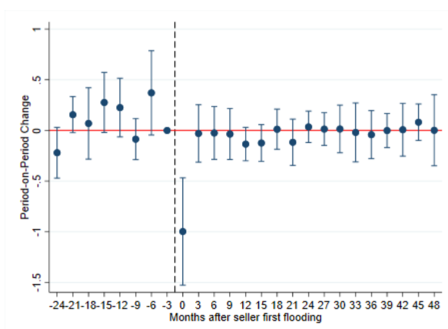
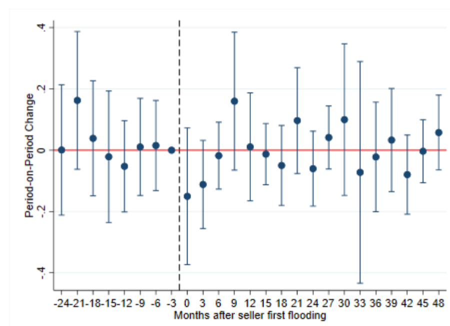


Figure C.20. Impact of supplier flooding on log number of suppliers (cross-validated reports)

C.5.2 Supplier choice



(a) All Suppliers within 3 months



(b) Non-Flooded Suppliers within 3 months

Figure C.21. Dynamic impact of supplier flooding on suppliers' weighted average Fathom flood risk (cross-validated reports)

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

Our central results relating to flood risk consider the combined fluvial and pluvial flood risk, measured as the expected flood depth in each location associated with a 1 in 100 year flood. This captures the most expansive definition of flood risk captured by the Fathom flood risk data, as shown in panel (c) of Figure 3. All key results are robust to measuring flood risk in relation to 1 in 10 year floods or 1 in 50 year floods.

C.6.1 Firm location

Table C.11. Impact of flooding on firm relocation

	Dependent Variable: Move Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Max Share of 2km Buffer Flooded	-0.0704	1.840**	1.752**	0.512	1.758**	1.651**
	(0.742)	(0.751)	(0.803)	(0.681)	(0.811)	(0.780)
District FE	Yes	Yes	Yes			
District × Fathom 1in10 FE				Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km	0km	5km	10km
R^2	0.005	0.021	0.046	0.011	0.037	0.066
N	43,831	43,841	43,848	43,698	43,686	43,665

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in10 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.12. Impact of flooding on Fathom flood risk of firm's location

	Dependent Variable: Change in Flood Risk				
	(1)	(2)	(3)	(4)	(5)
Max Share of 2km Buffer Flooded in Flood Month	-1.062	-1.511	-1.541	-1.159	-1.184
	(0.717)	(1.048)	(1.298)	(0.983)	(0.807)
District FE	Yes	Yes	Yes	Yes	Yes
District × Fathom 1in10 FE					
R^2	0.016	0.022	0.045	0.070	0.140
N	43,866	29,684	10,623	5,737	2,912
Max Share of 2km Buffer Flooded in Flood Month	-0.302	-0.451	-0.259	-0.0692	-0.202
	(0.331)	(0.451)	(0.714)	(0.606)	(0.597)
District FE					
District × Fathom 1in10 FE	Yes	Yes	Yes	Yes	Yes
R^2	0.150	0.219	0.343	0.380	0.455
N	43,830	29,643	10,581	5,689	2,860
Move Distance Restriction		>0km	>5km	>10km	>20km
Pr(Move=1)		0.68	0.24	0.13	0.07
Average 1in10 Flood Risk		0.10	0.11	0.12	0.12

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in10 year return period.

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

Table C.13. Impact of flooding on firm relocation

	Dependent Variable: Move Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Max Share of 2km Buffer Flooded	-0.0704	1.840**	1.752**	-0.401	1.707	2.012**
	(0.742)	(0.751)	(0.803)	(0.861)	(1.042)	(0.995)
District FE	Yes	Yes	Yes			
District × Fathom 1in50 FE				Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km	0km	5km	10km
R^2	0.005	0.021	0.046	0.019	0.041	0.068
N	43,831	43,841	43,848	43,463	43,570	43,522

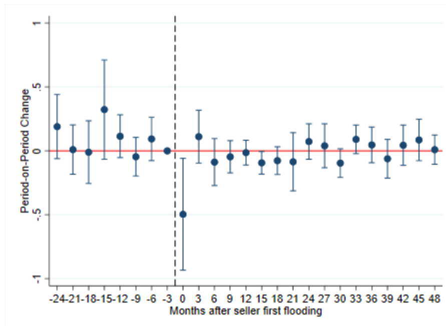
Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in50 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.14. Impact of flooding on Fathom flood risk of firm's location

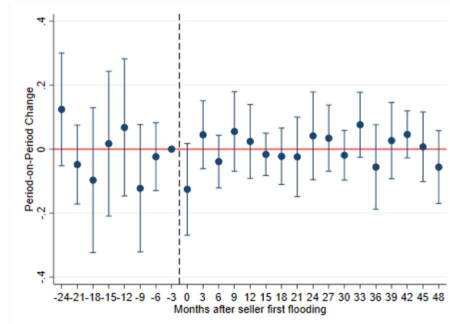
	Dependent Variable: Change in Flood Risk				
	(1)	(2)	(3)	(4)	(5)
Max Share of 2km Buffer Flooded in Flood Month	-1.342	-1.907	-2.284	-1.849	-1.856*
	(0.849)	(1.239)	(1.538)	(1.154)	(0.975)
District FE	Yes	Yes	Yes	Yes	Yes
District × Fathom 1in50 FE					
R^2	0.023	0.032	0.072	0.110	0.177
N	43,866	29,684	10,623	5,737	2,912
Max Share of 2km Buffer Flooded in Flood Month	-0.411	-0.585	-0.496	-0.331	-0.336
	(0.280)	(0.426)	(0.697)	(0.613)	(0.510)
District FE					
District × Fathom 1in50 FE	Yes	Yes	Yes	Yes	Yes
R^2	0.187	0.266	0.425	0.447	0.500
N	43,766	29,579	10,485	5,588	2,771
Move Distance Restriction		>0km	>5km	>10km	>20km
Pr(Move=1)		0.68	0.24	0.13	0.07
Average 1in50 Flood Risk		0.25	0.26	0.26	0.27

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019. Flood risk is measured in terms of expected depth of flooding in meters for a 1in50 year return period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.6.2 Supplier choice

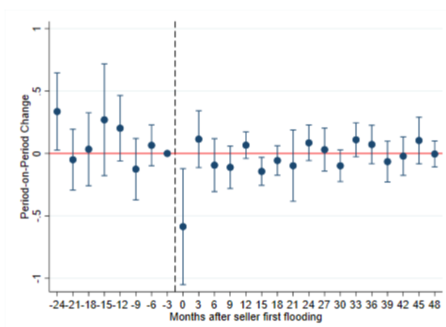


(a) All Suppliers within 3 months

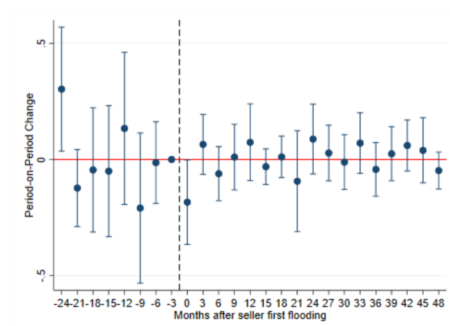


(b) Non-Flooded Suppliers within 3 months

Figure C.22. Dynamic impact of supplier flooding on suppliers' weighted average Fathom flood risk (1 in 10 year return period)



(a) All Suppliers within 3 months

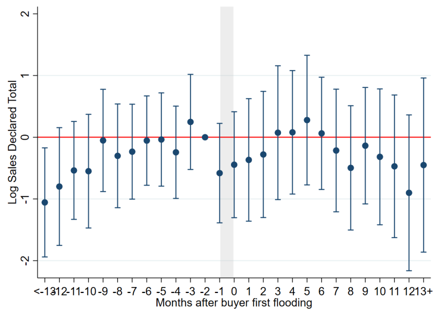


(b) Non-Flooded Suppliers within 3 months

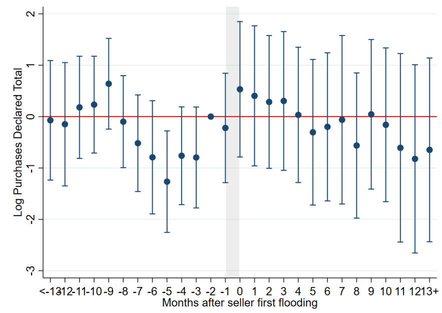
Figure C.23. Dynamic impact of supplier flooding on suppliers' weighted average Fathom flood risk (1 in 50 year return period)

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

C.7.1 Propagation of flood shocks

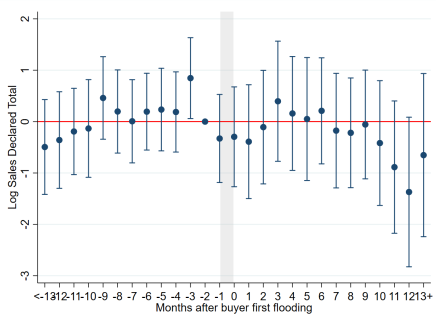


(a) Buyer within 6 months floods

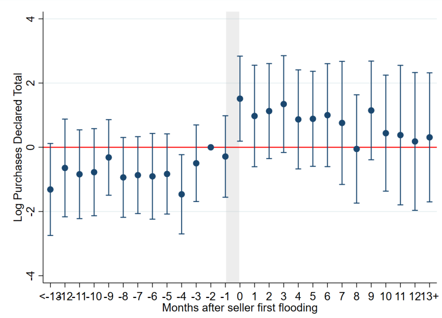


(b) Seller within 6 months floods

Figure C.24. Impact of buyer flooding on seller's sales, and of supplier flooding on buyer's purchases (6 month window)



(a) Buyer within 12 months floods



(b) Seller within 12 months floods

Figure C.25. Impact of buyer flooding on seller's sales, and of supplier flooding on buyer's purchases (12 month window)

C.7.2 Supplier diversification

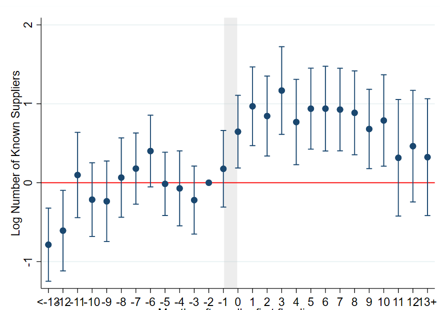


Figure C.26. Impact of supplier flooding on log number of suppliers (6 month window)

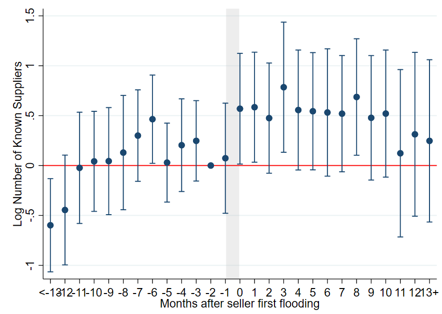
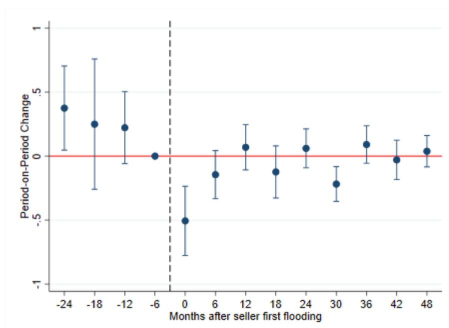
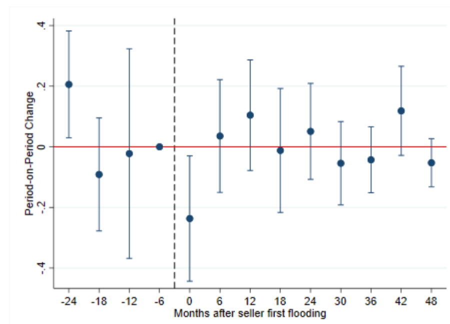


Figure C.27. Impact of supplier flooding on log number of suppliers (12 month window)

C.7.3 Supplier choice

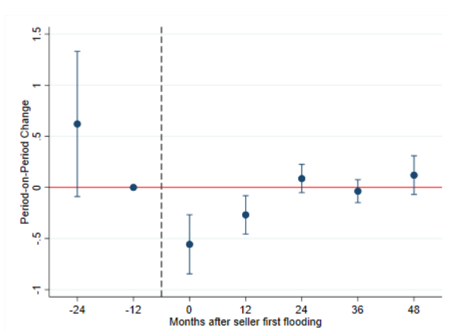


(a) All Suppliers within 6 months

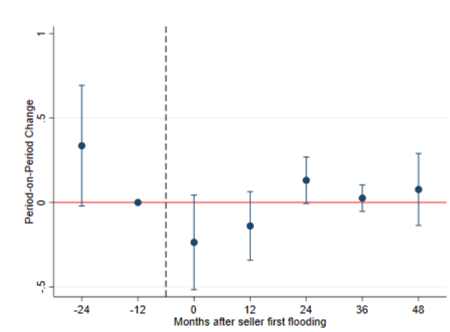


(b) Non-Flooded Suppliers within 6 months

Figure C.28. Dynamic impact of supplier flooding on suppliers' weighted average Fathom flood risk (6 month window)



(a) All Suppliers within 12 months



(b) Non-Flooded Suppliers within 12 months

Figure C.29. Dynamic impact of supplier flooding on suppliers' weighted average Fathom flood risk (12 month window)

C.8 Results including moving firms

C.8.1 Supplier Diversification

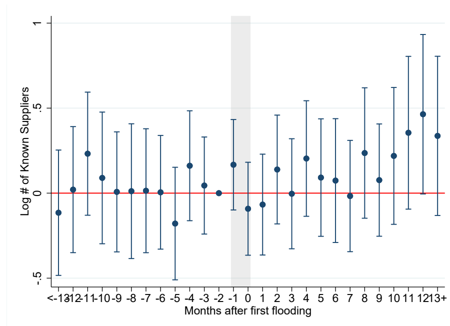


Figure C.30. Impact of flooding on log number of suppliers (including moving firms)

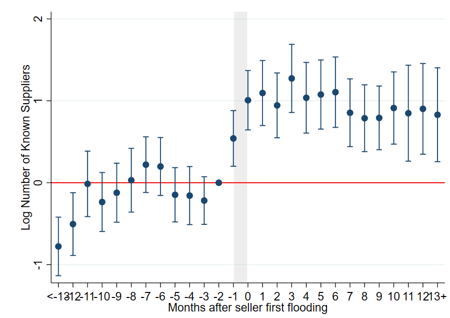
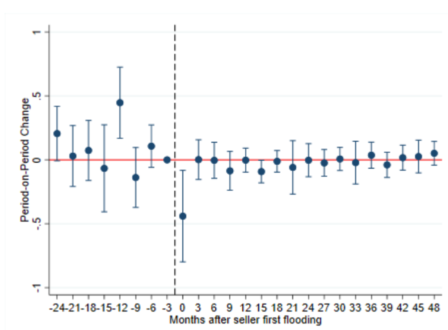
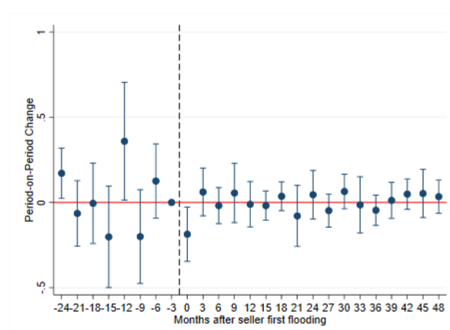


Figure C.31. Impact of supplier flooding on log number of suppliers (including moving firms)

C.8.2 Supplier Choice



(a) Suppliers' weighted average Fathom flood risk

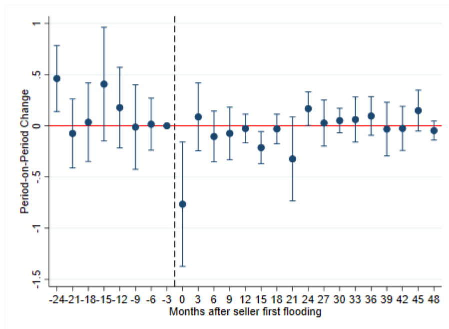


(b) Non-flooded suppliers' weighted average Fathom flood risk

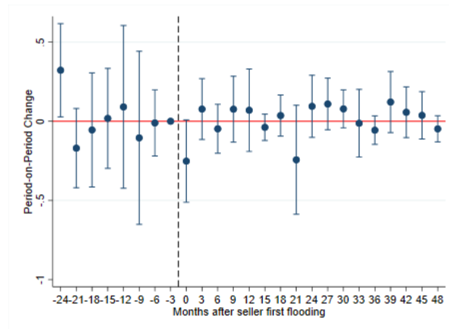
Figure C.32. Dynamic impact of supplier flooding on suppliers' weighted average Fathom flood risk (including moving firms)

C.9 Results excluding repeated exposures

C.9.1 Supplier Choice



(a) Suppliers' weighted average Fathom flood risk



(b) Non-flooded suppliers' weighted average Fathom flood risk

Figure C.33. Dynamic impact of supplier flooding on suppliers' weighted average Fathom flood risk (excluding repeat exposures)