Firm adaptation in production networks: Evidence from extreme weather events in Pakistan

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Introduction

- Increased frequency and severity of extreme weather events are key manifestations of projected climate change (IPCC 2021)
- Firms impacted directly (Indaco et al 2021) and via exposure of supply chain partners (Barrot & Sauvagnat 2016, Carvalho et al 2021)
- How costly these changes will be, and appropriate policy responses, depend on whether and how firms and economic systems adapt

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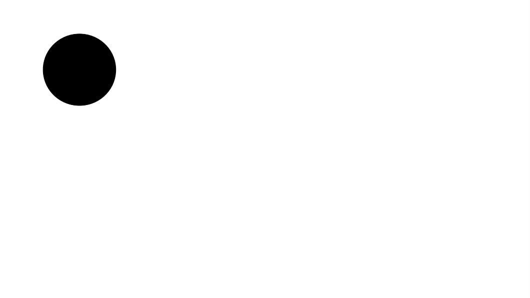

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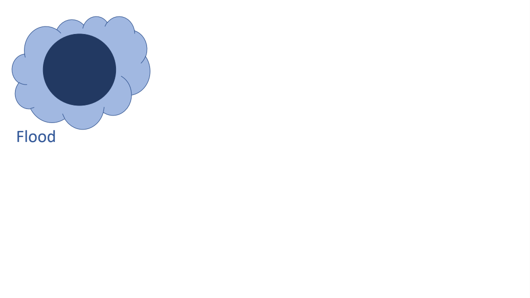

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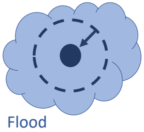

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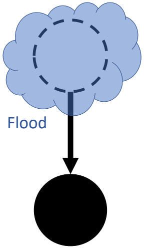

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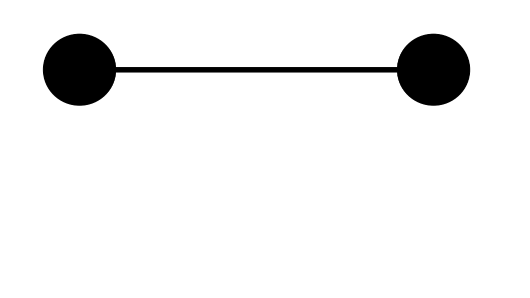

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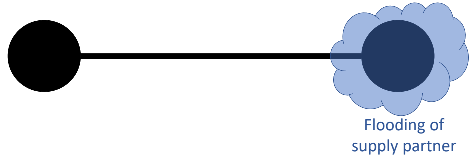

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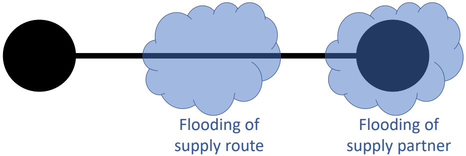

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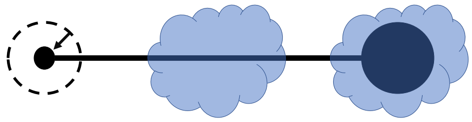

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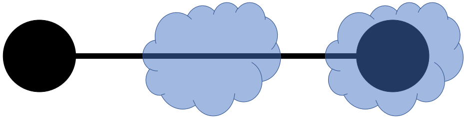

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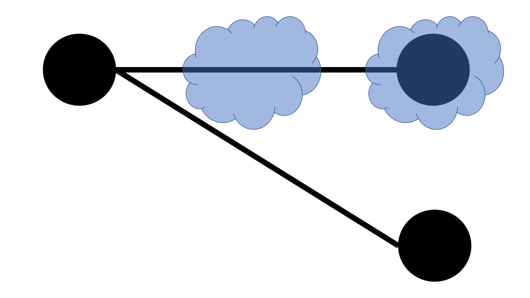

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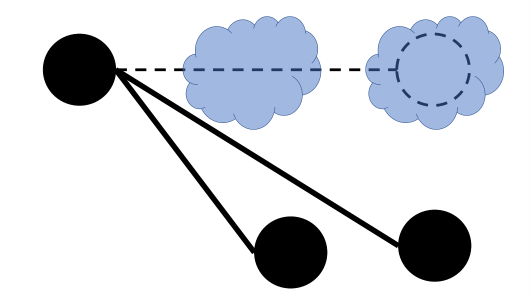

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- Adjustments may reflect both direct disruptive impacts of disasters and forward-looking decisions over future risk exposure

Key questions

Do firms adapt by changing production and network linkage decisions following natural disaster events?

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Do firms adapt by changing production and network linkage decisions following natural disaster events?

- What are the key margins of adaptation?
- What mechanisms underlie these adaptive responses?
- How important are adaptive decisions for aggregate outcomes?

Approach

Use detailed data on the near-universe of monthly firm-to-firm transactions among firms in Pakistan to study the impact of floods and subsequent adaptation

- VAT transactions data to capture response margins (moving, exit, supply chains)
- Combine with satellite flood maps to measure flooding of firms and their trading partners
- Use detailed GPS tracker data installed on trucks to get at road-level disruptions
- Use risk measures from a flood hazard model to capture location-specific flood risk

Reduced-form regressions to show responses in the aftermath of floods

- Once the temporary adverse effects of shocks have dissipated, adaptive responses are left $\Rightarrow$ identification

Model-based quantification of adaptation responses for subsequent and future floods

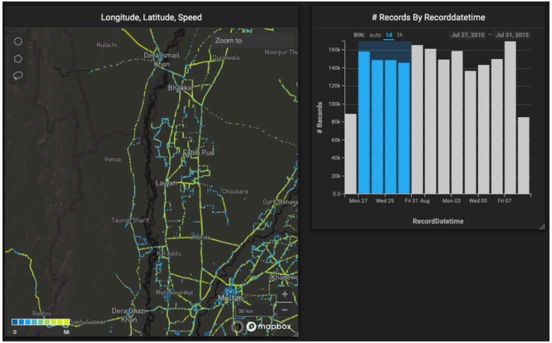
Outline

Four georeferenced micro-datasets

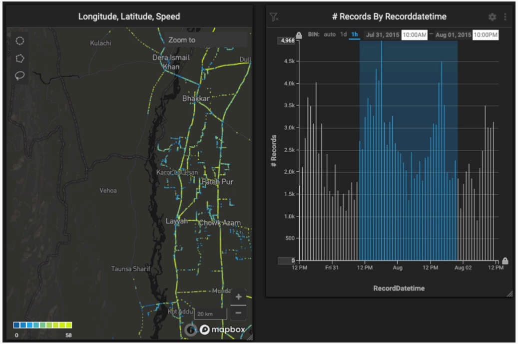
1. **Monthly firm transactions**, 2011-2018, from VAT records ▸ Firms Summary ▸ Transactions Summary
    - 73,000 firms, 89% of manufacturing GDP: bilateral sales, addresses ▸ Coding
    - Characterize production network linkages
    - Identify disruption to firms and relationships
    - Examine adaptation via firm location and supplier choice
2. **Flood extent polygons**, 2010-2019, from UNOSAT ▸ Details ▸ Share Firms Flooded
    - Intersect with firm and road locations to identify flood exposure
3. **Flood risk measures**, by 90m $\times$ 90m, from Fathom flood hazard model ▸ Details
    - Expected flood depth in 1-in-10, 1-in-50, 1-in-100 year floods
    - Used to characterize responses as adaptive to the extent they reduce flood risk
4. **GPS tracker signals**, >15,000 trucks, 6bn pings, 2012-2018 ▸ Measurement ▸ Coverage
    - Identify disruption to transportation routes ▸ Example: N-55 ▸ Example: Baddomalhi Road
    - Examine adaptation via trading route choice
    - Link-level flood exposure key for identification ▸ Many links affected

N-55 Indus Highway flooding disruption

Pakistan NDMA situation reports describe that at 09:15 on 31 July 2015: *“Floodwater coming from Koh-e-Suleman Range hill torrents hit Vehova Bridge on N-55 … swept away a 300-foot portion of the highway”*



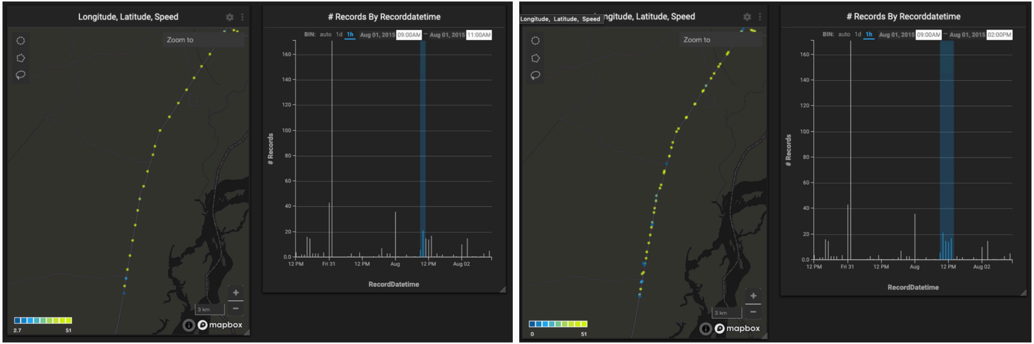
(a) Jul 27-30, 2015



(b) 10:00 Jul 31 - 10:00 Aug 1, 2015

▸ Baddomalhi Road example

At 09:15 of 31 Jul (day of closure), a vehicle approaches the closed bridge from the north

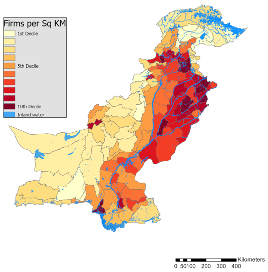


At 11:00 it is about halfway between Dera Ismail Khan and the river northeast of the closed bridge. The car slows down (blue dots).

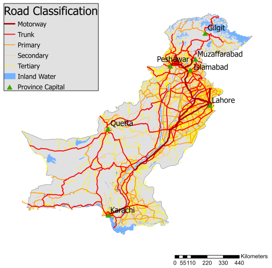
Then it turns around, going back to Dera Ismail Khan, which it reaches at 14:00.

Firm, road and flood risk locations

Firm Location by District

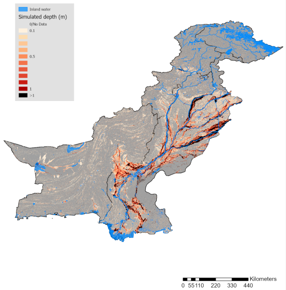


Major Roads



Fathom Flood Risk Map

Combined - 1 in 100 years



▶ All flood risk categories

Outline

Direct impacts of floods on firm-level outcomes

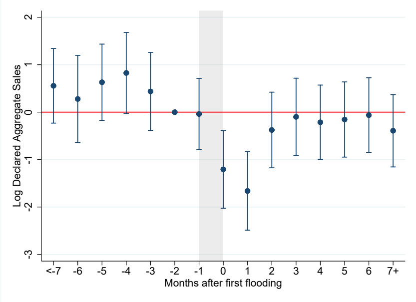
Empirical specification:

$$y_{it} = \sum_{\tau=-6,\tau\neq-2}^{6} \beta_\tau FloodExtent_{i,t-\tau} + \alpha_{im(t)} + \alpha_{iy(t)} + \alpha_t + \epsilon_{it}$$

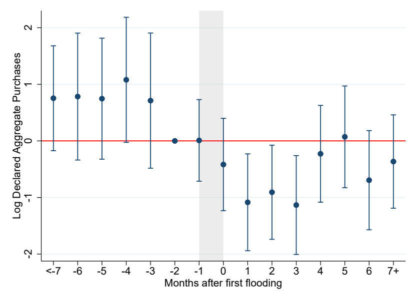
- y_{it}: outcome for firm i in month-year t
- $FloodExtent_{it}$: maximum % of firm i's 2km buffer flooded at t
- Firm-month, firm-year, month-year fixed effects
- Standard errors clustered at firm level

Negative but temporary effects on firm operations

Log sales



Log purchases



↓ 1.48% sales, ↓ 0.45% purchases for mean treated firm on impact

Other direct impacts on firms and firm relationships

- Being flooded increases the probability of exit ▸ Slide
  - Mean flooded firm in 2014: 0.4pp increase in the probability of exit
- Shocks propagate along relationships ▸ Slide
  - Supplier flooded $\Rightarrow$ bilateral transaction value decreases (1%)
  - Conditional on relationship surviving, full recovery after 6m
  - Supplier flooded $\Rightarrow$ probability of making transaction decreases (0.1pp)
- Floods temporarily disrupt traffic ▸ Slide
  - Road intersects flood polygon $\Rightarrow$ 6.6pp increase in traffic being disrupted (traffic volume below 1st percentile)
  - Probability of disruption reverts to mean after $\leq$ 3 weeks (roads get restored)

Firm and supply chain adaptation

- Floods have sizable, transient impacts on firm operations and traffic
  - If we observe long-term firm responses to flooding of firms and roads, these are not driven by persistent disruption
- Do firms undertake persistent adaptive actions following floods?
  1. Firm relocation jump
  2. Supplier diversification jump
  3. Shift towards less flood-prone suppliers jump
  4. Shift towards suppliers reached via less flood-prone routes jump

Margin 1: Firm relocation

Are flooded firms more likely to relocate?

$$Pr\left(Move_i\right) = F\left(\beta FloodExtent_i + \alpha_d\right)$$

- Logit regression
- $Move_i$: indicator =1 if firm i moved during the sample period
- $FloodExtent_i$: max % firm i's 2km buffer flooded during first flood
- α_d: district fixed effects

Do flooded firms relocate to safer areas?

$$\Delta FloodRisk_i = \beta FloodExtent_i + \alpha_d + \epsilon_i$$

- $\triangle FloodRisk_i$: $\triangle$ 1-in-100 year flood risk from i's 2011 to 2019 address

Do relocating firms take recent flood history elsewhere into account in deciding where to move? Yes [but won't cover this today]

Flooded firms more likely to relocate
Relocation summary statistics

	Dependent Variable: Move Dummy		
	(1)	(2)	(3)
Max Share of 2km Buffer Flooded	-0.0704	1.840**	1.752**
	(0.742)	(0.751)	(0.803)
District FE	Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km
R^2	0.005	0.021	0.046
N	43,831	43,841	43,848

Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

With district x flood risk decile FE

Mean flooded firm $\Rightarrow$ 2% increase in odds of relocating > 10km

Back

Flooded firms relocate to safer areas

	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
R^2	0.028	0.039	0.086	0.126	0.189
N	43,866	29,684	10,623	5,737	2,912
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.

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

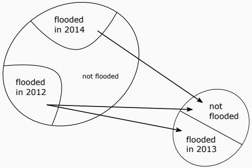
With district x flood risk decile FE

Mean flooded firm that moves > 10km sees 3.8cm reduction in expected 1-in-100y risk

Back

Firm response to flooding in other locations

- Intuition: within district pairs, are flooded firms that relocate more likely to move to destination areas that are flooded if, at the time the firm was flooded, the destination area had not yet been?



Poisson specification: $E(X_{ot_o dt_d}) = exp\left(\alpha_{od} + \alpha_{ot_o} + \alpha_{t_d} + \beta 1\left(t_o - t_d \geq 12\right)\right)$

- X_{od}: relocation flows from origin o to destination d
- ot_o: areas of origin district o flooded at time t_o
- dt_d: areas of destination district d flooded at time t_d
- $1\left(t_o - t_d \geq 12\right)$: 1 if ot_o flood post-dates dt_d flood by >12 months
- Standard errors clustered at level of origin-destination district pairs

Back

Firm response to flooding in other locations

	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 × 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	2,596	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.

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

Margin 2: Supplier diversification

Consider whether firms diversify suppliers following flooding of:

Own premises:

$$\log(\#suppliers)_{it} = \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_\tau FloodExtent_{i,t-\tau} + \alpha_{im(t)} + \alpha_{iy(t)} + \alpha_t + \epsilon_{it}$$

Any of their suppliers:

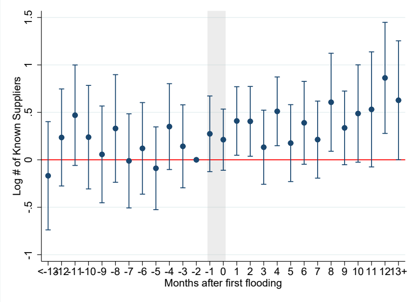
$$\log(\#suppliers)_{bt} = \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_{1,\tau} SellerFlood_{b,t-\tau} + \sum_{\substack{\tau=-12 \\ \tau\neq-2}}^{12} \beta_{2,\tau} OwnFlood_{b,t-\tau} + \alpha_{bm(t)} + \alpha_{by(t)} + \alpha_t + \epsilon_{bt}$$

- $SellerFlood_{b,t-\tau}$: maximum % of 2km buffer flooded across all suppliers accounting for >10% of buyer *b*'s purchases in prior 3 months; here supplier = firms from which *b* has purchased in prior 3 months
- $OwnFlood_{b,t-\tau}$: maximum % of firm *b*'s 2km buffer flooded at *t* (first observed supplier flooding event)

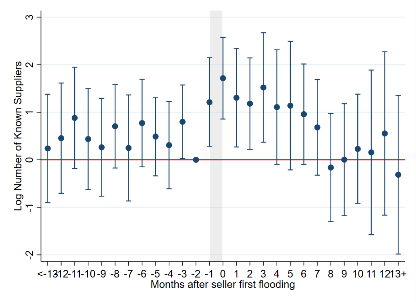
Flood-affected firms diversify suppliers (but response not persistent)

Dependent variable: log number of suppliers

Direct exposure



Indirect exposure



(cross-reported links only)

Back

Margin 3: Flood risk of suppliers

- Firms may adapt via composition as well as number of suppliers
- Empirical specification:

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

  - t^*: month-year of a flood event
  - $OwnFlood_{bt*}$: max % of buyer b's 2km buffer flooded at t^*
  - $SellerFlood_{bt*}$: max of max % of b's sellers' 2km buffers flooded at t^*
  - $\alpha_{d(b)t*}$: district of buyer $\times$ event fixed effects

- y_{bt*} captures period-on-period change in weighted flood risk of b's suppliers in 3 months before vs after t^*:

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

Flood-affected firms shift activity towards safer suppliers

	Dependent Variable: Change in Supplier Risk	
	(1)	(2)
Own Max Flood Ext.	0.0158	-0.0685
	(0.0334)	(0.0923)
3m Suppliers Max Flood Ext.	-0.589***	-0.634***
	(0.0293)	(0.173)
Time FE	Yes	
District $\times$ Time FE		Yes
R^2	0.0030	0.0111
N	146,740	146,643

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

Mean treated firm (max flood extent among its suppliers 3.2% of buffer) $\rightarrow$ 0.3cm $\searrow$ in wt. avg. supp. fld. risk

Not driven by exit/contraction of flooded suppliers

	Dependent Variable: Change in Supplier Risk	
	(1)	(2)
Own Max Flood Ext.	-0.0762***	-0.115
	(0.0282)	(0.0947)
3m Suppliers Max Flood Ext.	-0.236***	-0.269***
	(0.0327)	(0.0957)
Time FE	Yes	
District $\times$ Time FE		Yes
R^2	0.0006	0.0127
N	130,255	130,147

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.
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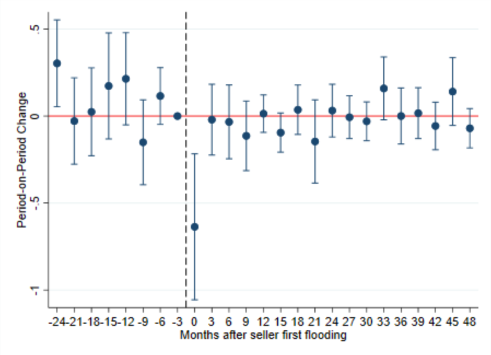
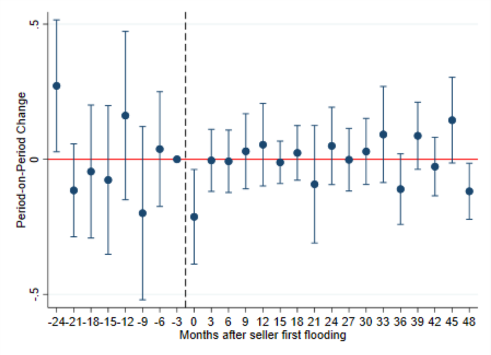
Change in supplier composition persists for at least 4 years

Specification in changes between 3m-windows: zero = no change

All suppliers



Non-flooded suppliers



▸ Non-movers

▸ To Model ▸ Back

Margin 4: Flood risk of supply routes

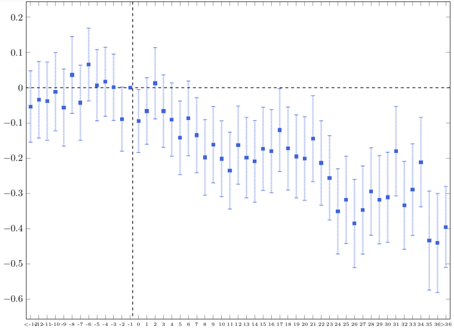
- Does flood-induced road disruption also induce firms to reduce dependence on suppliers reached via these routes?
- Leverage bilateral nature of transaction data to fully isolate adaptive behavior from potential confounding shocks using *bt* and *st* FEs

$$y_{bst} = \sum_{\tau=-12,\tau\neq-1}^{36} \beta_k ShareRouteFlooded_{bs,t-\tau} + \eta_{age(b,s),t} + \alpha_{bs} + \alpha_{st} + \alpha_{bt} + \epsilon_{bst}$$

  - y_{bst}: indicator = 1 if *b* and *s* transact during month-year *t*
  - $ShareRouteFlooded_{bst}$: share of ordinary-time (during non-flooded weeks) shortest-time route between *b* and *s* flooded at *t*
  - $\eta_{age(b,s),t}$: indicator variables for age of *bs* relationship

Temporary road flooding disrupts transactions persistently

- Short-lived flood disruption of transport routes between buyer-seller pairs ⇒ persistent cessation of transactions between them



- Median treated route ⇒ transaction prob declines by 0.1pp
- Substitution away from supply partners reached by flooded routes driven by transactions ceasing rather than intensive margin reductions

Back

Robustness

- Alternatives to TWFE event studies ▸ S & A ▸ BJS
- Reconciling buyer- and seller-level transaction reports ▸ Reconciled
- Flood return periods ▸ 1 in 10 years ▸ 1 in 50 years
- Partner window for indirect treatments ▸ 3 months ▸ 6 months
- Excluding gas and electric producers ▸ Excl gas electric
- Restricting to manufacturing firms ▸ Manufacturing
- Excluding purchases of capital goods ▸ Excl capital purchases

Outline

Data

Direct impacts on firms and firm relationships

Mechanisms

Quantification

Conclusions

What mechanisms might underlie adaptive responses?

Evidence consistent with firms updating priors over flood risk (cf individual decision-making on climate risk, e.g. Lybbert et al 2007, Moore 2017)

Alternative mechanisms?

1. Increased importance of flood risk in firm decision-making, e.g. availability bias ↑ salience of climate risk (Tversky & Kahneman 1973, Bordalo et al 2021)
    - Impact of floods on Firms' risk assessments should diminish as time passes.
    - Not observed over the horizon we study
    - No evidence of 'forgetting' in firm gravity ▸ Table
2. Lower fixed cost of making desirable changes
    - Consistent with adaptive relocation, shift towards safer suppliers
    - Does not explain shift among non-flooded suppliers

Outline

Purpose of the model

- Framework to study relevance of idiosyncratic and aggregate risk and its mediation by supply chains
- Clarify identification of adaptive responses
- Quantify relevance of post-flood adaptive responses for welfare (i) following individual subsequent flood events, (ii) over the entire distribution of future flood events

Model combines elements from Kopytov, Mishra, Nimark, Tascherau-Dumouchel (2022) and Boehm-Oberfield (2020, 2022)

Minimal set of assumptions on updating of firms' perceived flood risk: firms are not necessarily rational Bayesians

Short version

Model

Repeated static spatial economy. N locations with J_n firms.

Representative risk-averse household with CRRA utility:

$$u(q) = \frac{1}{1-\rho} q^{1-\rho}$$

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

Firms in n have production functions

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

- $a_{n(j)}$ is time-invariant productivity in location n
- $b_{n(j)}$ is the aggregate flood shock in location n
- ξ_j is an idiosyncratic flood shock to firm j
- $z(\phi)$ is idiosyncratic match-specific productivity (as in Oberfield, 2018)

In each period, two stages:

1. Firms invest to search for suppliers in different locations, under uncertainty over (and imperfect information about) flood risk.

$$\max_{(m_{ni})} \mathbb{E}\left(\lambda \pi_j(m_{n1}, \ldots, m_{nN}) | \mathcal{I}_n\right)$$

$$s.t. \qquad g(m_{n1}, \ldots, m_{nN}) = \bar{m}, \quad m_{ni} \geq 0$$

   where λ is the SDF of the households and $\mathcal{I}_n$ is the beliefs of firms in n

2. Aggregate and idiosyncratic flood shocks (as well as search outcomes) are realized. Conditional on that, firms choose suppliers to minimize costs (= maximize profits). No uncertainty anymore.

$$\max_{\phi \in \Phi_j} \pi(\phi)$$

   Firms sell to households (monopolistic competition, isoelastic demand) and to firms in other locations (marginal cost pricing).

Functional form assumptions

- If search effort is m_{ni}, then number of supplier draws from location i with a match-specific productivity above $\bar{z}$ is Poisson with mean

$$m_{ni}\bar{z}^{-\zeta}$$

  Higher search effort $m_{ni} \Rightarrow$ more (= better) draws. ζ is Pareto tail of idiosyncratic draws. Suppliers are drawn uniformly.

- Choose distribution of idiosyncratic flood shocks ξ so that $\xi^{\zeta/\alpha}$ follows a positive one-sided α-stable: distribution:

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

- Iceberg trade costs τ_{ni}

Lemma

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

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

where

$$\bar{c}_i^{-\zeta} = \left(\frac{a_i b_i}{w^{1-\alpha}}\right)^{\zeta}\left[\sum_{i'} m_{ii'}\tau_{ii'}^{-\zeta}\bar{c}_{i'}^{-\zeta}\right]^{\alpha}\Gamma\left(1-\frac{\alpha}{\beta}\right)$$

Corollary

The expenditure share of location n on inputs from i is

$$\frac{X_{ni}}{X_n} = \frac{m_{ni}\tau_{ni}^{-\zeta}\bar{c}_i^{-\zeta}}{\sum_{i'} m_{ni'}\tau_{ni'}^{-\zeta}\bar{c}_{i'}^{-\zeta}}.$$

Identification

Idea is to identify adaptation from persistent changes in sourcing shares:

$$\frac{X_{ni}}{X_n} = \exp\left[\log m_{ni} - \zeta \log \tau_{ni} - \zeta \log \bar{c}_i + \frac{\zeta}{\alpha} \log \Phi_n\right]$$

where

$$\Phi_n = \left[\sum_i m_{ni} \tau_{ni}^{-\zeta} \bar{c}_i^{-\zeta}\right]^{-1/\zeta}$$

Assuming that floods do not *persistently* change productivities a_n and trade costs τ_{ni}, we can write the gravity share in long-term changes from before a flood to until much after:

$$\widehat{\left(\frac{X_{ni}}{X_n}\right)} = \exp\left[\log \hat{m}_{ni} - \zeta \log \hat{\bar{c}}_i + \zeta \log \hat{\Phi}_n\right]$$

$$\hat{c}_n = \left[\sum_i \frac{X_{ni}}{X_n} \hat{m}_{ni} \hat{c}_i^{-\zeta}\right]^{-\alpha/\zeta} \qquad \hat{\Phi}_n = \left[\sum_i \frac{X_{ni}}{X_n} \hat{m}_{ni} \hat{c}_i^{-\zeta}\right]^{-1/\zeta}$$

- Calibrate ζ, α, β. Then estimate $\hat{m}$ in changes (with constraint that $\prod_i \hat{m}_{ni} = 1$) using PPML with constraints:

$$\widehat{\left(\frac{X_{ni}}{X_n}\right)} = \exp\left[\log \hat{m}_{ni} - \zeta \log \hat{\hat{c}}_i + \zeta \log \hat{\Phi}_n\right]$$

$$\hat{c}_n = \left[\sum_i \frac{X_{ni}}{X_n} \hat{m}_{ni} \hat{c}_i^{-\zeta}\right]^{-\alpha/\zeta} \qquad \hat{\Phi}_n = \left[\sum_i \frac{X_{ni}}{X_n} \hat{m}_{ni} \hat{c}_i^{-\zeta}\right]^{-1/\zeta}$$

  over long differences: t_1 is before the flood; t_2 is after direct impacts (i.e. b, τ) have dissipated.
- Could estimate at micro-level. Advantage: structural error term; tighter se's for $\hat{m}$. Disadvantage: more extensive-margin changes, computationally challenging. EKS, Head-Mayer (2019), Panigrahi (2022)

Welfare

Change in welfare following an aggregate flood shock:

$$\hat{u} = \left(\prod_n \hat{c}_n^{-\beta_n} \right)^{1-\rho}, \qquad \hat{c}_n = \hat{b}_n \left[\sum_i \frac{X_{ni}}{X_n} \hat{m}_{ni} \hat{c}_i^{-\zeta} \right]^{-\alpha/\beta}$$

Two exercises:

1. Identify (short-term) $\hat{b}$ and (long-term) $\hat{m}$ for each flood episode. How much does adaptation to flood X help (hurt?) in the wake of a subsequent flood Y?
2. (not today) How much does the adaptation in response to a particular flood, $\hat{m}$, change the distribution of outcomes over all flood states?

$$E(\hat{u}) = \int \left(\prod_n \hat{c}_n(\hat{m}, \hat{b})^{-\beta_n} \right)^{1-\rho} d\hat{B}(\hat{b})$$

Use DFO data on spatial extent of past floods to approximate spatial correlations of floods; Fathom flood risk measures (depth) to get flood extent under each scenario (1-in-10, 1-in-50, 1-in-100).

Implementation

Definition of locations n**:** choose locations to be districts $\times$ dummy for having at least one $> 10\%$ flooded supplier that accounts for at least 10% of pre-flood expenditures. Exclude cells with less than two active firms (or no purchases in pre-, during-, or post-flood period).

Quantification of floods impact on TFP: Assume that productivity shocks in each location n is related to the (sales-weighted) share of firms whose 2-kilometer buffer is flooded by more than 10% in a log-linear way:

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

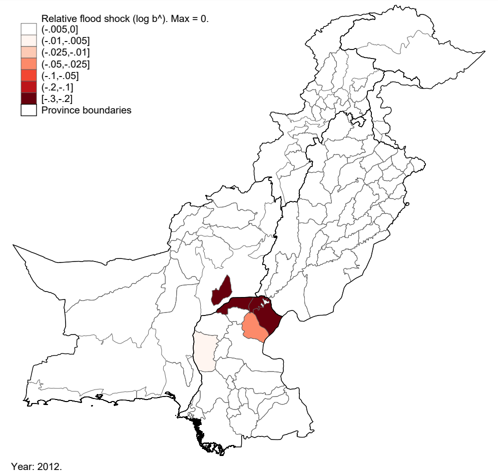
Estimating η from changes in observed sourcing shares (pre-flood to during-flood) using PPML yields $\hat{\eta} = -0.43$.

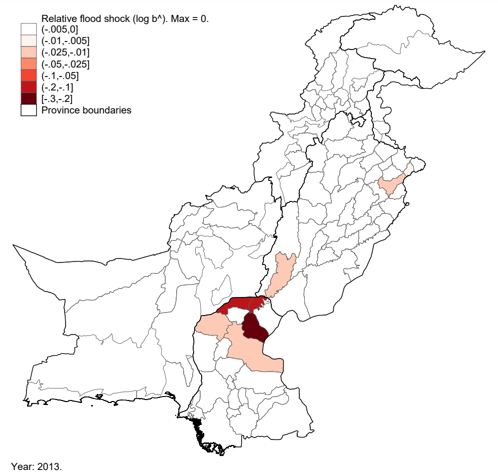
$\Rightarrow$ a location n where *all* firms have $> 10\%$ of 2km buffer flooded has a $\sim 30\%$ drop in TFP.

Calibrating other parameters: Set $\alpha = .77$ (mat. + capital in VA), and $\zeta = 4$ (trade elast.).

2012 and 2013 floods happen in *similar* locations

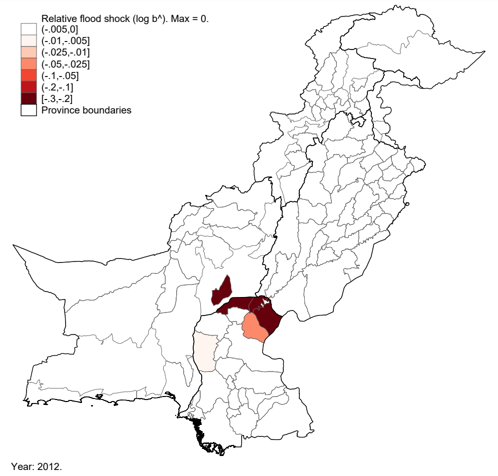
Estimated aggregate TFP drop from floods in 2012 and 2013

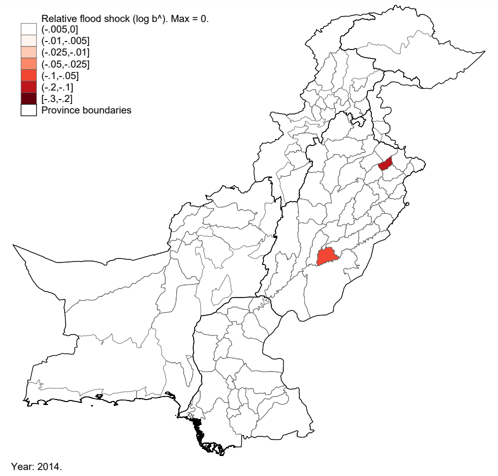




2012 and 2014 floods happen in *different* locations

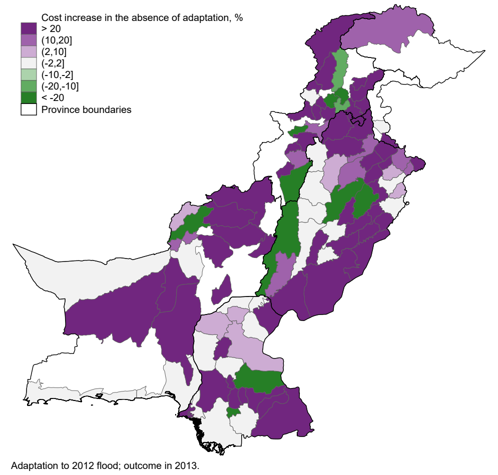
Estimated aggregate TFP drop from floods in 2012 and 2014



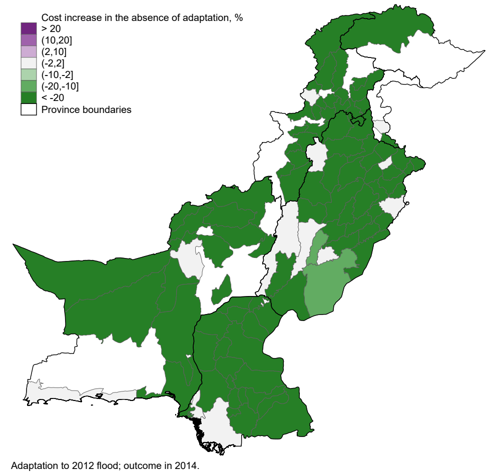


Adaptation to 2012 flood helps in 2013, but hurts in 2014

Counterfactual cost increase under no 2012 adaptation.



(i) 2013



(j) 2014

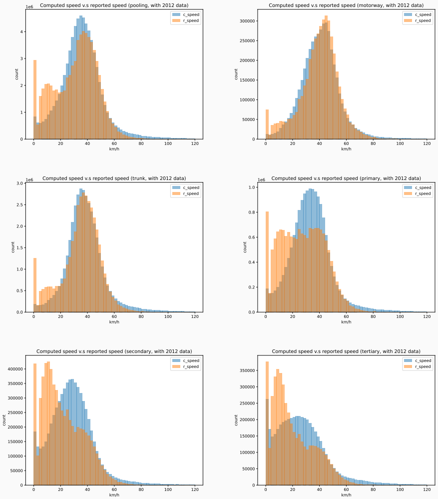
Outline

Conclusions

- Increasing frequency and severity of natural disasters are key manifestations of a changing climate
- Results suggest disasters might also mediate impacts of climate change by inducing firm-level adaptation
    - Temporary disruption to production and transport links
    - Persistent adaptive shifts in firm location, supplier and route choice
    - Consistent with persistent experience-based learning
- Channels and strength of adaptation crucial for understanding costs
    - Difficult to observe using standard firm panels
    - Sheds light on firms' forward-looking behavior
- Ongoing work on quantification of adaptation margins

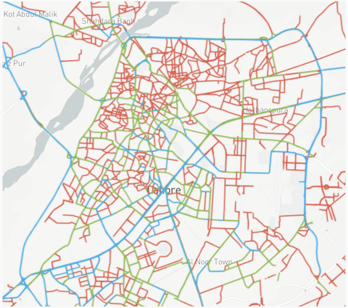
Appendices

GPS data overcomes selection bias in reported speeds



Histograms of computed speed and reported speed, using 2012 data

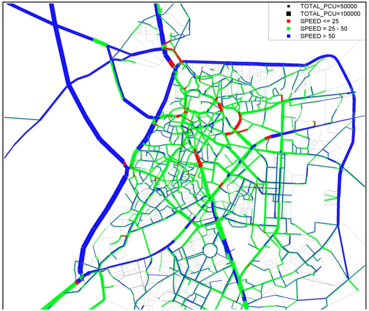
GPS data consistent with Lahore traffic maps



Average Truck speeds in Lahore, 2015. Monthly data from 2015; blue is speeds > 40 km/h, green is [20, 40] km/h, red is < 20 km/h.

The Project for Lahore Urban Transport Master Plan in the Islamic Republic of Pakistan
FINAL REPORT: VOLUME I of II
CHAPTER 7 – MASTER PLAN 2030

Figure 7.2.2 Current (2010) Road Network Performance



▸ return

Firm transactions data

- Near universe of formal firm-to-firm monthly sales transactions for VAT-registered firms from Federal Board of Revenue, 2011-2018
- Firm characteristics: name, industry, address in 2011 and 2019 ($\rightarrow$ geocoding)
- Monthly transactions, sales, purchases, imports, exports, VAT paid

Sample:

- 73,000 firms used in analysis capture 89% of 2018 manufacturing GDP
- Drop small 'firms' with incomplete or misreported data (3% sales)
  - Report never or $\leq$ twice in any transaction measure
  - Are or transact exclusively with invoice mills (Waseem 2019)
  - Cannot be geocoded
- Transaction specifications restrict to firm-pairs with >1 transaction

Back

GPS tracker data

- High frequency data from GPS trackers in >15,000 commercial trucks over 2012-2018 purchased from an original equipment manufacturer
- 6 billion observations showing location and speed of vehicles traveling on Pakistan's road network
- Used to generate accurate data on truck supply routes and traffic conditions: focus on disruptions caused by floods

Back

Flood disaster and hazard exposure data

- Satellite data on flood events and extents over 2010-2019 from UNOSAT Flood Portal

  ▸ Annual flood extents

  - Firm specifications aggregate satellite images to monthly level
  - Study flood-induced road disruption at weekly level

- Flood hazard data from Fathom-Global
  - Global flood hazard model combined with terrain and hydrography data
  - 90m resolution
  - Fluvial and pluvial flooding
  - Reports expected flood depth for of 1-in-10, 1-in-50 and 1-in-100 year floods

    ▸ Flood exposure of firms and routes

▸ Back

Firm transactions data

- Near universe of formal firm-to-firm monthly sales transactions for VAT-registered firms from Federal Board of Revenue, 2011-2018
- Firm characteristics: name, industry, address in 2011 and 2019
- Monthly transactions, sales, purchases, imports, exports, VAT paid

	Mean	SD
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%	

Transactions between a buyer and seller are only counted if the transaction value is greater than zero.

▸ Extended transaction-level summary statistics ▸ Back

Firm sample

- 73,000 firms used in analysis capture 89% of 2018 manufacturing GDP
- Drop small ‘firms’ with incomplete or misreported data (3% sales)
    - Report never or $\leq$ twice in any transaction measure
    - Are or transact exclusively with invoice mills (Waseem 2019)
    - Cannot be geocoded
- Transaction specifications restrict to firm-pairs with >1 transaction

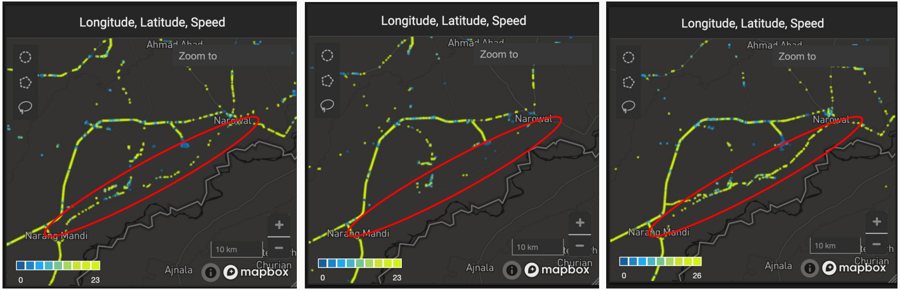
	Mean	SD
# Buyers = # Sellers	73,336	
Number of unique suppliers (monthly)	4.60	18.30
Number of unique buyers (monthly)	5.09	47.71
Share of firms with 2011 and 2019 geocodes	60%	
Share of firms whose 2km buffer ever flooded	28%	
Share of firms whose 2km buffer flooded more than once	4%	
Share of firms whose partners’ 2km buffer ever flooded	78%	
Share of firms whose partners’ 2km buffer flooded more than once	54%	
Average probability of firm exit in given month	0.43%	
Firm panel observations (nonzero)	3,736,834	

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.

▸ Extended firm-level summary statistics ▸ Back

Baddomalhi Road flooding disruption

8/25-9/3 (pre-flood) 9/3-9/10 (flood) 9/10-9/17 (post-flood)



return

Measuring travel speeds and disruption

- Calculate speed between consecutive GPS pings
  - Road edge level dataset based on Open Street Map
  - Project GPS observations to closest edge within 10m
  - Drop consecutive observations >30 min or >20 km apart
  - Infer average speed from shortest distance route and time stamps
- Aggregate mean speed and truck-day counts to week-edge level
- Construct least-time route between each buyer-seller pair
  - On average across non-flooded weeks
  - During each week when flood events recorded

Back

Data covers 88% length of motorways to tertiary roads

	Length with GPS data coverage (km)	Total Length (km)	Mean speed (km/hr)	Standard deviation
Motorway	4,241	4,264	41	16
Trunk road	18,261	18,301	37	14
Primary road	16,762	17,602	31	16
Secondary road	20,587	23,056	26	16
Tertiary road	48,597	59,785	23	18

▸ Overcomes selection bias in reported speeds ▸ Consistent with Lahore traffic maps

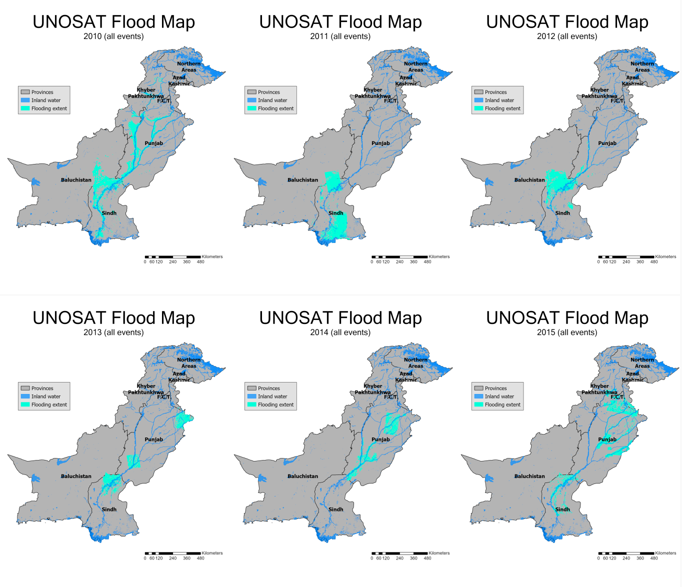
▸ Back

Large share of firm pairs exposed to supply route flooding

- At buyer-seller-week level for firm pairs that trade > once:
  - 0.7% see shortest path flooded
  - 25% during average flood week
- At buyer-seller level for firm pairs that trade > once:
  - 46% see shortest path flooded at least once
- Suggests restricted focus on firm nodes abstracts from important dimension of network's flood risk via transportation links

Back

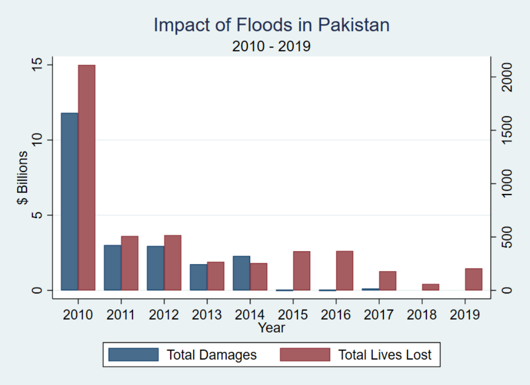
UNOSAT flood data



Observed flood impacts

	Share of Total Firms First Flooded
January 2011	0.0016
August 2011	0.0027
September 2011	0.0090
September 2012	0.0017
August 2013	0.0703
September 2014	0.0916
July 2015	0.1040
August 2015	0.0022

Captures major floods during study period



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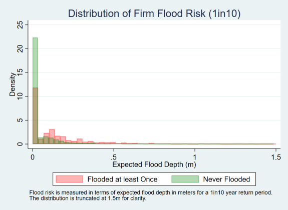
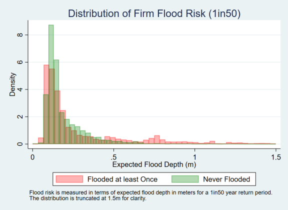
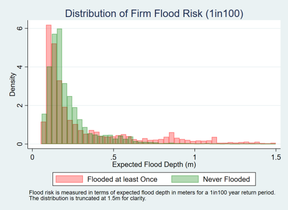
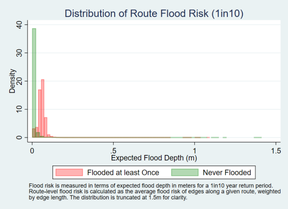
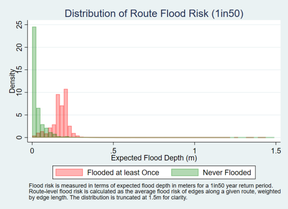
Flood exposure of firms and routes

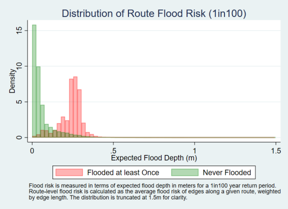












return

Flood risk summary statistics: 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.

return

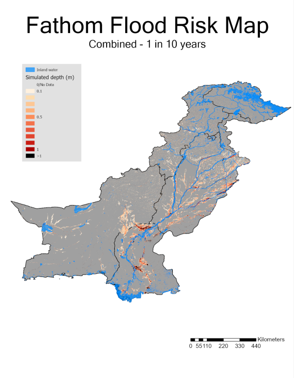
Flood risk summary statistics: routes

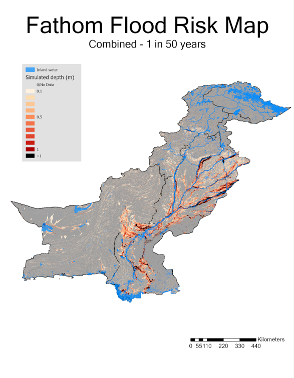
	# Routes	Mean	SD	Min	Max
Flooded Once in Sample					
Fathom (1in10) Flood Risk	112,742	0.05	0.05	0.00	1.03
Fathom (1in50) Flood Risk	112,742	0.14	0.11	0.00	2.27
Fathom (1in100) Flood Risk	112,742	0.19	0.15	0.00	2.64
Flooded more than Once in Sample					
Fathom (1in10) Flood Risk	649,568	0.06	0.02	0.00	1.01
Fathom (1in50) Flood Risk	649,568	0.18	0.05	0.00	2.39
Fathom (1in100) Flood Risk	649,568	0.25	0.06	0.00	2.81
Never Flooded in Sample					
Fathom (1in10) Flood Risk	869,597	0.00	0.02	0.00	1.67
Fathom (1in50) Flood Risk	869,597	0.04	0.06	0.00	3.39
Fathom (1in100) Flood Risk	869,597	0.06	0.09	0.00	4.42
Total					
Fathom (1in10) Flood Risk	1631907	0.03	0.04	0.00	1.67
Fathom (1in50) Flood Risk	1631907	0.10	0.09	0.00	3.39
Fathom (1in100) Flood Risk	1631907	0.15	0.13	0.00	4.42

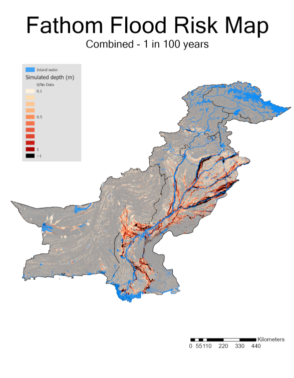
Flood risk is measured in terms of expected flood depth in meters for a given return period. Route-level flood risk is calculated as the average flood risk of edges along a given route, weighted by edge length.

return

UNOSAT flood data





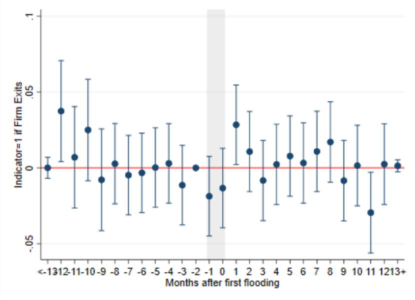


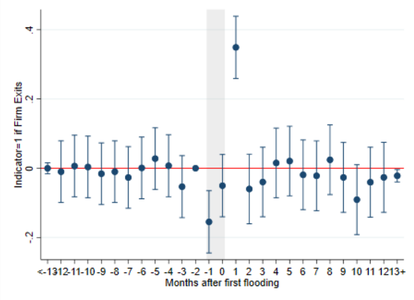
return

Strongest floods increase probability of firm exit

$$y_{it} = \sum_{\tau=-12,\tau\neq-2}^{12} \beta_\tau FloodExtent_{i,t-\tau} + \alpha_{dt} + \epsilon_{it}$$

- y_{it}: indicator = 1 if firm i in district d exits in month-year t





▸ Muted extensive margin effects conditional on survival (for mean treated firm in 2014: $P(exit) \nearrow$ 0.4pp)

▸ Back

Propagation of floods through supply networks

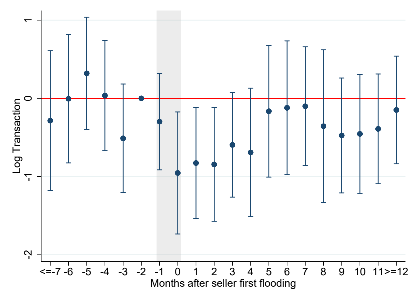
Buyer-seller level specification (and equivalently for buyer flooding):

$$y_{bst} = \sum_{\tau=-6,\tau\neq-2}^{12} \beta_\tau SellerFlood_{s,t-\tau} + \alpha_{bs} + \alpha_{bt} + \eta_{age(b,s),t} + \epsilon_{bst}$$

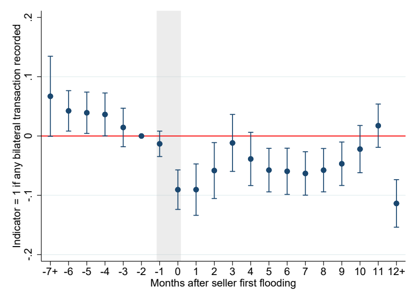
- $SellerFlood_{st}$: maximum % seller s's 2km buffer flooded at t
- $\eta_{age(b,s),t}$: indicator variables for age of bs relationship
- Standard errors clustered at level of flooded firm
- y_{bst} for buyer b and seller s at t:
    - Intensive margin: log transaction value
    - Extensive margin: indicator = 1 if positive sales

Shocks propagate through supply networks

Intensive margin



Extensive margin



Buyer flooding

Back

Flooding affects extensive and intensive margin road usage

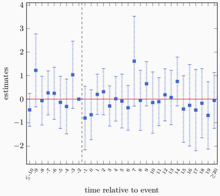
Roads closed by flooding reopen rapidly $\Rightarrow$ edge-week level specifications:

$$y_{iw} = \sum_{\tau=-10,\tau\neq-2}^{20} \beta_\tau 1\left\{i \textit{ flooded at } w-\tau \textit{ and } w-\tau \in y(w)\right\} FloodExtent_{i,y(w)} + \alpha_i + \alpha_{dw} + \epsilon_{iw}$$

- y_{iw}: outcome for road edge i in district d during week w
    - mean speed of trucks on edge
    - log day-truck count
    - disruption indicators (day-truck count < 1st or 3rd percentile)
- $FloodExtent_{i,y(w)}$: share of total length of i flooded in first week of flooding during year $y(w)$

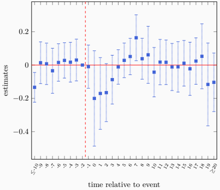
Flooding affects extensive and intensive margin of road usage

Mean speed



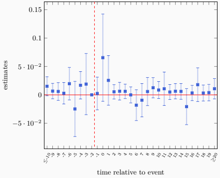
Note: N_obs = 13395395

Day-truck count

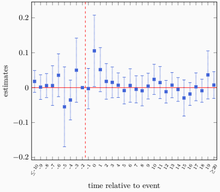


Note: N_obs = 11704088

Disruption indicator (below 1st & 5th percentile)



Note: N_obs = 11714830



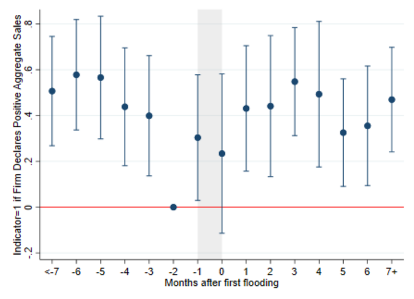
Note: N_obs = 11714830

Back

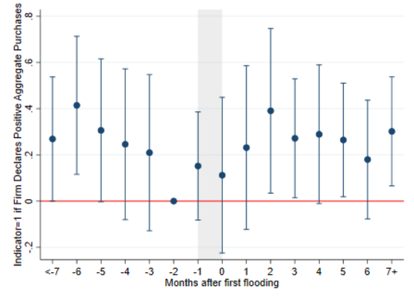
Speeds ↓ 0.8km/hr, day-trucks ↓ 16 – 20%, disruption (1st %ile) ↑ 7pp

Muted extensive margin effects conditional on survival

Positive sales



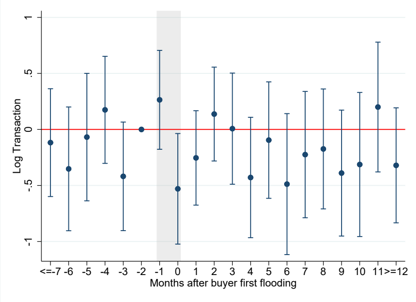
Positive purchases



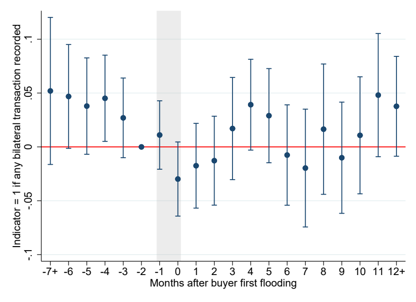
return

Shocks propagate through supply networks

Intensive margin



Extensive margin



▸ return

Firm move summary statistics

	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	

▸ return

Flooded firms more likely to relocate ▸ return

	Dependent Variable: Move Dummy		
	(1)	(2)	(3)
Max Share of 2km Buffer Flooded	-0.297	1.604*	1.848**
	(0.726)	(0.952)	(0.834)
District $\times$ Fathom 1in100 FE	Yes	Yes	Yes
Move Dummy Threshold	0km	5km	10km
R^2	0.017	0.041	0.067
N	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.

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

Flooded firms relocate to safer areas

return

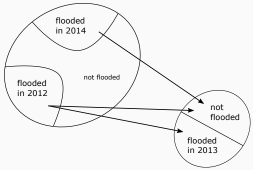
	Dependent Variable: Change in Flood Risk				
	(1)	(2)	(3)	(4)	(5)
Max Share of 2km Buffer Flooded in Flood Month	-0.533*	-0.770	-0.665	-0.516	-0.510
	(0.304)	(0.466)	(0.672)	(0.616)	(0.457)
District $\times$ Fathom 1in100 FE	Yes	Yes	Yes	Yes	Yes
R^2	0.190	0.268	0.424	0.449	0.492
N	43,754	29,569	10,481	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.

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

Firm response to flooding in other locations

- Intuition: within district pairs, are flooded firms that relocate more likely to move to destination areas that are flooded if, at the time the firm was flooded, the destination area had not yet been?



Poisson specification: $X_{ot_o dt_d} = \alpha_{od} + \alpha_{ot_o} + \alpha_{t_d} + \beta 1\left(t_o - t_d \geq 12\right) + \epsilon_{ot_o dt_d}$

- X_{od}: relocation flows from origin o to destination d
- ot_o: areas of origin district o flooded at time t_o
- dt_d: areas of destination district d flooded at time t_d
- $1\left(t_o - t_d \geq 12\right)$: 1 if ot_o flood post-dates dt_d flood by >12 months
- Standard errors clustered at level of origin-destination district pairs

Firm response to flooding in other locations

	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 × 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	2,596	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.

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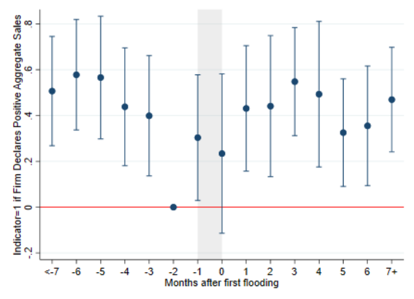
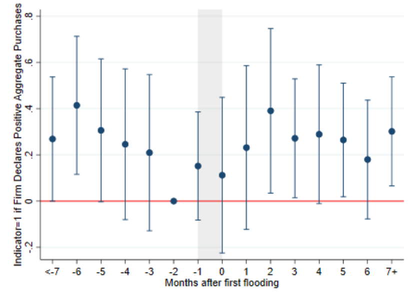
Back

Muted extensive margin effects conditional on survival

Positive sales



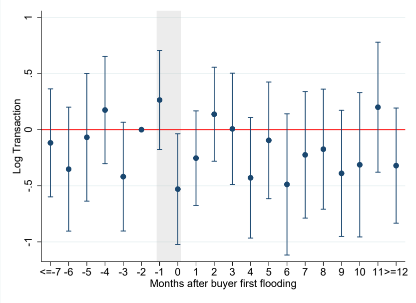
Positive purchases



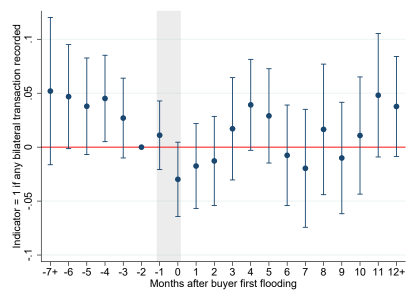
return

Shocks propagate through supply networks

Intensive margin



Extensive margin



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▶ return

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Flooded firms relocate to safer areas ▸ return

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

Flood-affected firms shift activity towards safer suppliers

Two outcome variables y_{bt*} capturing year-on-year change in weighted flood risk of b's suppliers before and after $t*$

- Change in risk profile of all suppliers in 12 months before vs after flood

$$y_{bt*} = \frac{\sum_{(s,t)\in(S_b(t*,t*+12],(t*,t*+12])} Risk_s x_{bst}}{\sum_{(s,t)\in(S_b(t*,t*+12],(t*,t*+12])} x_{bst}} - \frac{\sum_{(s,t)\in(S_b[t*,t*-12),[t*,t*-12))} Risk_s x_{bst}}{\sum_{(s,t)\in(S_b[t*,t*-12),[t*,t*-12))} x_{bst}}$$

- Change in transaction volumes with suppliers with whom buyer had transacted in 12 months before flood

$$y_{bt*} = \frac{\sum_{(s,t)\in(S_b(t*,t*-12],(t*,t*+12])} Risk_s x_{bst}}{\sum_{(s,t)\in(S_b(t*,t*-12],(t*,t*+12])} x_{bst}} - \frac{\sum_{(s,t)\in(S_b[t*,t*-12),[t*,t*-12))} Risk_s x_{bst}}{\sum_{(s,t)\in(S_b[t*,t*-12),[t*,t*-12))} x_{bst}}$$

▸ Return

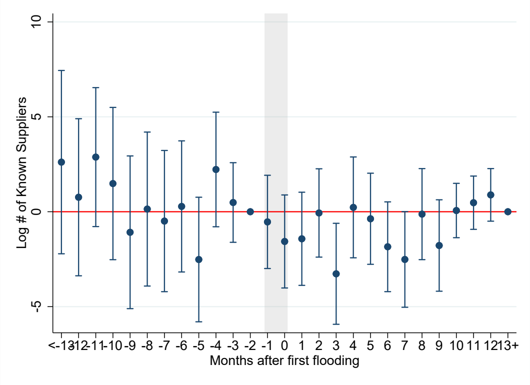
Adaptive relocation among firms previously flooded in 2010 ▸ Return

	Dependent Variable: Change in Flood Risk				
	(1)	(2)	(3)	(4)	(5)
Max Share of 2km Buffer Flooded in Flood Month	0.253	0.411	-0.0573	-0.157	-0.300
	(0.294)	(0.337)	(0.164)	(0.201)	(1.306)
District × Fathom 1in100 FE	Yes	Yes	Yes	Yes	Yes
R^2	0.320	0.410	0.739	0.770	0.830
N	894	587	222	181	125
Move Distance Restriction		>0km	>5km	>10km	>20km
Pr(Move=1)		0.68	0.29	0.24	0.17
Average 1in100 Flood Risk		0.81	0.69	0.67	0.71

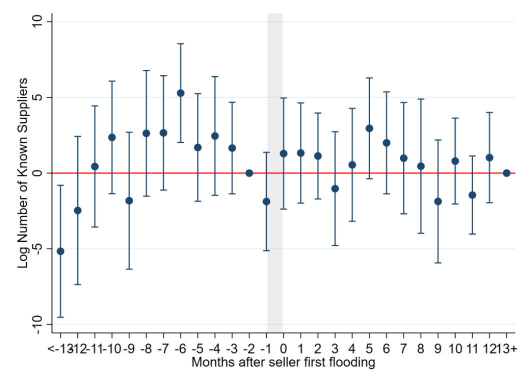
Standard errors in parentheses, clustered at the district level. Sample is restricted to firms fully geocoded in 2011 and 2019 and those firms flooded prior to the start of the period. Flood risk is measured in terms of expected depth of flooding in meters for a 1in100 year return period.

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

Sun & Abraham (2021): supplier diversification



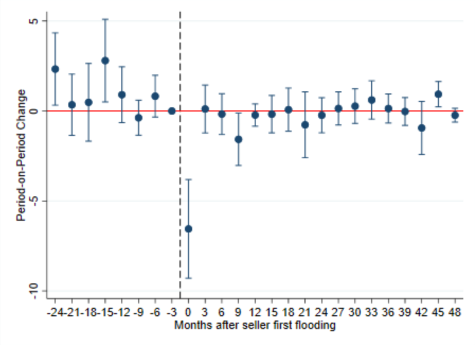
(a) Direct Exposure



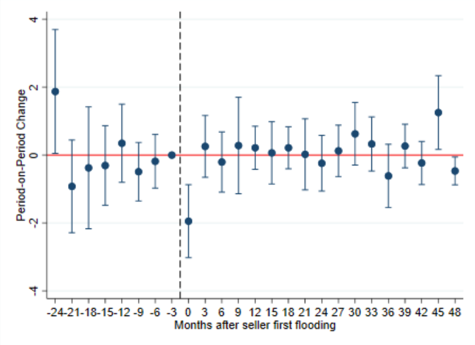
(b) Indirect Exposure

▸ Return

Sun & Abraham (2021): supplier choice



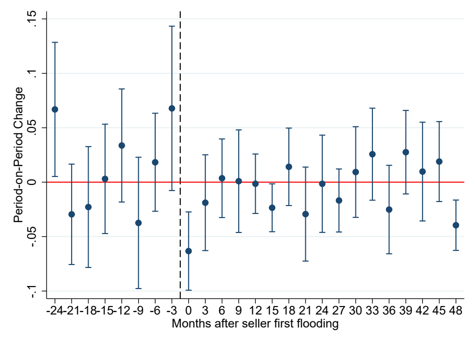
(a) All Suppliers



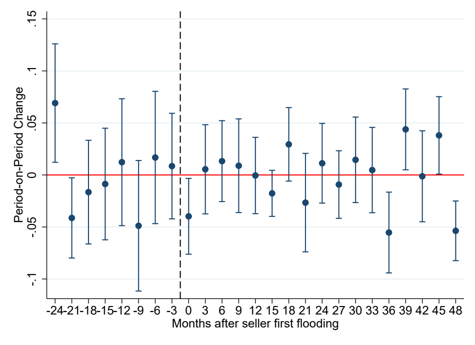
(b) Non-flooded Suppliers

Return

Borusyak-Jaravel-Spiess (2022): supplier choice



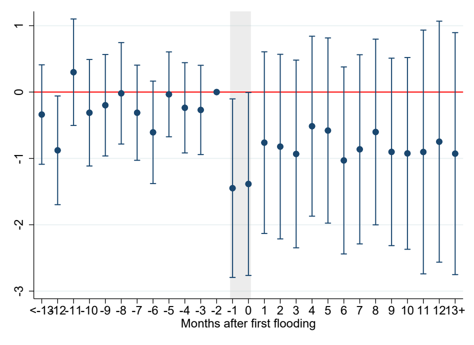
(a) All Suppliers



(b) Non-flooded Suppliers

Return

Cross-validated reports: supplier diversification



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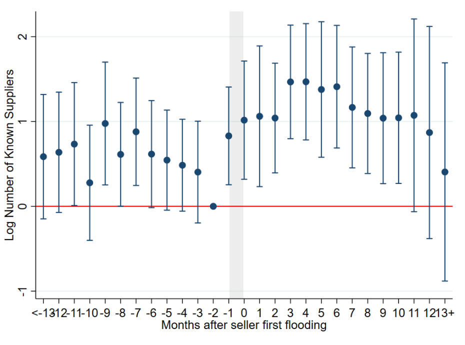
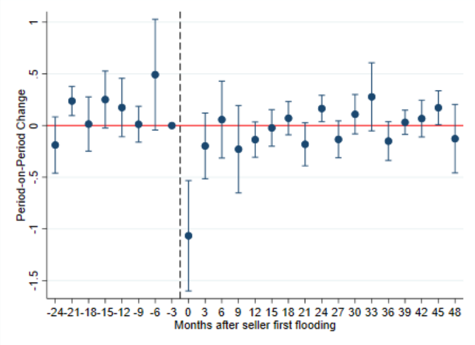


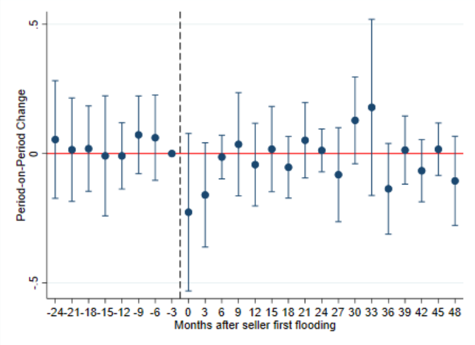
(b) Indirect Exposure

Return

Cross-validated reports: supplier choice



(a) All Suppliers



(b) Non-flooded Suppliers

Return

1 in 10 year flood return period: 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 $\times$ 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.

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

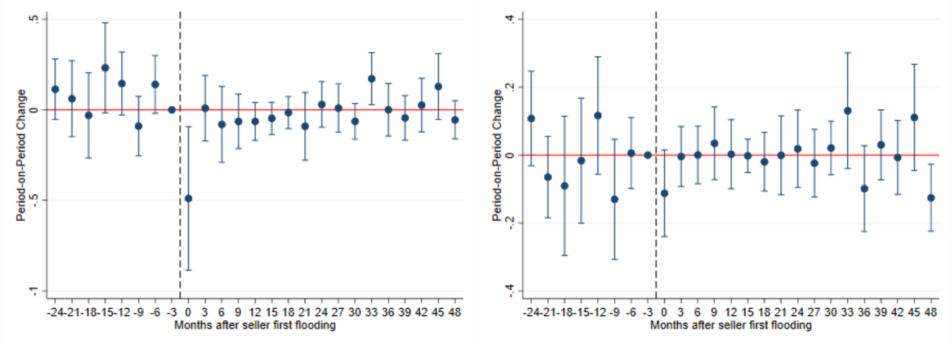
Return

1 in 10 year flood return period: adaptive relocation

	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

1 in 10 year flood return period: supplier choice



(a) All Suppliers (b) Non-flooded Suppliers

▸ Return

1 in 50 year flood return period: 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 $\times$ 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.

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

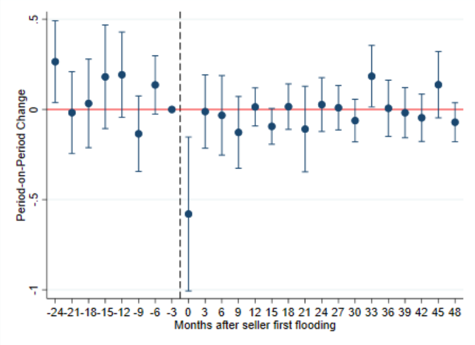
Return

1 in 50 year flood return period: adaptive relocation

	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

1 in 50 year flood return period: supplier choice



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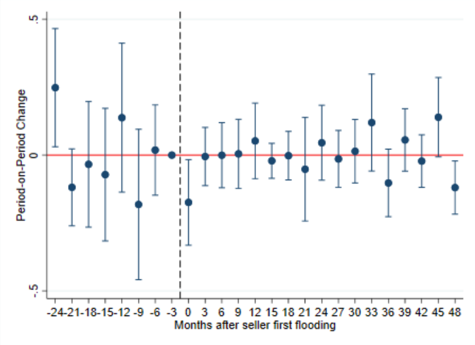
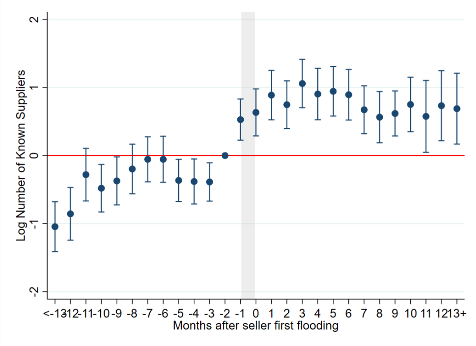


(b) Non-flooded Suppliers

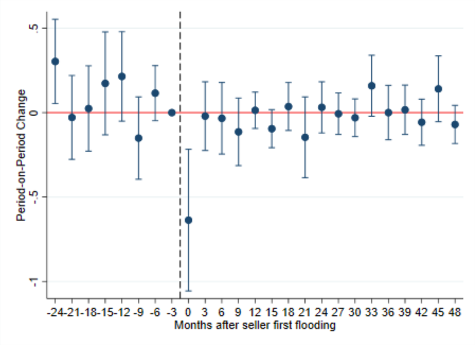
Return

3-month supplier window: diversification (indirect exposure)

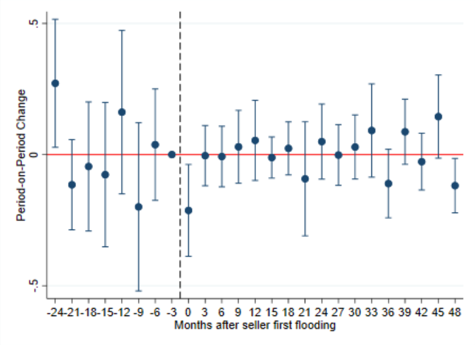


Return

3-month supplier window: supplier choice



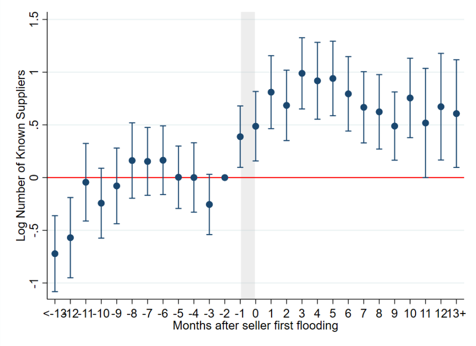
(a) All Suppliers



(b) Non-flooded Suppliers

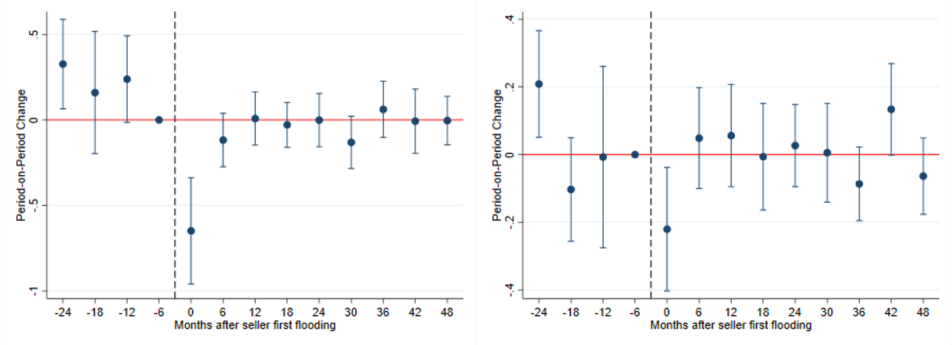
▸ Return

6-month supplier window: diversification (indirect exposure)



Return

6-month supplier window: supplier choice

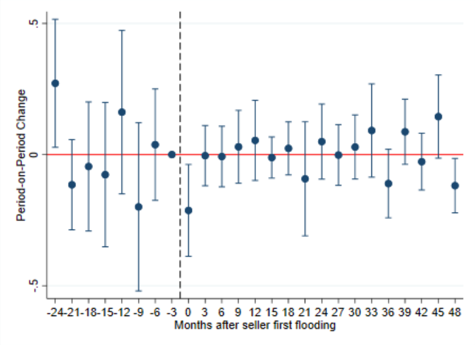


(a) All Suppliers

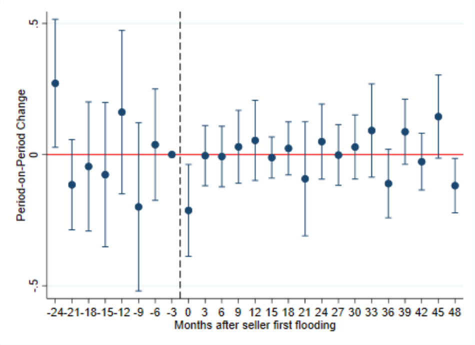
(b) Non-flooded Suppliers

Return

Non-movers: supplier choice



(a) All suppliers



(b) Non-flooded suppliers

▸ Return

Excl electricity/gas: 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 $\times$ 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.

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

Return

Excl electricity/gas: adaptive relocation

	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

Excl electricity/gas: firm relocation gravity

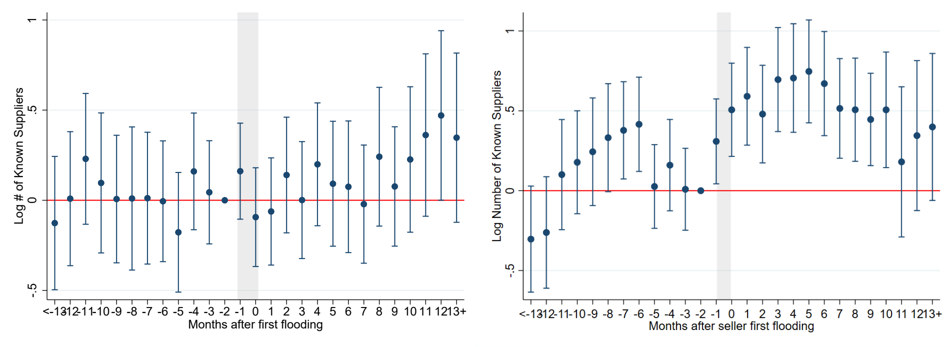
	Dependent Variable: Number of Firms Moved			
	(1)	(2)	(3)	(4)
Dest. flooded 12mo prior	-1.854***	-0.786***	-0.737***	-0.898***
	(0.269)	(0.216)	(0.225)	(0.283)
Origin × Destination FE	Yes	Yes	Yes	Yes
Origin × Flood Event (month) FE	Yes	Yes	Yes	Yes
Flood Event of Destination FE	Yes	Yes	Yes	Yes
Move Dummy 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.

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

▸ Return

Excl electricity/gas: supplier diversification

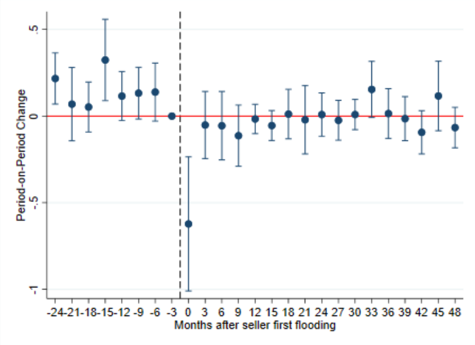


(a) Direct Exposure

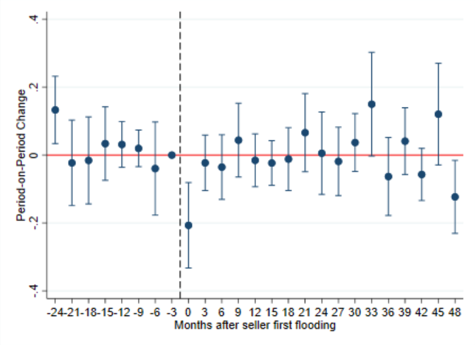
(b) Indirect Exposure

▸ Return

Excl electricity/gas: supplier choice



(a) All Suppliers



(b) Non-flooded Suppliers

Return

Manufacturing firms: 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 $\times$ 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.

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

Return

Manufacturing firms: adaptive relocation

	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

Manufacturing firms: firm relocation gravity

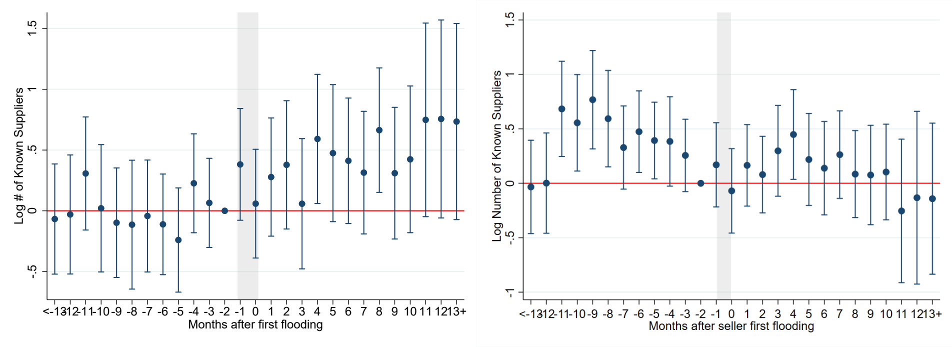
	Dependent Variable: Number of Firms Moved			
	(1)	(2)	(3)	(4)
Dest. flooded 12mo prior	-1.482***	-0.684**	-0.894***	-0.963**
	(0.343)	(0.312)	(0.264)	(0.404)
Origin × Destination FE	Yes	Yes	Yes	Yes
Origin × Flood Event (month) FE	Yes	Yes	Yes	Yes
Flood Event of Destination FE	Yes	Yes	Yes	Yes
Move Dummy 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.

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

▸ Return

Manufacturing firms: supplier diversification

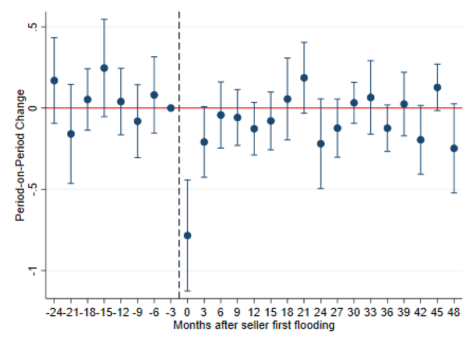


(a) Direct Exposure

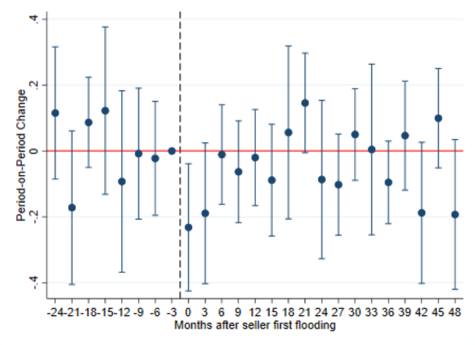
(b) Indirect Exposure

▸ Return

Manufacturing firms: supplier choice



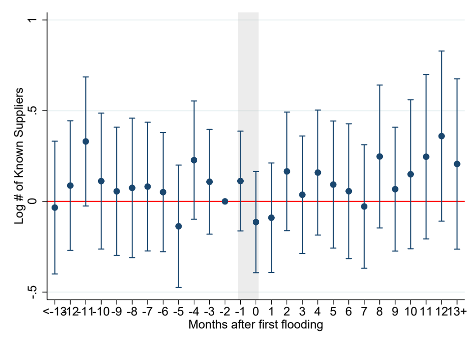
(a) All Suppliers



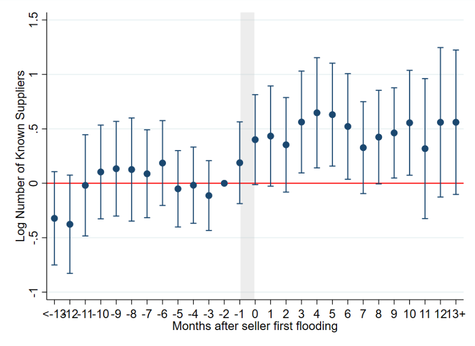
(b) Non-flooded Suppliers

▸ Return

Excl capital purchases: supplier diversification



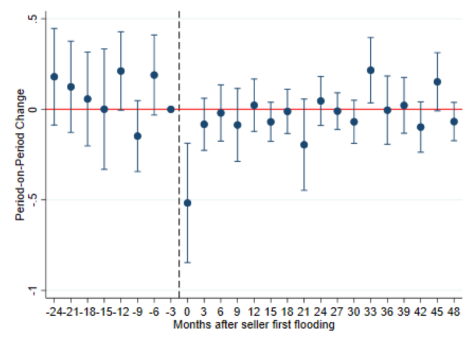
(a) Direct Exposure



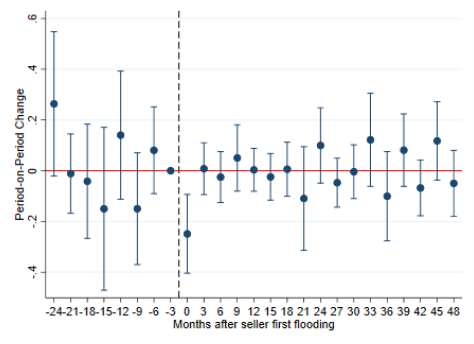
(b) Indirect Exposure

▸ Return

Excl capital purchases: supplier choice



(a) All Suppliers



(b) Non-flooded Suppliers

▸ Return

Response to flooding in other locations after 24/36 months

	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 $\times$ Destination FE	Yes	Yes	Yes
Origin $\times$ 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.

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

Back

Model: Short overview

Quantitative Spatial Model with N locations. Static setup repeated in each period.

- Mass of monopolistically competitive firms in each location that sell to a representative household.
- Firm production function:

$$y_j(\phi) = \underbrace{a_{n(j)}}_{\text{time-invariant prod. }|} \underbrace{b_{n(j)}}_{\text{agg. flood }|} \underbrace{\xi_{jt}}_{\text{idiosync. flood}} l_j^{1-\alpha} \left(z(\phi)x_j\right)^{\alpha}$$

Two stages:

1. Firms in n exert search effort m_{ni} to search for suppliers in each region i subject to a resource constraint

$$g\left(m_{n1}, \ldots, g_{nN}\right) = \bar{m}$$

   to maximize expected (discounted) profits under a set of beliefs $\mathcal{I}$ about flood shocks
2. Results from search are realized at the same time as flood shocks. Choose supplier to minimize cost.

Model: Short overview

Functional form assumptions on z, ξ.
Then: gravity equation for trade across locations:

$$\frac{X_{ni}}{X_n} = \frac{m_{ni}(\mathcal{I}_n)\tau_{ni}^{-\zeta}(\bar{c}_i(b))^{-\zeta}}{\sum_{i'} m_{ni'}(\mathcal{I}_n)\tau_{ni'}^{-\zeta}(\bar{c}_{i'}(b))^{-\zeta}}.$$

Divide time into three periods: **before**, **during**, and **after** flood.

- **Before** and **after** the flood: no flood shocks, $b = 1$. **During** the flood, $b \leq 1$. Productivity decrease temporary!
- Only thing that changes from **before** to **after** is firm's beliefs $\mathcal{I}$

Write gravity equation in changes (holding everything but $\mathcal{I}$ constant) to back out $\hat{m}$:

$$\widehat{\left(\frac{X_{ni}}{X_n}\right)} = \exp\left[\log \hat{m}_{ni} - \zeta \log \hat{\bar{c}}_i + \zeta \log \hat{\Phi}_n\right]$$

$$\hat{c}_n = \left[\sum_i \frac{X_{ni}}{X_n}\hat{m}_{ni}\hat{c}_i^{-\zeta}\right]^{-\alpha/\zeta} \qquad \hat{\Phi}_n = \left[\sum_i \frac{X_{ni}}{X_n}\hat{m}_{ni}\hat{c}_i^{-\zeta}\right]^{-1/\zeta}$$

Counterfactuals: what if $\hat{m}_{2012}$, $\hat{m}_{2013}$, $\hat{m}_{2014}$ had not happened?

1. How would impact of subsequent floods $\hat{b}$ have been different in the absence of prior adaptation responses $\hat{m}_{2012}$, $\hat{m}_{2013}$, $\hat{m}_{2014}$?
2. (not today) How would the distribution of response of aggregate economy to overall *distribution* of flood shocks look differently without prior adaptation $\hat{m}_{2012}$, $\hat{m}_{2013}$, $\hat{m}_{2014}$?

▸ To Results for 1