

Supplemental Appendix

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

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A Supplementary Tables and Figures

Table A.1. Firm-level summary statistics

Buyers = Sellers	73,339			
Share of firms with 2011 and 2019 geocodes	60%			
Share of firms ever flooded	30%			
Share of firms ever flooded >5% of 2km buffer	2%			
Share of firms ever flooded >10% of 2km buffer	1%			
Share of firms flooded more than once	5%			
Share of firms ever had important recent supplier flooded	19%			
Share of firms had important recent supplier flooded more than once	3%			
Median firm age at end of sample period (years)	32			
Average probability of firm exit in given month	0.25%			
	Monthly Mean	SD	Annual Mean	SD
Log total declared sales	14.74	2.07	16.73	2.15
Share of months with positive declared sales	49%	34pp		
Log self-reported sales	14.84	2.08	17.01	2.10
Share of months with positive self-reported sales	50%	33pp		
Log all aggregated sales	14.78	2.14	16.86	2.20
Share of months with positive aggregated sales	51%	33pp		
Log total declared purchases	14.45	2.15	16.35	2.20
Share of months with positive declared purchases	45%	34pp		
Log self-reported purchases	14.46	2.22	16.42	2.25
Share of months with positive self-reported purchases	47%	34pp		
Log all aggregated purchases	14.27	2.38	16.28	2.39
Share of months with positive aggregated purchases	52%	34pp		

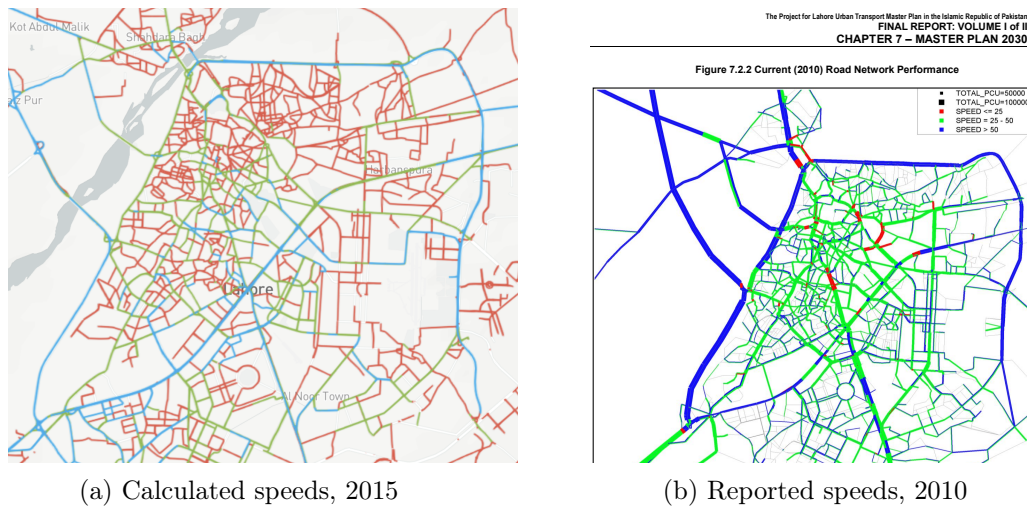
All firms are considered both buyers and sellers because the sample is restricted to firms that report at least three nonzero values for each transaction measure. Sales and purchases may be measured in one of three ways: (1) declared as aggregate by a firm, (2) aggregated based on self-reported transaction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

Table A.2. Transaction-level summary statistics

Transaction panel observations (positive transaction)	15,474,620	
Buyer-seller-pairs ever reported	1,658,128	
Share active pairs among all possible combinations	0.031%	
	Mean	SD
Log transaction value	12.43	2.27
Transactions per pair in years with ≥ 1	4.30	3.81
Transactions per pair per year over sample period if ≥ 1	1.33	2.27
Months between transactions of pair if ≥ 2	2.13	4.10
Distinct suppliers per buyer if ≥ 1	25.35	81.41
Distinct quarterly suppliers per buyer if ≥ 1	7.77	24.14
Share of quarterly buyer purchases from average supplier	52%	37pp
Share of sellers supplying $\geq 10\%$ of buyer's quarterly purchases	72%	34pp
Distinct buyers per seller if ≥ 1	29.23	111.83
Distinct quarterly buyers per seller if ≥ 1	10.58	54.98
Share of quarterly seller sales to average buyer	46%	38pp
Share of buyers purchasing $\geq 10\%$ of seller's quarterly sales	65%	36pp

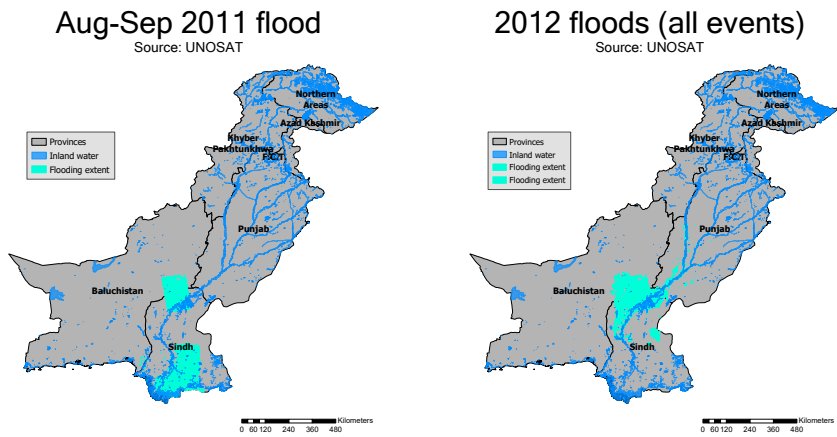
All sales and purchases are denominated in Pakistani Rupee (PKR) before logging. Transactions refer to buyer-seller-year-month observations with a positive transaction value. Both the number of distinct active buyer-seller-pairs and the number of possible buyer-seller-pairs are defined as permutations.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

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



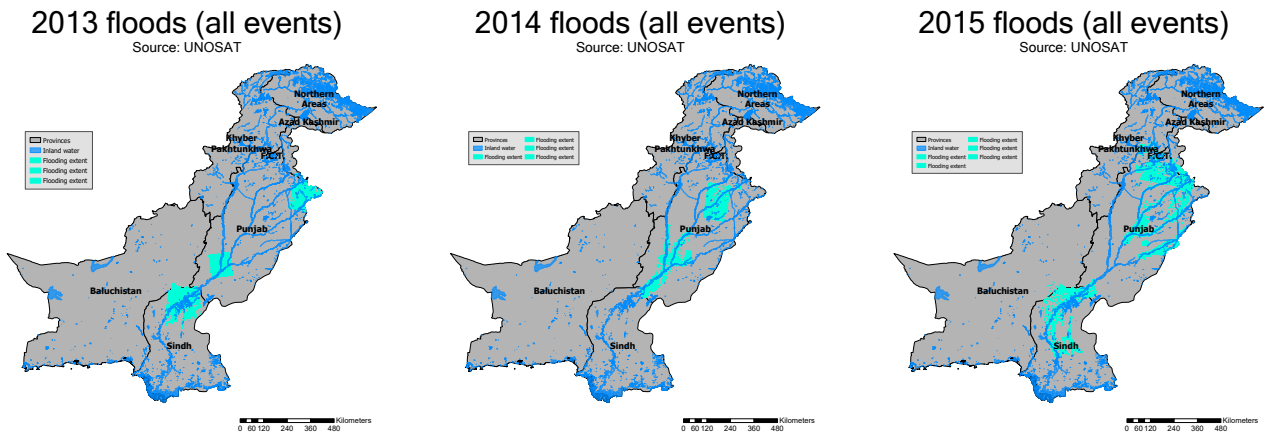
Notes: Panel (a) maps computed 2015 speeds and panel (b) maps 2010 speeds reported in [Japan International Cooperation Agency \(2012\)](#) for the same area in Lahore.

Figure A.2. Flood extent maps during sample period



(a) 2011: Aug.-Sep.

(b) 2012



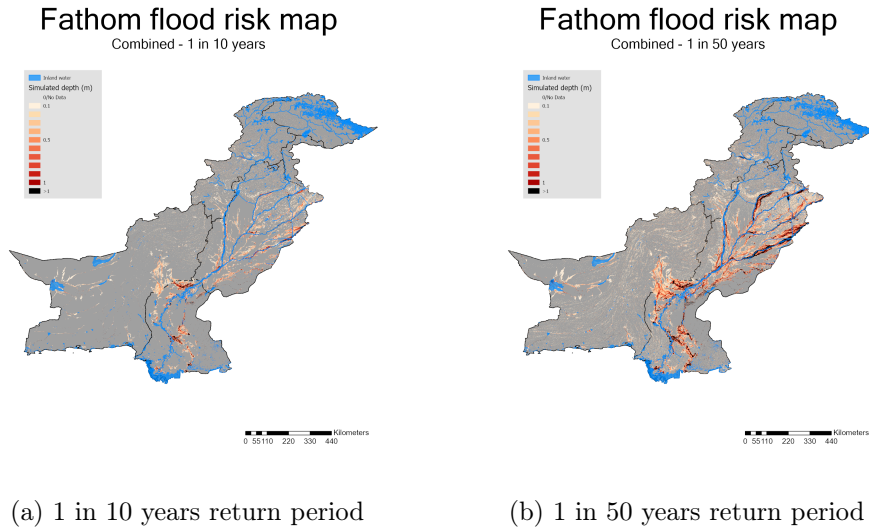
(c) 2013

(d) 2014

(e) 2015

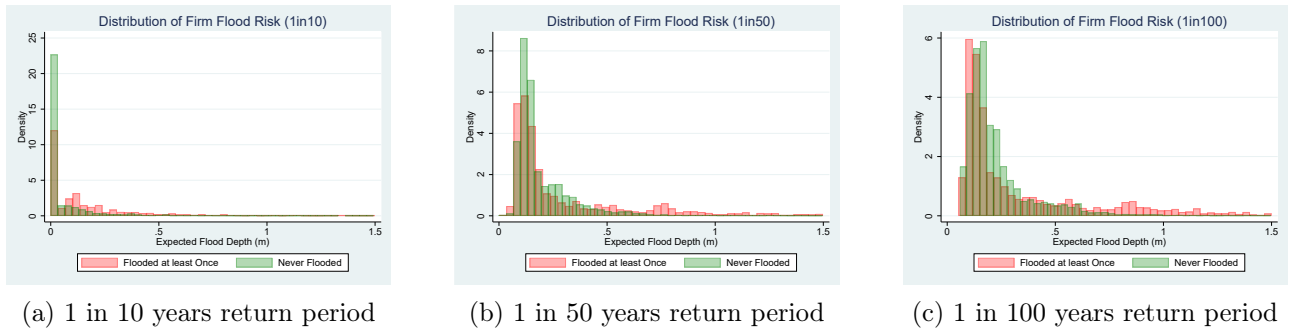
Notes: The figure maps the aggregate extent of flooding in the sample period in different years in which we observe flood events. Panel a) omits the January 2011 flood since it lies outside the sample period.

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



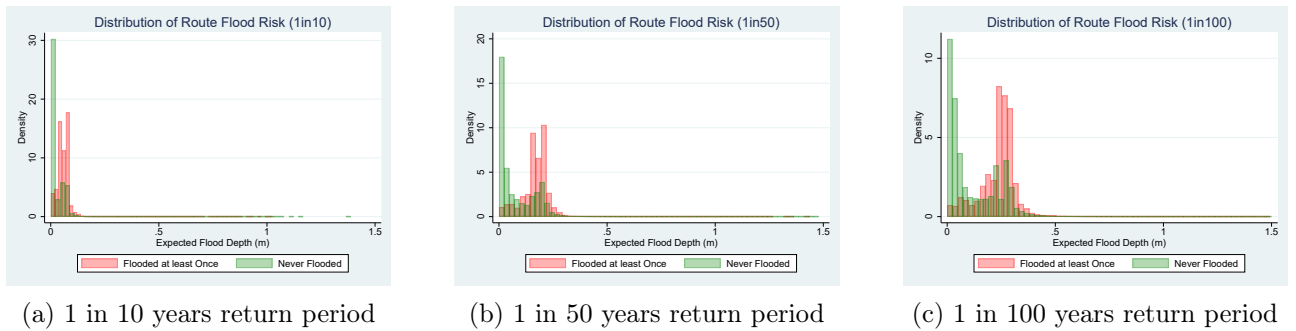
Notes: The maps display flood risk across Pakistan for a 1 in 10 and a 1 in 50 year return period. Flood risk is defined as the maximum across pluvial and fluvial flood risk, measured as expected flood depth in meters.

Figure A.4. Distribution of firms by Fathom flood risk



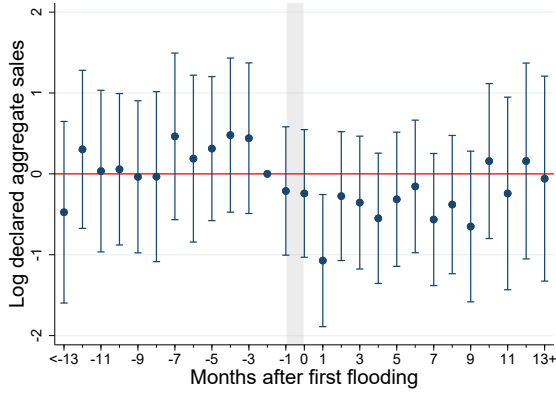
Notes: The histograms display the density of firms' flood risk by whether a firm's buffer was flooded at least once over the sample period. Flood risk is measured as expected flood depth in meters. The histograms are truncated at 1.5m.

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

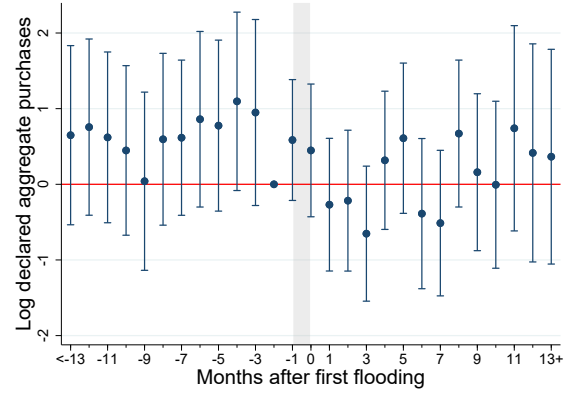


Notes: The histograms display the density of firm-pair-route flood risk by whether the route was flooded at least once over the sample period. Flood risk is measured as the length weighted average expected flood depth in meters of edges along a give route. The histograms are truncated at 1.5m.

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



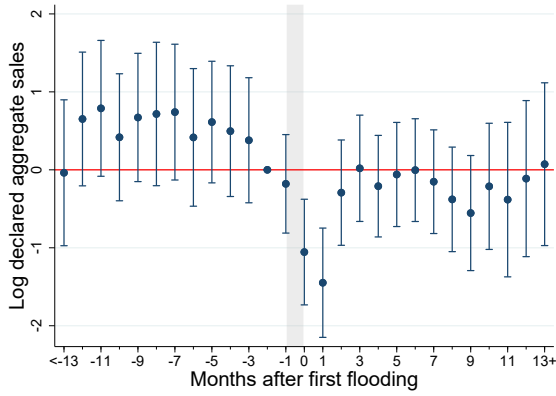
(a) Log sales



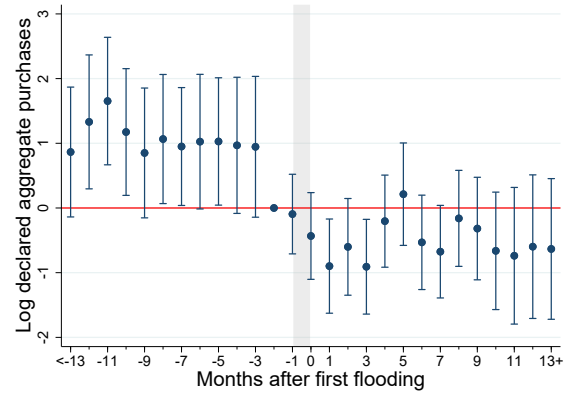
(b) Log purchases

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

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



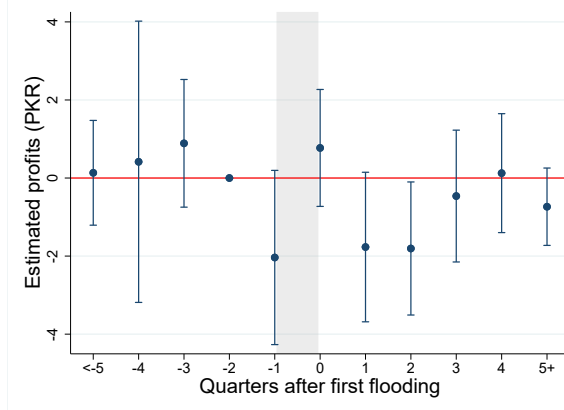
(a) Log sales



(b) Log purchases

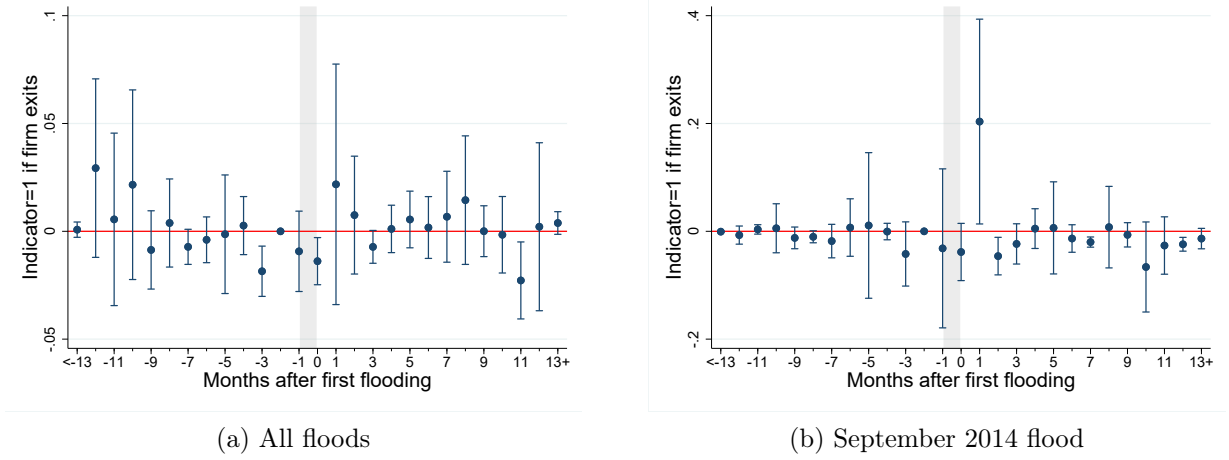
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases following equation (1). Here, we use flood-risk-decile $\times$ time FEs instead of time FEs. The flood risk decile is defined as the decile of a firm's expected flood depth in meters for a 1 in 100 year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

Figure A.8. Impact of flooding on firm estimated profits



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

Figure A.9. Impact of flooding on firm exit



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

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

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

confidence intervals. Standard errors are clustered at the district level.

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

	Share of Firms Moved	# of Firms Moved
Moved >0km	0.68	29,694
Moved >5km	0.31	13,453
Moved >10km	0.17	7,491
Moved >15km	0.11	4,739
Moved >20km	0.08	3,480
Observations	43879	

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

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

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

	Move Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Max share of 2km buffer flooded	0.942 (0.682)	2.181*** (0.778)	1.955** (0.887)	1.225* (0.722)	2.712*** (0.901)	2.418*** (0.818)
District FE	Yes	Yes	Yes			
District $\times$ Fathom 1 in 100 FE				Yes	Yes	Yes
Move Dummy Threshold	0km	5km	15km	0km	5km	15km
McFadden's Pseudo R^2	0.005	0.017	0.057	0.017	0.036	0.082
N	43,831	43,849	43,846	43,498	43,546	43,326

Notes: The table reports logit estimates of the effect of flooding on a 0, 5, or 15km-relocation indicator following equation (3). Observations are firms fully geocoded in 2011 and 2019. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2 . * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	Δ Flood Risk (cm)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max share of 2km buffer flooded	-138.9* (79.22)	-189.8* (111.1)	-249.8* (149.9)	-178.6* (90.50)	-49.78 (34.59)	-71.15 (46.50)	-56.92 (56.84)	-20.57 (39.28)
District FE	Yes	Yes	Yes	Yes				
District $\times$ Fathom 1 in 100 FE					Yes	Yes	Yes	Yes
Move Distance Restriction	None	>0km	>5km	>15km	None	>0km	>5km	>15km
R^2	0.029	0.039	0.074	0.128	0.188	0.268	0.418	0.506
N	43,868	29,681	13,434	4,722	43,750	29,555	13,286	4,575

Notes: The table report OLS estimates of the effect of flooding on moving firms' change in flood risk as specified in equation (4). Observations are firms fully geocoded in 2011 and 2019 regardless of relocation or which moved by more than 0, 5, or 15km. Standard errors (in parentheses) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	Number of Firms Moved		
	(1)	(2)	(3)
Dest. flooded 12mo prior	-1.761*** (0.291)	-1.013*** (0.281)	-0.913*** (0.262)
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 Distance Restriction	>0km	>5km	>15km
N	1,767	1,632	1,577

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

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

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	2.212*** (0.859)	2.211** (0.925)	-182.2* (101.7)	-22.54 (40.92)
District FE	Yes		Yes	
District $\times$ Fathom 1 in 100 FE		Yes		Yes
R^2	0.036	0.060	0.113	0.471
N	29,541	29,063	4,719	4,582

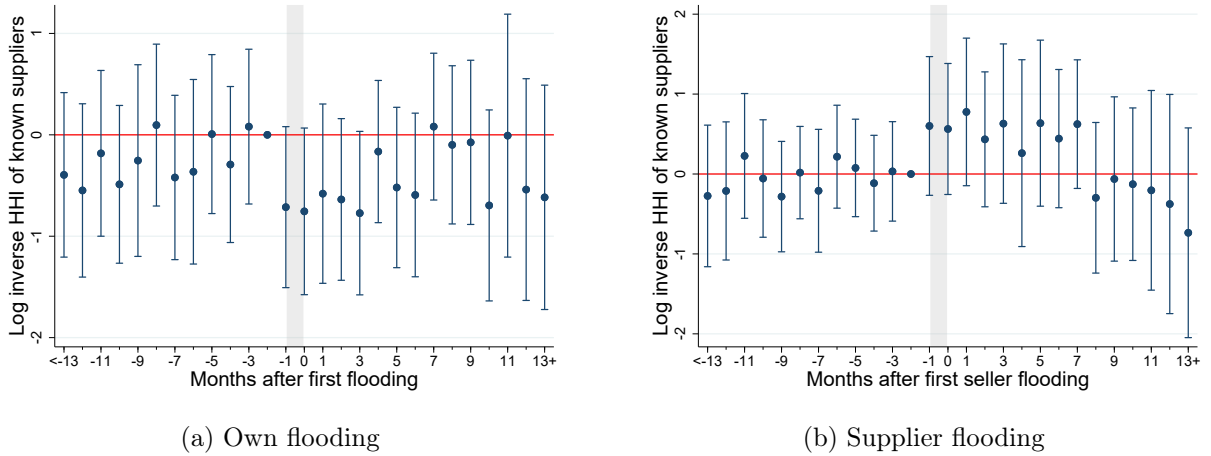
Notes: Columns (1) and (2) display logit estimates of the effect of flooding on a 10km-relocation indicator. Columns (3) and (4) report OLS estimates of the effect of flooding on moving firms' change in flood risk. Observations are firms fully geocoded in 2011 and 2019 for which the business register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

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

	Number of Firms Moved	
	(1)	(2)
Dest. flooded 24mo prior	-0.886*	
	(0.474)	
Dest. flooded 36mo prior		-1.640**
		(0.649)
Origin $\times$ Destination FE	Yes	Yes
Origin $\times$ Flood Event (month) FE	Yes	Yes
Flood Event of Destination FE	Yes	Yes
Move Distance Restriction	>10km	>10km
N	1,593	1,593

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

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



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

Table A.9. Impact of flooding on supplier flood risk: varying supplier flood threshold

	Δ Flood Risk of Suppliers Flooded by					
	$\leq 1\%$			$\leq 10\%$		
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	-13.12 (9.866)	-9.079 (6.119)	-18.02 (12.30)	-11.20 (10.01)	-7.514 (6.396)	-15.27 (12.56)
Suppliers' max flood extent	-15.11* (8.995)	-14.81* (8.705)	-12.56 (10.07)	-45.99** (19.30)	-46.94** (19.88)	-48.15** (21.72)
Time $\times$ District FE	Yes			Yes		
Time $\times$ District $\times$ Risk decile FE	Yes			Yes		
Time $\times$ District $\times$ Industry FE	Yes			Yes		
R^2	0.0097	0.0305	0.0617	0.0102	0.0293	0.0605
N	137,421	136,652	132,327	137,887	137,122	132,789

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

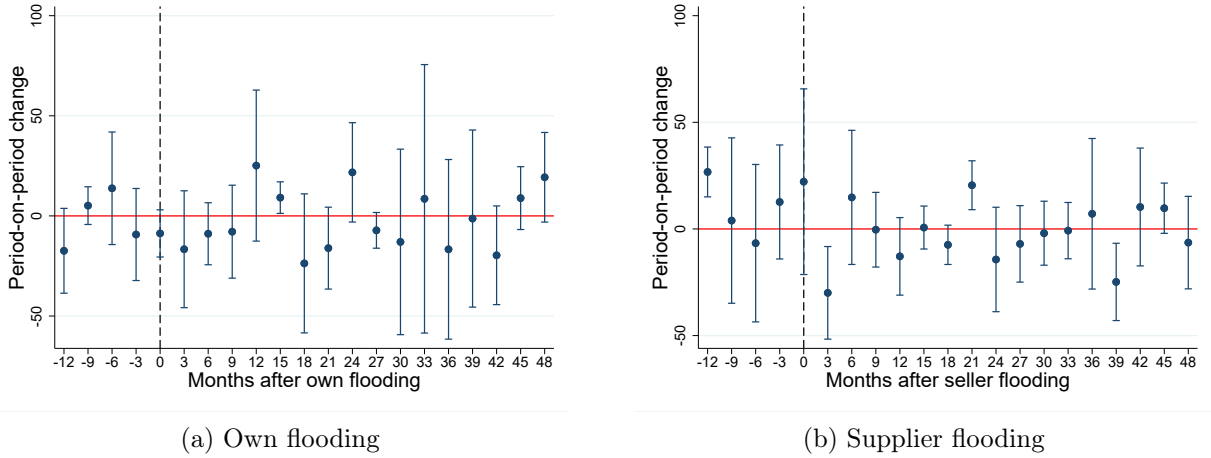
Figure A.11. Dynamic impact of supplier and own flooding on flood risk of $\leq 5\%$ flooded suppliers

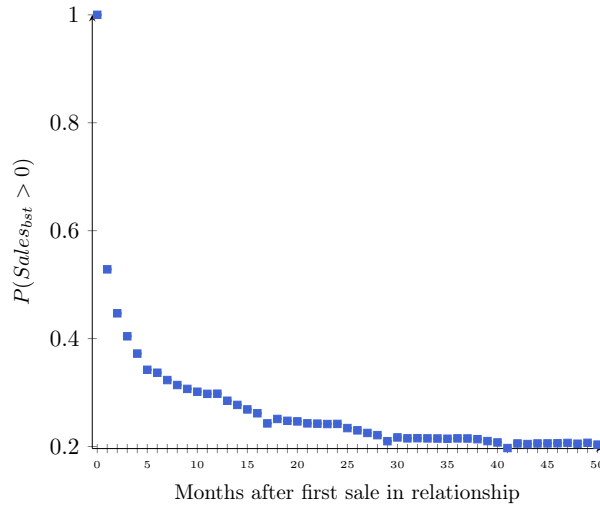
Figure A.11 plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$. The specification for the estimate at lag $l \in \{-12, -9, -6, \dots, 48\}$ is defined analogously to equation (8), but with the dependent variable lagged by l months:

$$\Delta y_{b(t^*+l)} = \beta_1 \text{OwnFlood}_{bt^*} + \beta_2 \text{SellerFlood}_{bt^*} + \alpha_{d(b)t^*} + \epsilon_{bt^*} \quad (2)$$

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^* ; $\text{SellerFlood}_{bt^*}$ is the maximal maximum share of the 2km buffer flooded at t^* across all sellers which account for $\geq 10\%$ of b 's purchases over the previous three months; and

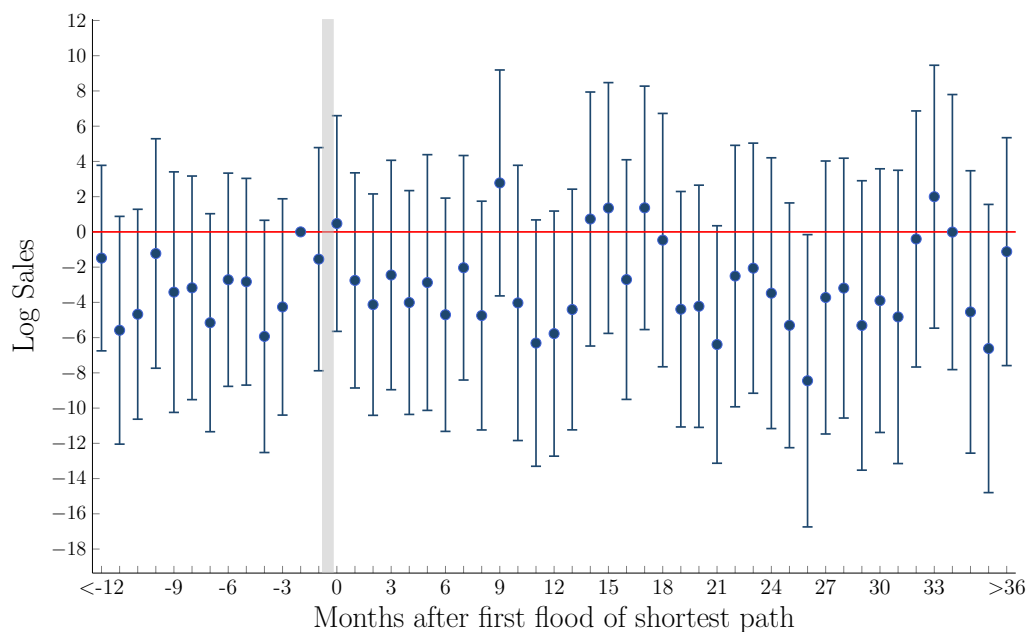
$\alpha_{d(b)t^*}$ are buyer district $\times$ time fixed effects. $\Delta y_{b(t^*+l)}$, denotes the change in the sales-weighted average flood risk of b 's suppliers from $(t^* + l - 6, t^* + l - 3]$ to $(t^* + l - 3, t^* + l]$ which were not flooded by $>5\%$ before or at $t^* + l$. Otherwise, flood risk is defined analogously to equation (9). The set of observations consists of all firm-by-flood-year-month pairs (b, t^*) for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. To ensure later lags capture long term effects, we exclude all buyers which are flooded themselves or experience supplier flooding (defined like the treatment) in the period before or at $t^* + l$ but excluding the flood event around t^* . We note that this allows both the buyer-flood-year-month sample and the set of suppliers entering the dependent variable to change across lags. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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



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

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



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

Table A.10. Percentage difference in household price index in flood year in absence of adaptation following adaptation year flood

Adaptation year	Flood year		
	2013	2014	2015
2012	5%	-3.5%	1%
2013		-14%	-1%
2014			3%

The table displays counterfactual changes in the household price index estimated as described in section IVB. Values are rounded to nearest percentage point.

Table A.11. Adaptation potential

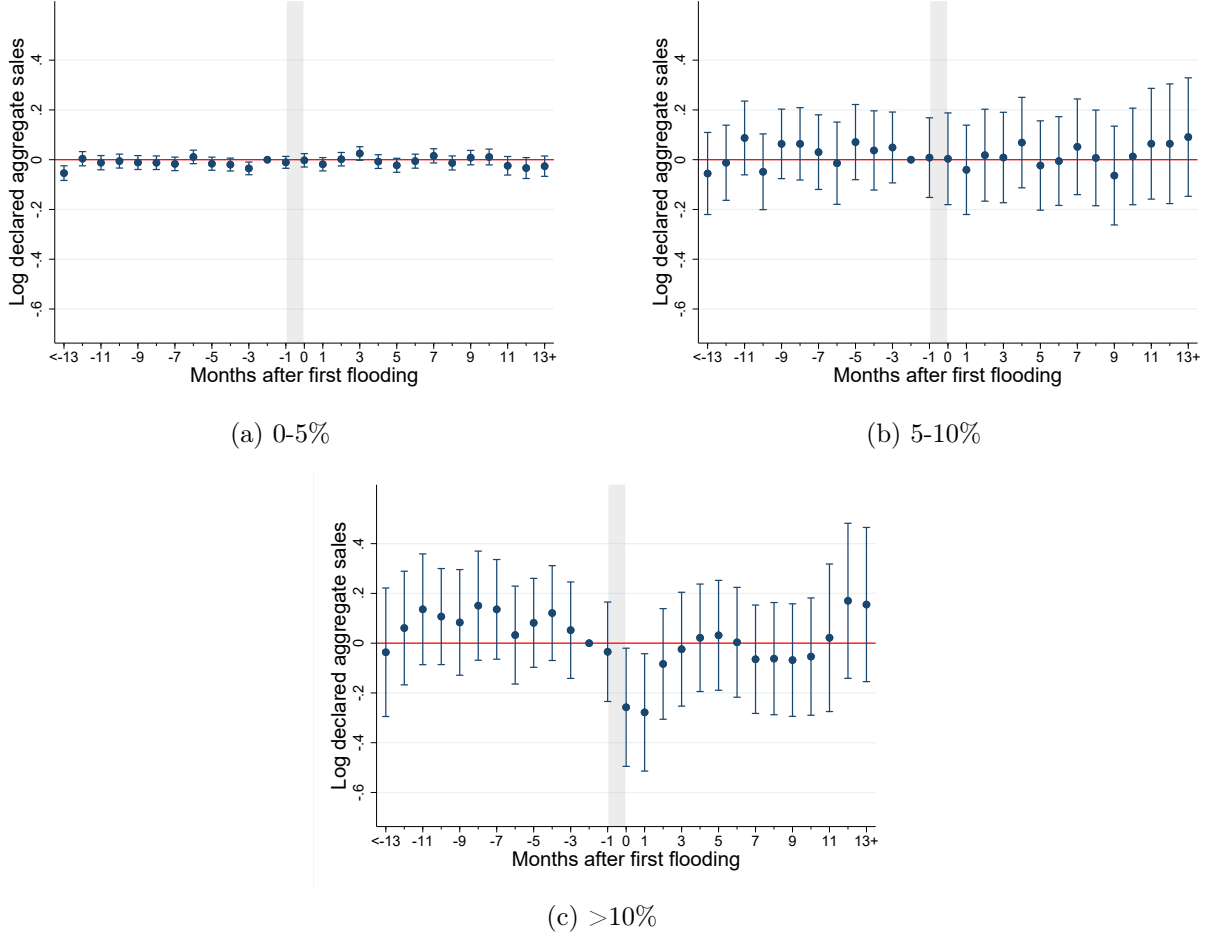
	Radius r , in km		
	25	50	100
Prob. that a non-flooded alternative supplier exists within r	89.9%	95.1%	99.0%
Prob. that a less flood-prone alternative supplier exists within r			
$< 1.0 \cdot \text{FloodRisk}_s$	92.1%	95.1%	96.7%
$< 0.9 \cdot \text{FloodRisk}_s$	89.9%	93.2%	95.2%
$< 0.8 \cdot \text{FloodRisk}_s$	86.4%	90.0%	92.8%
$< 0.7 \cdot \text{FloodRisk}_s$	79.6%	83.4%	86.3%
$< 0.6 \cdot \text{FloodRisk}_s$	63.7%	67.6%	70.7%
$< 0.5 \cdot \text{FloodRisk}_s$	51.0%	54.2%	58.1%
Prob. that a less flood-prone, larger alternative supplier exists within r			
$< 1.0 \cdot \text{FloodRisk}_s$	76.6%	79.9%	82.6%
$< 0.9 \cdot \text{FloodRisk}_s$	73.4%	76.7%	79.3%
$< 0.8 \cdot \text{FloodRisk}_s$	68.5%	71.7%	74.8%
$< 0.7 \cdot \text{FloodRisk}_s$	61.3%	64.3%	67.2%
$< 0.6 \cdot \text{FloodRisk}_s$	49.9%	52.5%	55.4%
$< 0.5 \cdot \text{FloodRisk}_s$	39.7%	41.7%	44.3%

Note: The sample consists of all firm-supplier-time combinations (b, s, t^*) where b has purchased from s within 12 months prior to t^* and s has a nonzero overlap of its 2km buffer with a flood polygon at t^* . 'Alternative supplier' denotes firms from the same two-digit industry as s . 'Less flood-prone' is measured using the 1-in-100 year flood risk measure. Firm size is measured by the total sales over the sample period.

B Heterogeneity analysis

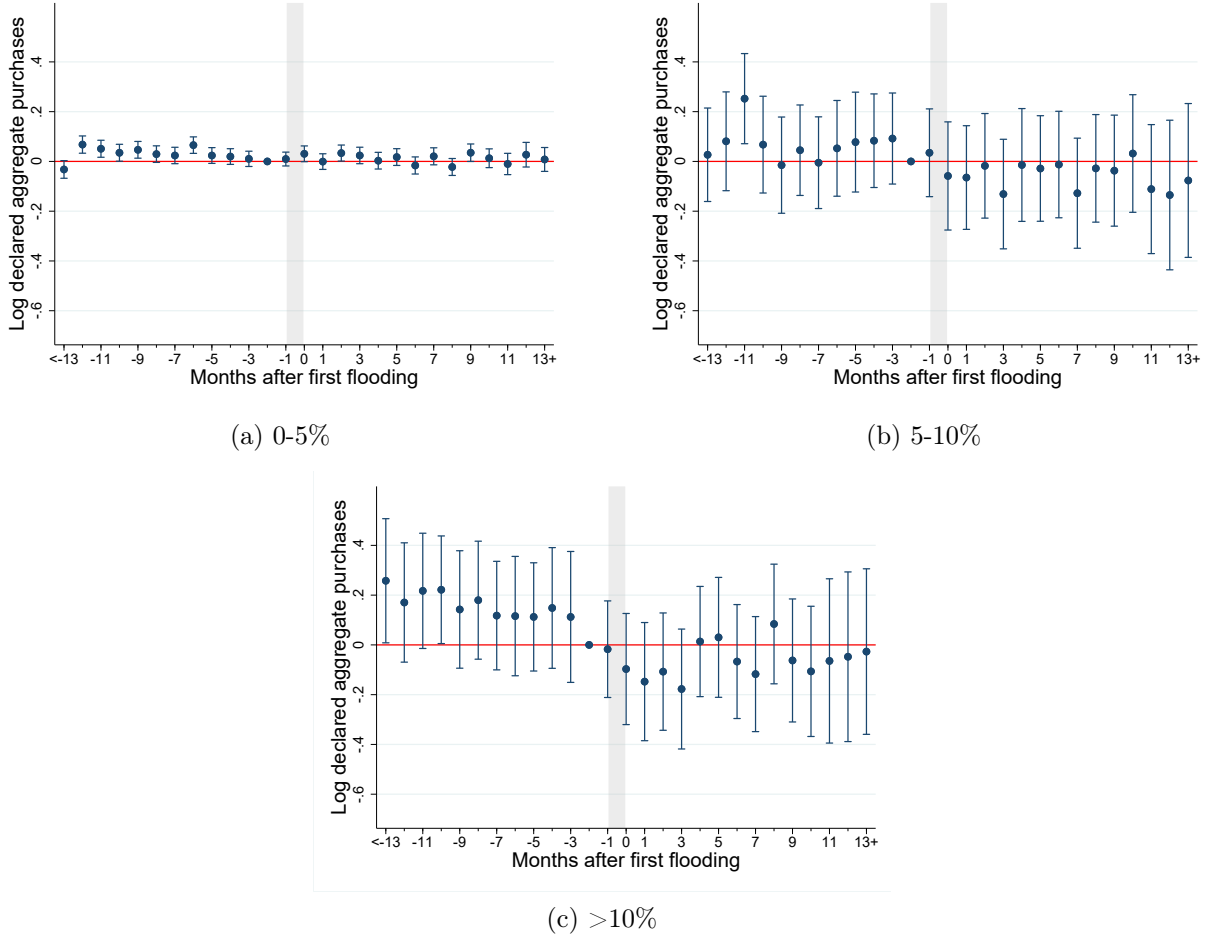
B.1 Flood severity

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



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

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



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

B.2 Firm size

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

	Move Dummy				Δ Flood Risk (cm)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max share of 2km buffer flooded	1.459** (0.663)	4.222** (1.806)	1.626* (0.884)	8.044*** (2.793)	-88.39 (78.50)	-437.0* (248.4)	13.21 (32.95)	-235.9 (221.2)
Sales sample	High	Low	High	Low	High	Low	High	Low
District FE	Yes	Yes			Yes	Yes		
District $\times$ Fathom 1 in 100 FE			Yes	Yes			Yes	Yes
R^2	0.034	0.039	0.057	0.067	0.132	0.131	0.500	0.476
N	14,548	14,520	14,196	14,130	2,473	2,463	2,360	2,373

Notes: Columns (1) through (4) display logit estimates of the effect of flooding on a 10km-relocation indicator following equation (3). Columns (5) through (8) report OLS estimates of the effect of flooding on moving firms' change in flood risk as specified in equation (4). Observations are firms fully geocoded in 2011 and 2019 with average yearly declared sales in the upper (High) or lower (Low) tercile. The flood risk regressions only include firms which moved by >10 km. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2 for columns (1) through (4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	-19.76 (13.18)	4.977 (12.16)	-15.28* (9.161)	-1.659 (18.43)	-27.39* (15.23)	-10.99 (23.07)
Suppliers' max flood extent	-40.41*** (9.708)	-147.7* (79.00)	-41.79*** (9.478)	-163.0* (88.10)	-51.68*** (9.280)	-159.7* (88.84)
Sales sample	High	Low	High	Low	High	Low
Time $\times$ District FE	Yes	Yes				
Time $\times$ District $\times$ Risk decile FE			Yes	Yes		
Time $\times$ District $\times$ Industry FE					Yes	Yes
R^2	0.0281	0.0227	0.0677	0.0551	0.1111	0.1004
N	56,328	34,818	55,571	34,301	52,804	32,365

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart with average yearly declared sales in the upper (High) or lower (Low) tercile. Standard errors (in parentheses) are clustered at the time $\times$ district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	-23.09*	-7.705	-13.63	-1.143	-26.96*	-15.75
	(13.70)	(11.32)	(10.02)	(15.40)	(15.26)	(24.82)
Suppliers' max flood extent	-14.87	-44.92	-17.28*	-44.68	-16.03**	-42.71
	(9.666)	(36.28)	(9.159)	(38.17)	(7.790)	(35.68)
Sales sample	High	Low	High	Low	High	Low
Time $\times$ District FE	Yes	Yes				
Time $\times$ District $\times$ Risk decile FE			Yes	Yes		
Time $\times$ District $\times$ Industry FE					Yes	Yes
R^2	0.0262	0.0174	0.0680	0.0508	0.1126	0.0966
N	56,273	34,770	55,513	34,254	52,753	32,319

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart with average yearly declared sales in the upper (High) or lower (Low) tercile. Standard errors (in parentheses) are clustered at the time $\times$ district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Single vs. multiple branches

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

	Move Dummy				Δ Flood Risk (cm)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max share of 2km buffer flooded	1.560	2.087**	2.556	2.015**	-174.4	-172.2*	-93.60	-16.18
	(1.423)	(0.916)	(2.241)	(0.940)	(105.2)	(98.49)	(87.24)	(41.88)
Branch sample	Multiple	Single	Multiple	Single	Multiple	Single	Multiple	Single
District FE	Yes	Yes			Yes	Yes		
District $\times$ Fathom 1 in 100 FE			Yes	Yes			Yes	Yes
R^2	0.030	0.040	0.055	0.065	0.203	0.112	0.501	0.465
N	5,524	29,927	5,302	29,474	1,291	4,761	1,201	4,634

Notes: Columns (1) through (4) display logit estimates of the effect of flooding on a 10km-relocation indicator following equation (3). Columns (5) through (8) report OLS estimates of the effect of flooding on moving firms' change in flood risk as specified in equation (4). Observations are firms fully geocoded in 2011 and 2019, which the business register indicates have a branch (Multiple) or have no branch (Single). The flood risk regressions only include firms which moved by > 10 km. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2 for columns (1) through (4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	37.35* (20.19)	-14.26 (10.49)	-4.318 (20.33)	-13.11* (7.191)	27.85 (34.47)	-15.79 (12.15)
Suppliers' max flood extent	-54.15*** (13.88)	-63.10*** (20.47)	-58.37*** (15.63)	-63.00*** (21.33)	-72.51*** (13.29)	-74.30*** (23.57)
Branch sample	Multiple	Single	Multiple	Single	Multiple	Single
Time $\times$ District FE	Yes	Yes				
Time $\times$ District $\times$ Risk decile FE			Yes	Yes		
Time $\times$ District $\times$ Industry FE					Yes	Yes
R^2	0.0278	0.0138	0.0681	0.0359	0.1193	0.0722
N	17,963	103,191	17,447	102,421	15,790	99,068

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart and which the business register indicates have a branch (Multiple) or have no branch (Single). Standard errors (in parentheses) are clustered at the time $\times$ district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	20.22 (14.22)	-17.60* (10.39)	-22.75 (14.76)	-11.79** (5.510)	-5.474 (12.16)	-18.50* (10.52)
Suppliers' max flood extent	-21.69** (9.157)	-25.93** (12.47)	-15.89* (8.884)	-25.05** (11.91)	-13.82 (8.813)	-23.94** (10.66)
Branch sample	Multiple	Single	Multiple	Single	Multiple	Single
Time $\times$ District FE	Yes	Yes				
Time $\times$ District $\times$ Risk decile FE			Yes	Yes		
Time $\times$ District $\times$ Industry FE					Yes	Yes
R^2	0.0308	0.0115	0.0745	0.0350	0.1179	0.0714
N	17,945	103,089	17,426	102,318	15,779	98,962

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart and which the business register indicates have a branch (Multiple) or have no branch (Single). Standard errors (in parentheses) are clustered at the time $\times$ district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.4 Input specificity

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

	Move Dummy				Δ Flood Risk (cm)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max share of 2km buffer flooded	2.045 (1.718)	2.225*** (0.706)	2.942 (2.126)	2.741** (1.114)	-355.8** (154.2)	-98.28 (63.45)	-79.50 (76.57)	15.13 (29.93)
Input specificity	High	Low	High	Low	High	Low	High	Low
District FE	Yes	Yes			Yes	Yes		
District $\times$ Fathom 1 in 100 FE			Yes	Yes			Yes	Yes
R^2	0.041	0.033	0.072	0.061	0.177	0.120	0.488	0.466
N	13,308	13,314	12,953	12,933	2,323	2,333	2,215	2,217

Notes: Columns (1) through (4) display logit estimates of the effect of flooding on a 10km-relocation indicator following equation (3). Columns (5) through (8) report OLS estimates of the effect of flooding on moving firms' change in flood risk as specified in equation (4). Observations are firms fully geocoded in 2011 and 2019 with input specificity in the upper (High) or lower (Low) tercile. The flood risk regressions only include firms which moved by >10km. Standard errors (in parentheses) are clustered at the district level. R^2 refers to McFadden's Pseudo R^2 for columns (1) through (4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	9.849 (10.05)	-9.412 (15.78)	14.53 (12.97)	-10.99 (12.14)	12.78 (10.83)	-18.10 (16.68)
Suppliers' max flood extent	-123.8*** (35.10)	-38.00*** (12.17)	-119.9*** (36.53)	-46.57*** (11.82)	-108.1*** (33.71)	-64.12*** (14.73)
Input specificity	Specific	Unspec	Specific	Unspec	Specific	Unspec
Time $\times$ District FE	Yes	Yes				
Time $\times$ District $\times$ Risk decile FE			Yes	Yes		
Time $\times$ District $\times$ Industry FE					Yes	Yes
R^2	0.0187	0.0276	0.0529	0.0640	0.1142	0.1123
N	36,869	50,802	36,286	49,905	34,357	47,414

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart with input specificities in the upper (Specific) or lower (Unspec) tercile. Standard errors (in parentheses) are clustered at the time $\times$ district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	Δ Supplier Flood Risk (cm)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own max flood extent	1.134 (8.704)	-13.50 (14.20)	2.522 (9.652)	-13.57 (11.52)	6.917 (9.201)	-21.32 (14.53)
Suppliers' max flood extent	-51.35** (22.74)	-7.970 (7.092)	-45.57** (21.75)	-11.82* (7.173)	-34.23* (17.79)	-13.51* (7.405)
Input specificity	Specific	Unspec	Specific	Unspec	Specific	Unspec
Time $\times$ District FE	Yes	Yes				
Time $\times$ District $\times$ Risk decile FE			Yes	Yes		
Time $\times$ District $\times$ Industry FE					Yes	Yes
R^2	0.0174	0.0261	0.0521	0.0619	0.1117	0.1111
N	36,847	50,744	36,266	49,840	34,336	47,359

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart with input specificities in the upper (Specific) or lower (Unspec) tercile. Standard errors (in parentheses) are clustered at the time $\times$ district level. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

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

	Δ Share of New Supplier Purchases		
	(1)	(2)	(3)
Own max flood extent	0.0391 (0.0750)	-0.0376 (0.0858)	0.131** (0.0607)
Suppliers' max flood extent	0.293** (0.113)	0.281** (0.115)	0.255** (0.126)
Average effect of mean flooded supplier buffer	0.004	0.004	0.004
Average effect of 10% flooded supplier buffer	0.029	0.028	0.026
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE		Yes	
Time $\times$ District $\times$ Industry FE			Yes
R^2	0.5136	0.5193	0.5389
N	137,957	137,192	132,854

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

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

	Δ Share of New Supplier Purchases		
	(1)	(2)	(3)
Own max flood extent	0.0459 (0.0744)	-0.0182 (0.0872)	0.123** (0.0533)
Suppliers' max flood extent	0.412*** (0.102)	0.405*** (0.102)	0.388*** (0.109)
Average effect of mean flooded supplier buffer in cm	0.006	0.006	0.006
Average effect of 10% flooded supplier buffer in cm	0.041	0.041	0.039
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.5137	0.5194	0.5389
N	137,822	137,057	132,724

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in purchase shares from new suppliers among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon) . Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

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

	Δ Share of Multibranch Supplier		
	(1)	(2)	(3)
Own max flood extent	0.0967 (0.0919)	0.0510 (0.0799)	0.129 (0.108)
Suppliers' max flood extent	0.0752 (0.0823)	0.0673 (0.0844)	0.0878 (0.0925)
Average effect of mean flooded supplier buffer	0.001	0.001	0.001
Average effect of 10% flooded supplier buffer	0.008	0.007	0.009
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0044	0.0166	0.0472
N	124,193	123,494	119,537

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

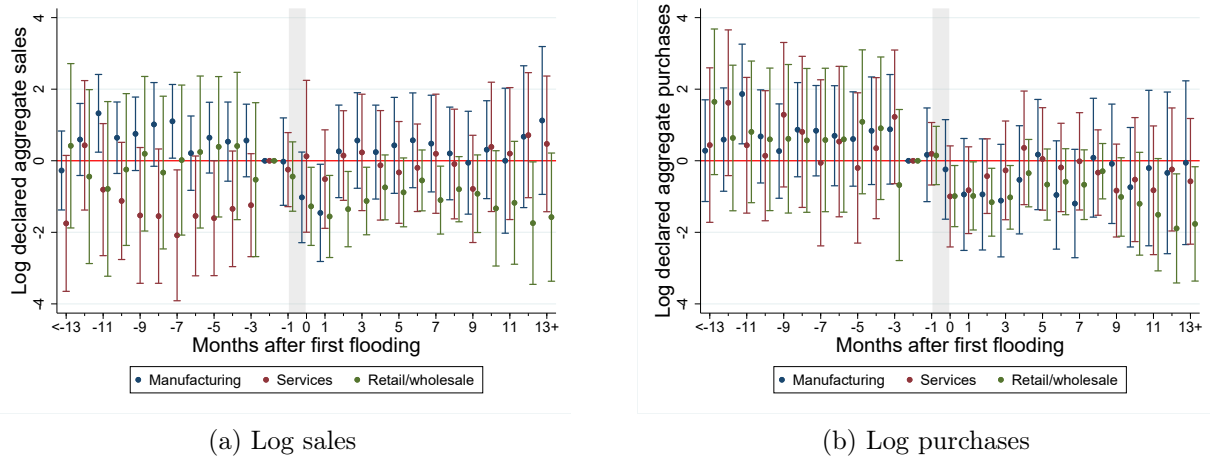
Table B.13. Impact of supplier flooding on share of < 5% flooded, multiple-plants suppliers

	Δ Share of Multibranch Supplier		
	(1)	(2)	(3)
Own max flood extent	0.0790 (0.0885)	0.0535 (0.0753)	0.105 (0.101)
Suppliers' max flood extent	0.159*** (0.0538)	0.170*** (0.0529)	0.187*** (0.0599)
Average effect of mean flooded supplier buffer in cm	0.002	0.003	0.003
Average effect of 10% flooded supplier buffer in cm	0.016	0.017	0.019
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0046	0.0170	0.0473
N	124,092	123,394	119,440

Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average of multibranch suppliers among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.7 By sector and industry

Figure B.3. By sector: Impact of flooding on firm sales and purchases



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

C Data Appendix

C.1 Firm transaction data

The firm transactions data are described in Section IA. Here we describe additional cleaning steps for this dataset.¹

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

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

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

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

3. For each firm, calculate the fraction f of its S-only-reported sales transactions that are B-duplicates (over the course of its whole life). Drop all S-only-reported B-duplicates transactions of firms that have this fraction above 90% and report more than five S-only-reported sales transactions and are before November 2014.
4. Drop all S-only-reported B-duplicates transactions $T = (b, s, x, t)$ where b and s never report any transactions that are confirmed by both parties.

¹Firms and products in these data are classified using the Pakistan Standard Industrial Classification ([Federal Bureau of Statistics, 2010](#)) and the Pakistan Customs Tariff codes ([Federal Board of Revenue of Pakistan, 2013](#)); industry codes are supplemented, for firms with valid national tax numbers, using Orbis ([Bureau van Dijk, 2023](#)). The heterogeneity analysis additionally draws on the Census of Manufacturing Industries ([Federal Bureau of Statistics, 2006](#)) and on measures of input relationship specificity from [Boehm et al. \(2025\)](#).

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

C.2 Firm addresses

Firm address information was obtained from multiple lists from the Federal Board of Revenue (2019), including the Pakistan Active Taxpayer Portal and Business Register.²

Duplicate identifier–address pairs or empty addresses were dropped. When duplicate firms with multiple identifiers had different addresses, both were kept. The variable "address_type" was used to differentiate address types and branch numbers, single-field sources are "business" address by default. For sources with multiple address fields, the additional fields often contained leftover strings, outdated addresses, or status notes. Irrelevant entries were cleaned and supplemental address fields were concatenated if they were shorter than 30 characters (95th percentile of address string length) since these were found to contain continuations of the main address field. Longer entries were retained as separate addresses for geocoding.

The resulting dataset is in long form, with multiple possible addresses per firm. Using the list of cities/municipalities and alternative Urdu romanization, obtained by aggregating municipality data from public sources³, we performed a fuzzy string match on the address strings for the city names, before merging in the corresponding city geocodes for the string's highest match score. We allow up to six city or alternative-name matches per address string and, after geocoding, select the city closest to the firm's geocode. This procedure identified cities for 90% of addresses.

A first round of geocoding firm addresses was conducted in 2019 on a partial set of addresses. Once additional addresses were obtained, a second round of geocoding was conducted for all addresses in 2021. Both rounds used Google Maps API (Google, 2021), although the results are not necessarily identical due to differences in string cleaning procedures and changes to the Google Maps API. We use geocodes from both rounds, prioritizing 2019 geocodes since these were manually verified, and using 2021 geocodes if 2019 geocodes are not available or valid. 2019 geocoding was conducted in Excel.⁴ 2021 geocoding was conducted in Python by directly querying the Google Maps API.⁵

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

²Portal link: <https://e.fbr.gov.pk/esbn/Service.aspx?PID=YAKaq8jRWzAjzvb3k8criw==>

³For cities, we use the list obtained from LatitudeLongitude.org (<https://latitudelongitude.org/pk/>) and for tehsils (sub-district units), we use the OCHA administrative map of Pakistan (OCHA Field Information Services Section, 2018). The resulting list of cities and alternative romanizations is distributed in the paper's data supplement (Balboni et al., 2026).

⁴This procedure can no longer be implemented efficiently for large queries due to restrictions in the Google Maps API, but a guide can be found here: <https://www.adventuresincre.com/auto-populate-latitude-longitude-excel/>.

⁵More details about the Google Maps API can be found here: <https://developers.google.com/maps/documentation/geocoding/overview>.

completeness and trustworthiness.

C.3 Flood data

Flooding data in Pakistan was obtained from UNOSAT over the period 2010-2019, as described in Section IC.⁶ UNOSAT flood data have been used in a number of papers assessing flooding in Pakistan and assessed to be generally accurate in representing flood extents.⁷ These studies note that, although the UNOSAT data include shortcomings such as 1) uncertainty due to cloud interception, 2) potential failures to capture peak inundation, and 3) overestimation of maximal flood extent, the data are generally reliable. The UNOSAT data capture the most severe flood events in Pakistan, as measured by the number of deaths and displacements reported in other sources. For instance, compared to the EM-DAT natural disaster database (EM-DAT, 2022), the UNOSAT data excludes 10 floods over 2010-2015, most of which are flash floods or relatively minor in terms of casualties; all flood events associated with over 100 deaths and 25,000 displacements are captured. The geographic coverage of the UNOSAT data appears best in the heavily-populated provinces of Punjab and Sindh, and worst in northern areas.

C.4 Flood risk data

Flood risk data from Fathom-Global (Fathom, 2019) are described in Section ID. The raw raster values represent the expected depth in meters of flooding for the return period of the specific flood type. We treat missing cells (raw value -9999) as "0" in our raster, as suggested by FATHOM staff, and treat base water cells (raw value 999) as empty cells ("NODATA").

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

$$\text{Firm flood risk} = \frac{\sum_{i \in \text{cropped_buffer}} \text{Depth}_i}{N_{i \in \text{cropped_buffer}}}$$

C.5 Constructing the aggregated cell panel

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

⁶The last flood event observed during our study period is in 2015, reflecting the fact that UNOSAT did not receive a request for their service in the years 2016, 2017, 2018 or 2019.

⁷For example, see Sayama et al. (2012), Jilani et al. (2007), Ushiyama et al. (2014), as well as analyses for popular reporting in the New York Times (Burgess and Tse, 2010; Gall, 2010).

after, and from 6 to 12 months after each flood event. We additionally calculate cell-level measures of flood incidence capturing flood extent and the share of flooded firms.

C.6 GPS tracker data from commercial trucks

Data from GPS trackers installed in commercial trucks ([Tracking World Pvt. Limited, 2020](#)) is described in Section [IB](#). Here we described additional steps in data preparation and cleaning.

C.6.1 Constructing road network graph from shapefile

OpenStreetMap data on Pakistan’s road network was retrieved from Geofabrik ([Geofabrik GmbH, 2021](#)), and cropped to Pakistan’s country outline shapefile from GADM ([Global Administrative Areas, 2018](#)).

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

C.6.2 Cleaning GPS tracker data

Deduplicate truck id

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

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

- When $|A| > |A \cap B| < |B|$, we mark A and B as NOT duplicates.
- When $|A| \approx |A \cap B| < |B|$, all of A ’s pings are covered by B ’s. We mark A as the duplicate that needs to be removed (and vice versa).

- When $|A| \approx |A \cap B| \approx |B|$, meaning that A and B perfectly duplicate each other, we mark either one of A or B as a duplicate that needs to be removed.
- $|A| \approx |A \cap B|$ or $|A \cap B| \approx |A|$ is defined as True when

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

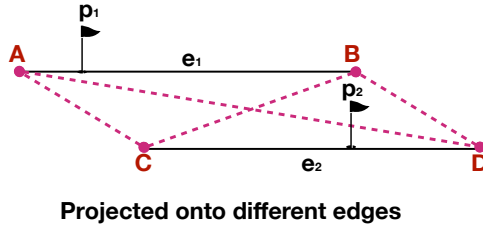
is satisfied and False otherwise.

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

Compute the ping-pair distance

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

Case 1: $e_1 \neq e_2$



When both e_1 and e_2 are twoway, we define the shortest path on the graph as:⁸

$$|p_1 p_2| := \min\{p_1 A C p_2, p_1 A D p_2, p_1 B C p_2, p_1 B D p_2\}$$

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

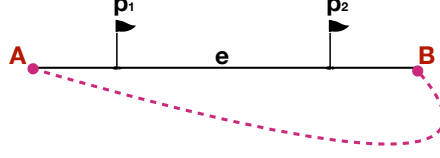
$$|p_1 p_2| := \min\{p_1 B C p_2, p_1 B D p_2\}$$

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

$$|p_1 p_2| := p_1 B C p_2$$

⁸We denote the shortest path on the graph between p_1 and p_2 as $|p_1 p_2|$. In more precise notation, $\min\{X\}$ here can be considered as $\operatorname{argmin}_{x \in X} \text{length}(x)$.

Case 2: $e_1 \equiv e_2$



Projected onto the same edge

When e is twoway:

$$|p_1 p_2| := \min\{p_1 p_2, p_1 A B p_2\}$$

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

$$|p_1 p_2| := p_1 p_2$$

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

$$|p_1 p_2| := p_1 A B p_2$$

Detecting possible errors

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

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

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

Disaggregating into edges

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

Aggregating on the edge $\times$ day $\times$ truck level

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

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

We also define the reported speed on edge $\times$ day $\times$ truck as:

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

Fill missing counts

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

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

Flood-disruption variable

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

$$\text{pctx_flood_disrupted}_{it} = \begin{cases} 1 & \text{if } \text{nth_pct_disrupted}_{it} = 1 \text{ and } \text{FloodedRatio}_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Data on buyer-seller-week level

To construct graphs that enable us to compute the least time (rather than distance) route, we update edge weights based on travel time between two vertices. The initial graph is g_0 . We are interested in graphs during the non-flooded year-weeks and flooded year-weeks.⁹ For non-flooded year-weeks, for an edge i , we take the average speed of i through all year-weeks where no flood is recorded in any part of Pakistan. For flooded year-week t' , we select the speed on edge i during year-week t' as the speed used to construct the graph. We obtained 12 sets of speed (non-flooded speed, the speed in

⁹Though no satellite picture of flooding in week 2015-32 is recorded, it is considered flooded because 2015-31 and 2015-33 are all flooded.

2012-37, 2012-38, 2012-39, 2013-33, 2013-34, 2013-35, 2014-37, 2014-38, 2015-31, 2014-32, 2014-33), which correspond to 12 graphs indexed by g .

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

We update the graph weights for the 12 new graphs.¹⁰

$$\text{weight}(i; g) = \frac{\text{length}(i)}{\text{speed}(i; g)} = \frac{\text{weight}(i; g_0)}{\text{speed}(i; g)} \quad (4)$$

To solve all g , we obtained the lowest travel time between any vertex-pair. Using a similar method to that used to compute the shortest route between pings, we compute the least time route between a buyer-seller pair p for each g , and the ratio $w_{i,p}$ that each edge i in the path contributed to the total length of the path. Denote the total number of buyer-seller pair as P , and total number of edges I .¹¹ We can write this data as a vector of I -by- P matrices $\mathbf{A}_g$:

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

where

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

and

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

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

$$[\mathbf{B}_v]_{v \in V} = [\mathbf{B}_{\text{flood_extent}} \quad \mathbf{B}_{\text{pct1_disrupted}} \quad \cdots \quad \mathbf{B}_{\text{pct5_flood_disrupted}}]^T$$

where

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

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

¹⁰weight($i; g$) denotes the weight of edge i in graph g . speed($i; g$) denotes the speed of i that is assigned in the construction of g .

¹¹In this section we use the uppercase letters P, I, T, G, V to denote the set or the number of elements in the set, and the lowercase p, i, t, g, v to denote the element or the index of the element.

and $[\mathbf{B}_v]_{v \in V}$

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

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

Missing values arise due to the following reasons:

- Buyer and seller are not connected in the graph g . This is always accompanied by a lowest travel time of `inf`. If all paths are connected, $\mathbf{A}^T \mathbf{1} = \mathbf{1}$, i.e. the contributions of each edge in the path sum up to one. For disconnected buyer-sellers, their corresponding column in $\mathbf{A}$ sums up to zero, which we flag with NaN.
- For the graph weighted by non-flooded speeds only, not all edges have a valid speed in all year-weeks. As a simple example, consider a case where, for week 1, the valid edges are edge a and edge b ; for week 2, the valid edges are edge c and edge d ; for week 3, the valid edges are edge a and edge d . A path consists of edge a and b . This path would have real data in week 1 and 3, but not week 2. In week 1, both edges are taken into consideration. In week 3, only edge a is considered, and is assigned full weight since b is absent.

D Theory Appendix

D.1 Proofs of results in the main text

Lemma 1 (Shanbhag and Sreehari, 1977). *If Z is a standard exponential random variable and X is a positive α -stable random variable defined by*

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

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

Proof.

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

□

Lemma 2. *Let X be Fréchet distributed with*

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

and Y independent from X such that $E[e^{-uY}] = e^{-u^\beta}$. Then $(X/Y^{1/\theta})^\alpha$ 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 $T(X)^\theta$ is standard exponential:

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

From the Shabthag-Sreehari lemma above we know that

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

Rearrange to get

□

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

Lemma 3. *Let X be Frechet with*

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

Then $\log X$ has the characteristic function

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

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 4 (Lemma 1 in the main text). *Conditional on the realization of the aggregate flood shocks*

b , the cost distribution of firms in n is Weibull:

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

where:

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

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

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

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

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

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

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

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

is Weibull distributed. Hence

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

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

Apply now Lemma 2,

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

with¹²

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

to get

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

which is the first part of the statement of the Lemma. For the second part, use the definition of $\bar{c}$ and Lemma 3:

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

□

¹²Note that $c_j \xi_j$ does not depend on ξ_j , so X and Y are independent.

Lemma 5 (Lemma 2 in the main text). *Let $\alpha > 0$. Then for each realization of the aggregate shocks b_n an equilibrium exists and is unique.*

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

D.2 Adaptation potential

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

$$\min_{\{d \log(X_{ni}/X_n)\}_{i \in I}} \sum_i \frac{\partial \text{Var}_{\hat{b}}(\hat{c}_n(\hat{b}))}{\partial \log(X_{ni}/X_n)} d \log\left(\frac{X_{ni}}{X_n}\right) \quad (5)$$

$$\text{s.t.} \quad \sum_i \frac{\partial \log E_b(c(b, X))}{\partial \log(X_{ni}/X_n)} d \log(X_{ni}/X_n) \leq 0 \quad (6)$$

$$\sum_i \frac{X_{ni}}{X_n} d \log\left(\frac{X_{ni}}{X_n}\right) = 0 \quad (7)$$

$$-1 \leq d \log(X_{ni}/X_n) \leq 1 \quad \forall i \quad (8)$$

has a solution where the objective function value is negative. Equation (6) is the constraint that expected cost should not increase. Equation (7) is the constraint that sourcing shares should add up to 1. Equation (8) ensures that the solution of the optimization problem remains bounded.

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

Lemma 6. *The two expressions*

$$\frac{\partial \text{Var}_{\hat{b}}(\hat{c}_n(\hat{b}))}{\partial (X_{ni}/X_n)} \quad \text{and} \quad \frac{\partial \log E_b(\bar{c}(b, X))}{\partial \log(X_{ni}/X_n)}$$

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

Proof. We have that

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

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

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

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

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

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

$$\left(\frac{\partial \log \bar{\mathbf{c}}}{\partial \log m_{ni}} \right) = \alpha [\mathbf{X}] \left(\frac{\partial \log \bar{\mathbf{c}}}{\partial \log m_{ni}} \right) - \left(\frac{\alpha}{\zeta} \right) \left(0, \dots, \frac{X_{ni}}{X_n}, \dots, 0 \right)' \quad (9)$$

where $\partial \log \bar{\mathbf{c}} / \partial \log m_{ni}$ is a vector with j -th element $\partial \log \bar{c}_j / \partial \log m_{ni}$, $\mathbf{X}$ is the matrix with (n, i) -th element X_{ni}/X_n , and $(0, \dots, \frac{X_{ni}}{X_n}, \dots, 0)$ is a vector with only X_{ni}/X_n in the n -th element, and zeros otherwise. Equation (9) is a linear system of equations that can be solved for $\partial \log \bar{\mathbf{c}} / \partial \log m_{ni}$. This means we can solve also for

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

and hence together,

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

□

E Parameterizing the joint distribution of flood shocks across locations

In order to use the model to evaluate the potential for adaptation in Section IVD, we need to parameterize the joint distribution of flood shocks across locations. The Fathom flood risk data used elsewhere in the paper is not sufficient for this purpose as it only contains moments from the marginal distributions of flood risk in each location, and therefore does not provide information about correlations across locations. For this exercise, we therefore augment the Fathom flood risk data with additional data from the Global Flood Database¹³ and EM-DAT (EM-DAT, 2022)¹⁴, which report the centroid and total area of 51 historical floods in Pakistan dating back to 1979.¹⁵

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 100 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 100 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.¹⁶ To aggregate to the level of summer monsoon seasons, we take the union of all simulated floods in a given summer.

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

¹³<https://global-flood-database.cloudtostreet.ai/>

¹⁴<https://www.emdat.be/>

¹⁵We 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.

¹⁶The shape of the modeled flood extent will therefore be similar to the shape of high flood risk areas in the Fathom data rather than circular extents.

F Robustness specifications

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

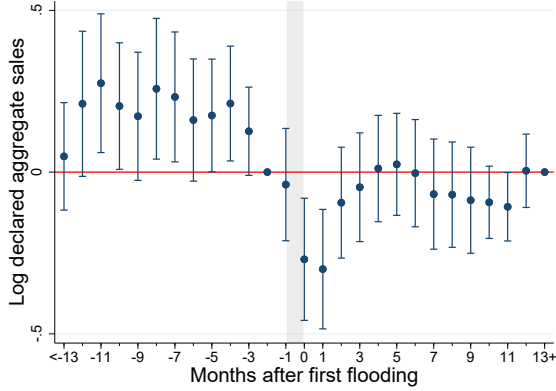
A recent literature has highlighted potential challenges with the use of two-way fixed effects regressions including treatment leads and lags, since variation in treatment timing may give rise to contamination of coefficients on lead or lag terms by effects from other periods ([Callaway and Sant’Anna, 2021](#); [Sun and Abraham, 2021](#)). While the major floods in our sample are generally close to a year apart so that such effects may not be first order, we re-run all key results using the estimator proposed in [Sun and Abraham \(2021\)](#). This estimator aims to overcome the challenges that may be associated with two-way fixed effects event study regressions by using never-treated (or, if these are not available, last-treated) firms to form the control group. We do not use this estimator in the preferred specification in the main text since it relies on a binary treatment variable. In order to implement this estimator for robustness specifications, we construct a binary treatment variable as follows. Since [Figure B.1](#) suggests that the impact of flooding is concentrated among firms which have more than 10% of their buffer flooded, we consider a firm treated only if the treatment variable is greater than 10%, and drop all firms with a treatment variable $\in (0\%, 10\%]$. We use never treated firms as the control cohort.

As an additional test, we present results separately by flood event, restricting the sample to firms which are either never treated or treated only in a given flood event. The flood events in our sample period are Aug-Sep 2011, Sep 2012, Aug 2013, Sep 2014, and Jul-Aug 2015. For flood events lasting two months, we define event time relative to the first month of the event. This specification shuts down variation in treatment timing while using the standard continuous treatment variable, and allows us to explore heterogeneity across flood events. Since the panel begins in July 2011 and ends in June 2018, coefficients for earlier and later periods are omitted. One coefficient in each fiscal year is omitted in the sales, purchases, and log number of supplier regressions because the full set of treatment variables, the firm-fiscal-year fixed effects and the firm-month-of-the-year fixed effects are perfectly collinear when restricting to a single flood event. We include the number of treated firms, $N_{treated}$, with each specification below. These results show that negative impacts of flood events on sales and purchases are observed broadly across all of the flood events in the sample, with the exception of the 2013 flood. Heterogeneity in the impacts of each individual flood event reflects heterogeneity in the extent and location of flooding, as well as the overlap of flood polygons with firm locations.

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

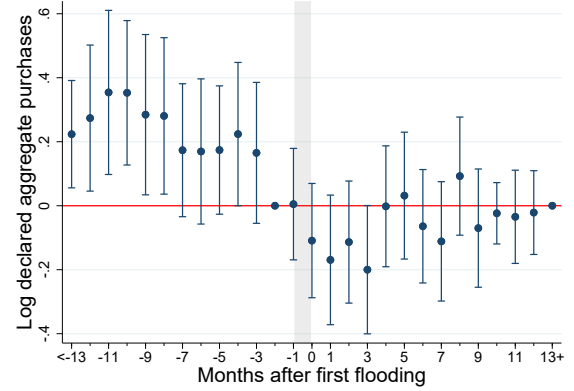
F.1.1 Impact of flooding on firm sales and purchases

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



(a) Log sales

$N_{treated} = 708$

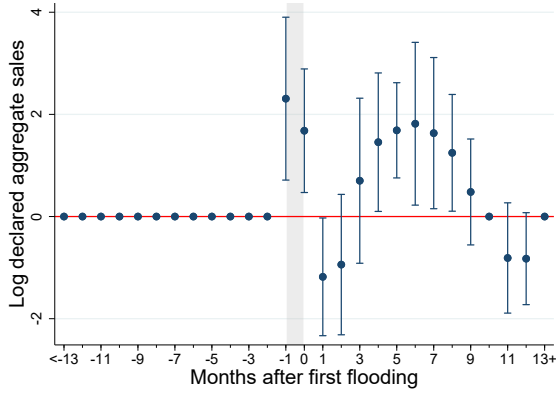


(b) Log purchases

$N_{treated} = 708$

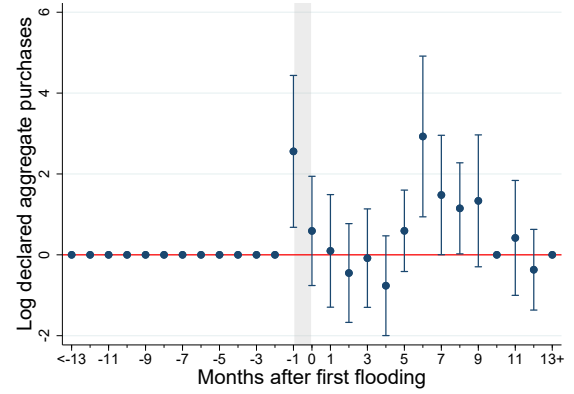
Notes: The panels plot the effect of flooding on log declared sales and purchases. We use the method in [Sun and Abraham \(2021\)](#) to estimate equation (1) but with a binary treatment variable based on a 10% cutoff. Observations are firm-month-years which are never flooded or flooded by $> 10\%$ in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

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



(a) Log sales

$N_{treated} = 1050$

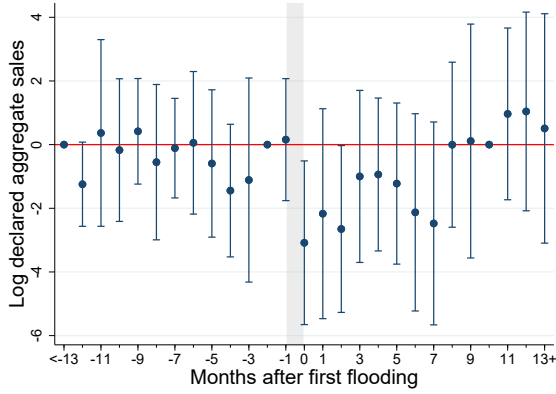


(b) Log purchases

$N_{treated} = 1050$

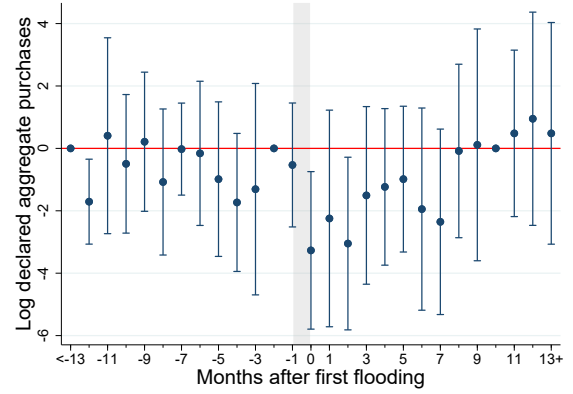
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Aug-Sep 2011 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

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



(a) Log sales

$N_{treated} = 42$

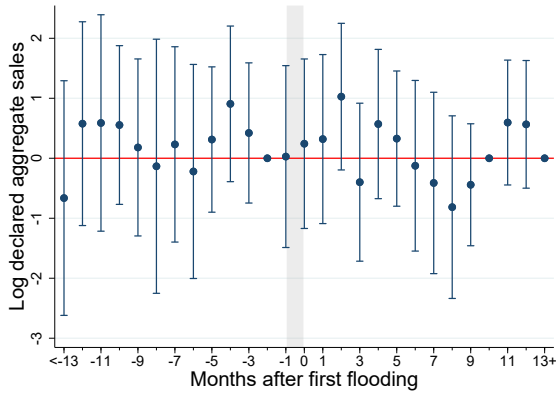


(b) Log purchases

$N_{treated} = 42$

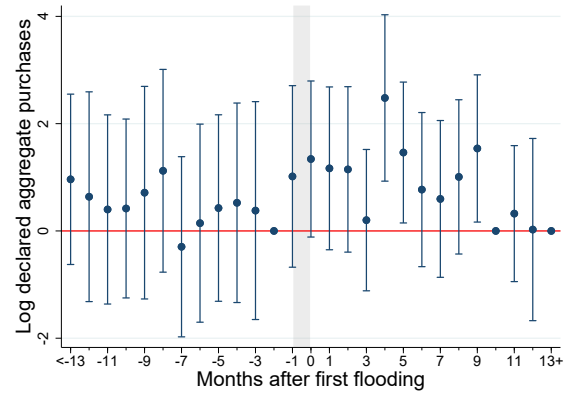
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Sep 2012 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

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



(a) Log sales

$N_{treated} = 3734$

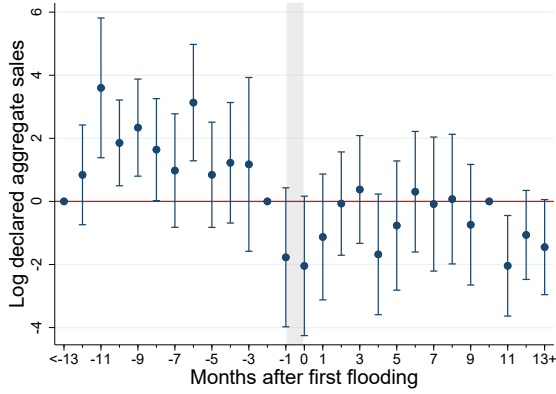


(b) Log purchases

$N_{treated} = 3734$

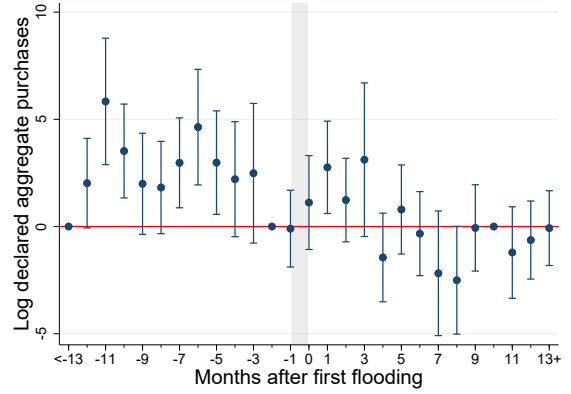
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Aug 2013 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

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



(a) Log sales

$$N_{treated} = 8213$$

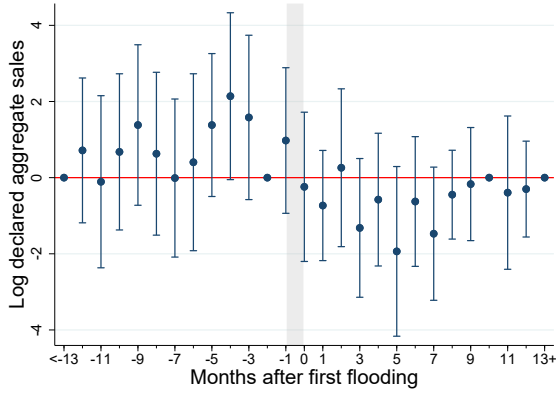


(b) Log purchases

$$N_{treated} = 8213$$

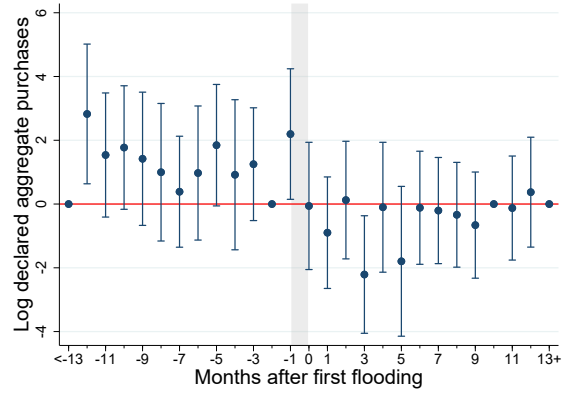
Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observation are firm-month-years which are never flooded or first flooded in the Sep 2014 event. The 95% confidence intervals rely on standard errors clustered at the firm-level.

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



(a) Log sales

$$N_{treated} = 9772$$



(b) Log purchases

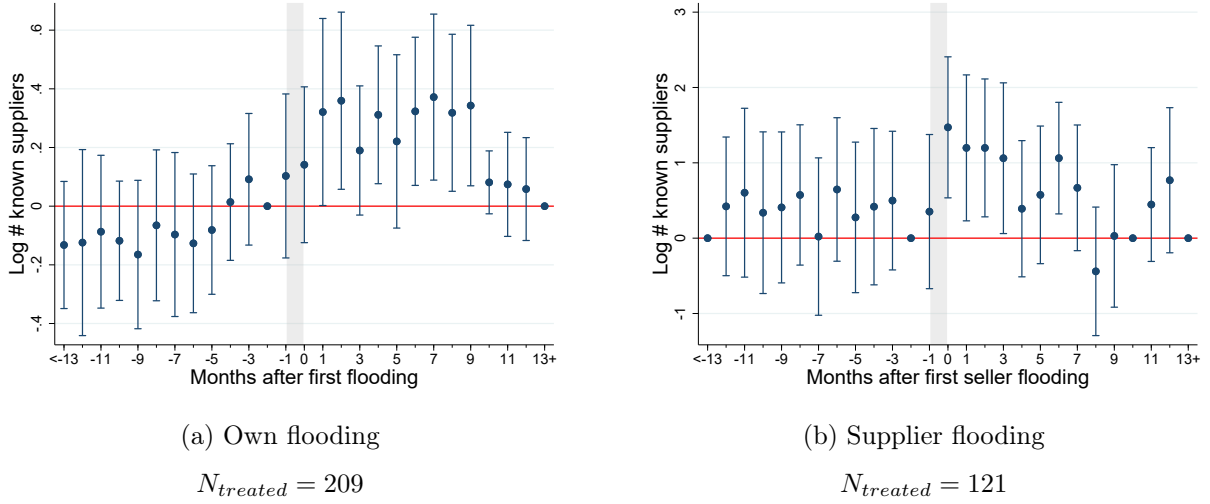
$$N_{treated} = 9772$$

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

F.1.2 Supplier diversification

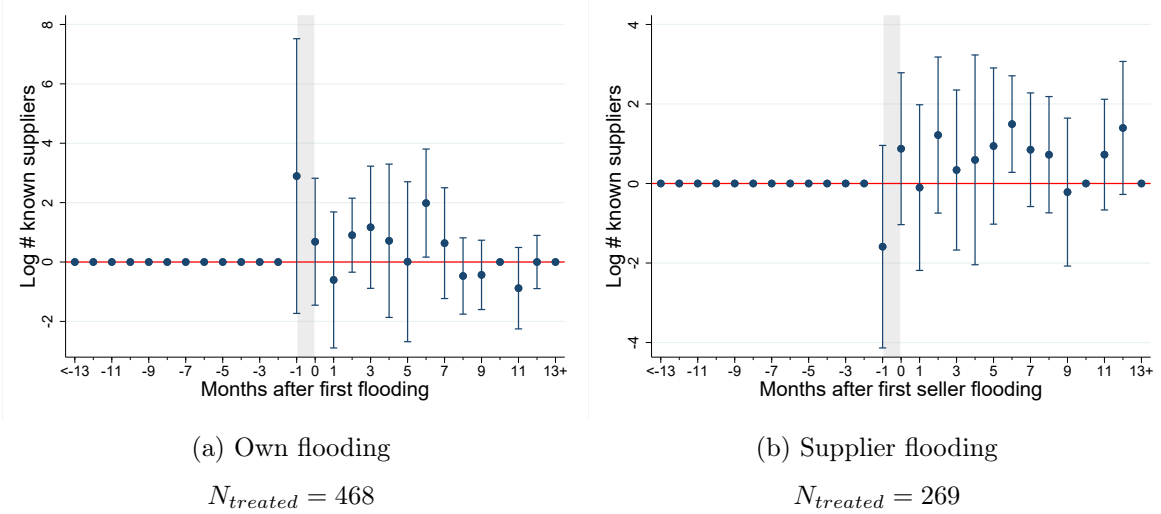
We omit the impact of own flooding in the September 2012 flood in this section since only six firms with a non-missing dependent variable experienced flooding during this episode.

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



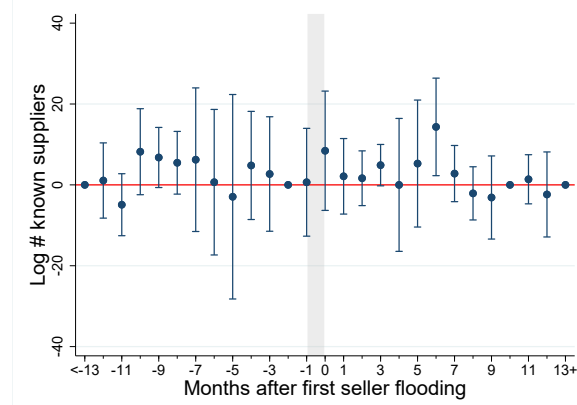
Notes: The panels plot the effect of own flooding or supplier flooding on log number of suppliers. We use the method in [Sun and Abraham \(2021\)](#) to estimate equations (6) and (7), but with a binary treatment variable based on a 10% threshold. Observations are firm-month-years whose 2011 and 2019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

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



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

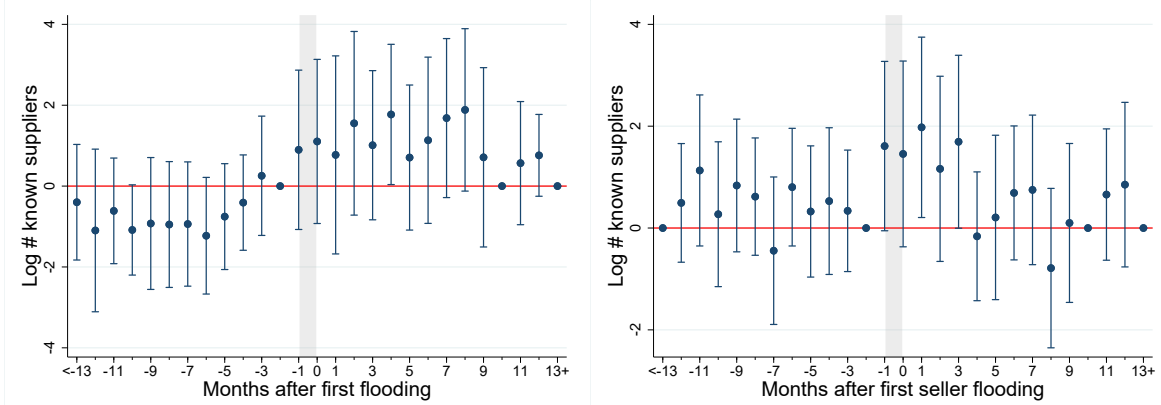
Figure F.9. Impact of supplier flooding on log number of suppliers (Sep 2012)



$$N_{treated} = 36$$

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

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



(a) Own flooding

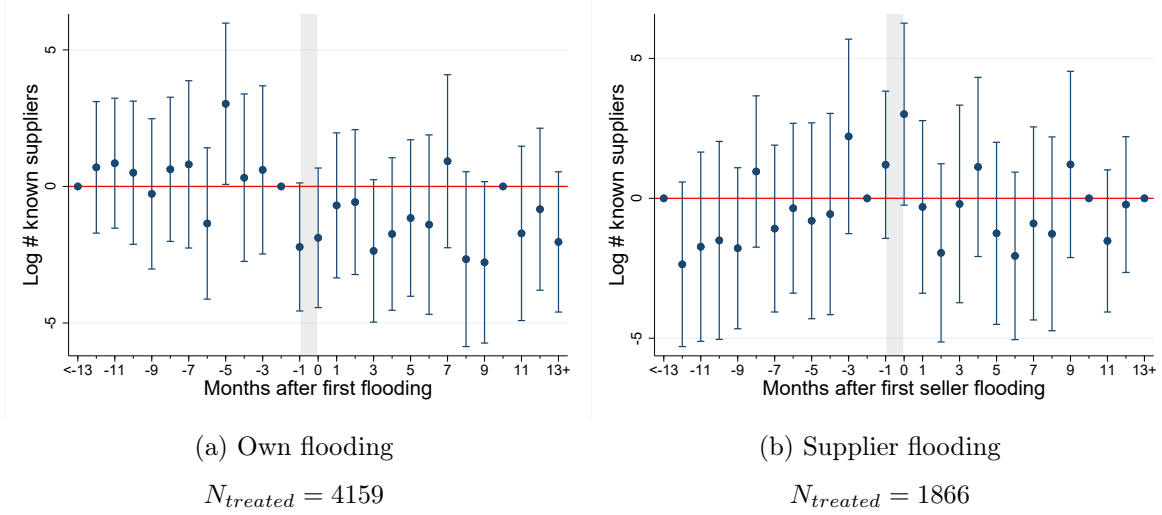
$$N_{treated} = 1635$$

(b) Supplier flooding

$$N_{treated} = 1062$$

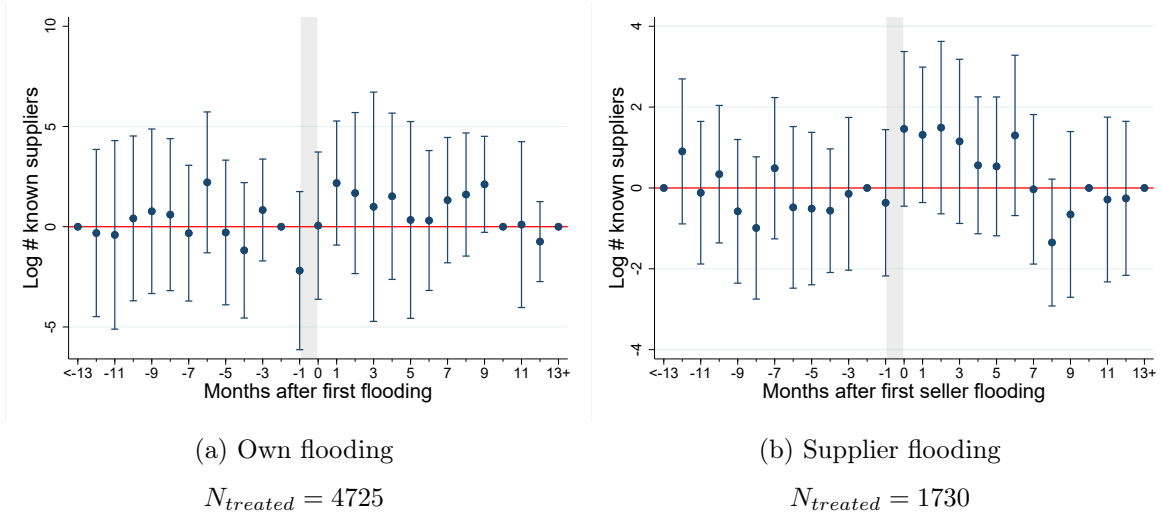
Notes: The panels plot OLS estimates of the effect of own flooding or supplier flooding on log number of suppliers following equations (6) and (7). Observations are firm-month-years whose 2011 and 2019 addresses are known, ≤ 10 km apart and which are never treated or first treated in the Aug 2013 event.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

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



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

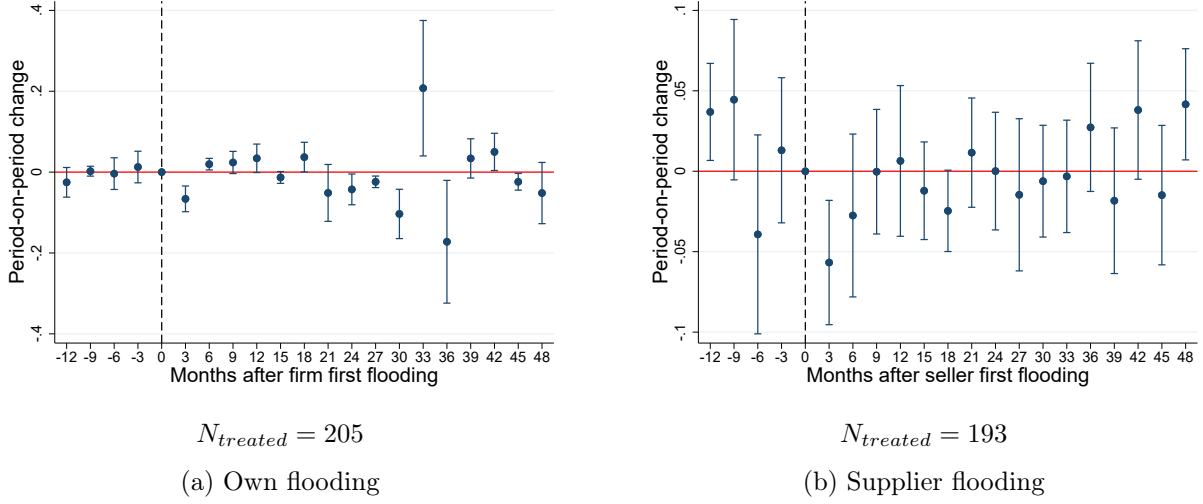
Figure F.12. Impact of flooding on log number of suppliers (Jul-Aug 2015)



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

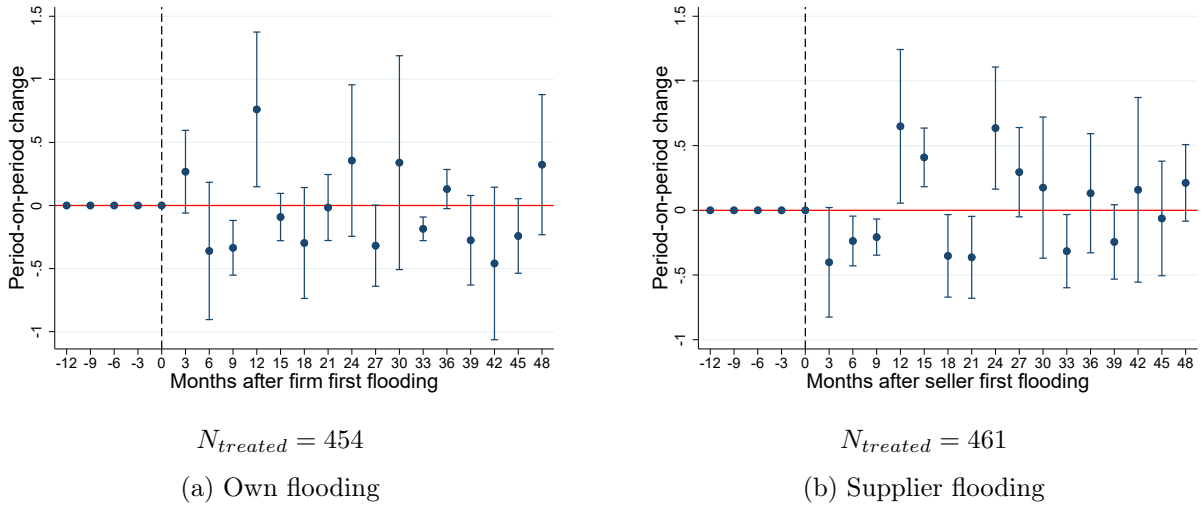
F.1.3 Supplier choice

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



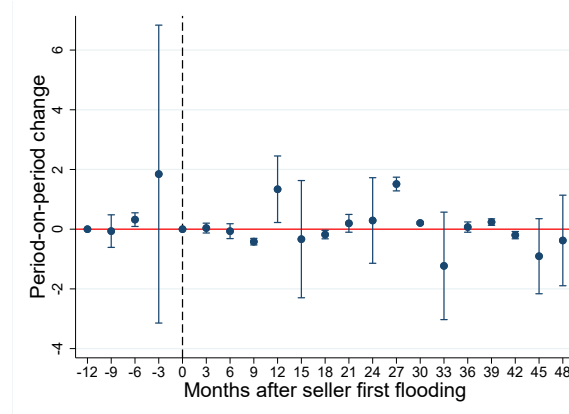
Notes: The panel plots estimates of the effect of own and supplier flooding on the change in sales-weighted average flood risk among all suppliers. We use the method by [Sun and Abraham \(2021\)](#) to estimate equation (10) with a binary treatment variable based on a 10% threshold. Observations are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

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



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

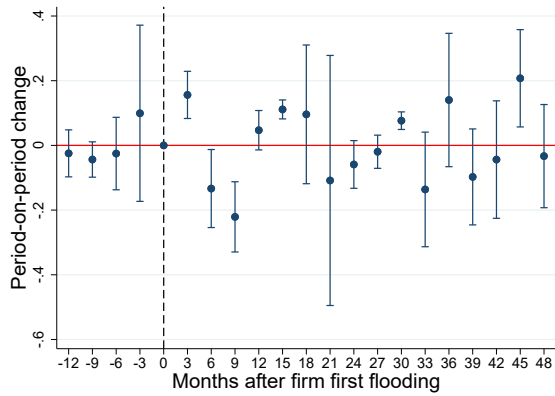
Figure F.15. Dynamic impact of supplier flooding on flood risk of all suppliers (Sep 2012)



$$N_{treated} = 49$$

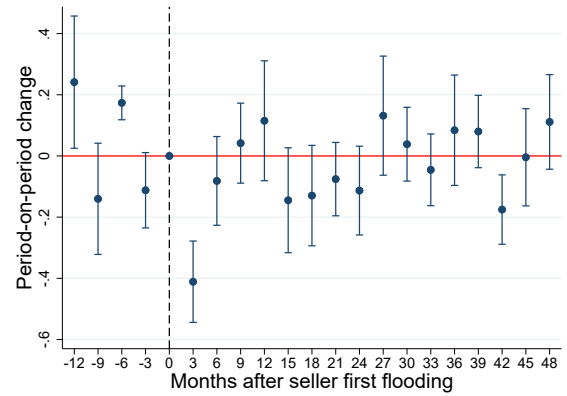
Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq 10\text{km}$ apart and which are never treated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

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



$$N_{treated} = 1499$$

(a) Own flooding

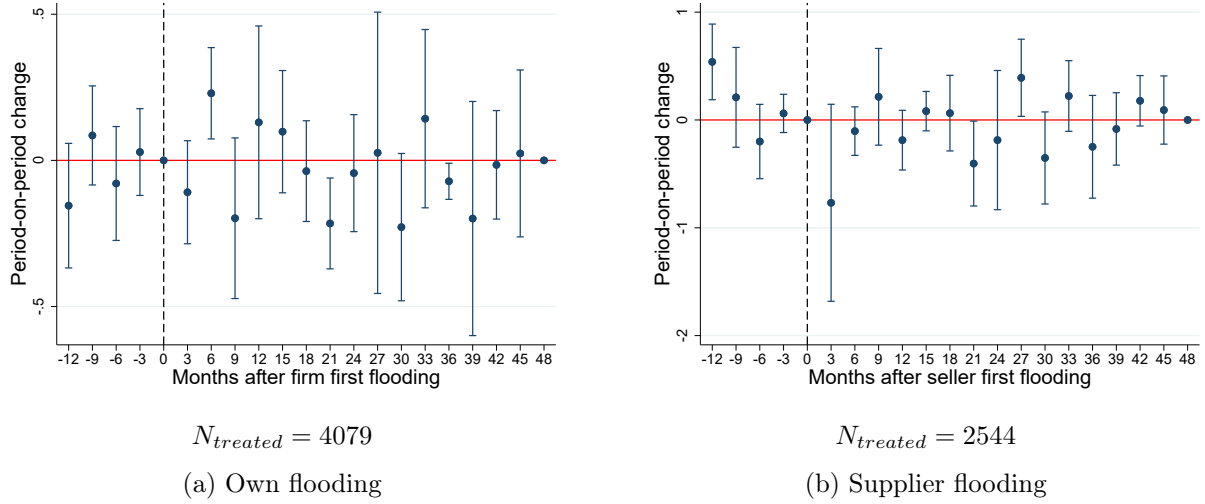


$$N_{treated} = 1467$$

(b) Supplier flooding

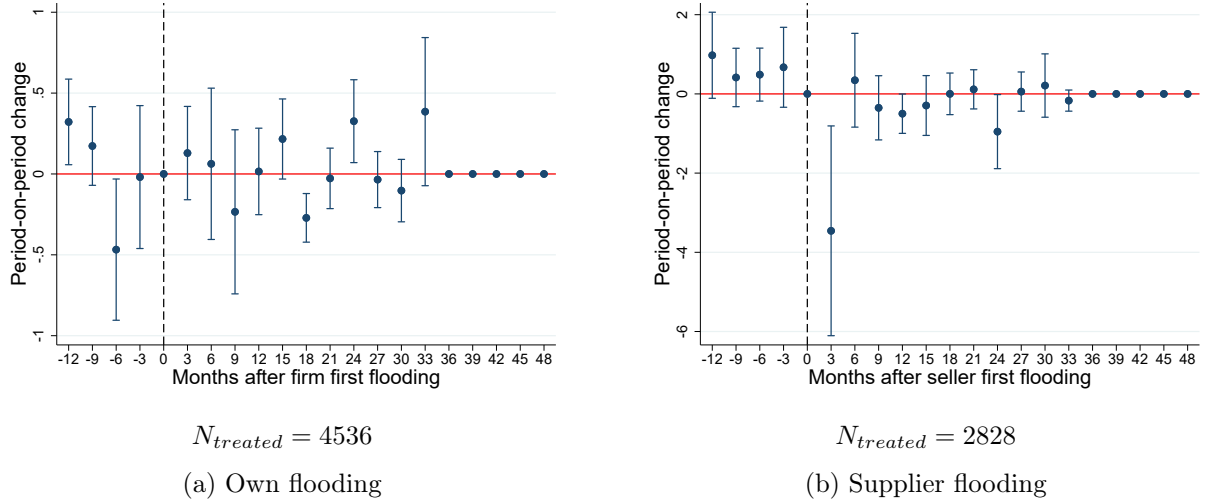
Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq 10\text{km}$ apart and which are never treated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

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



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

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



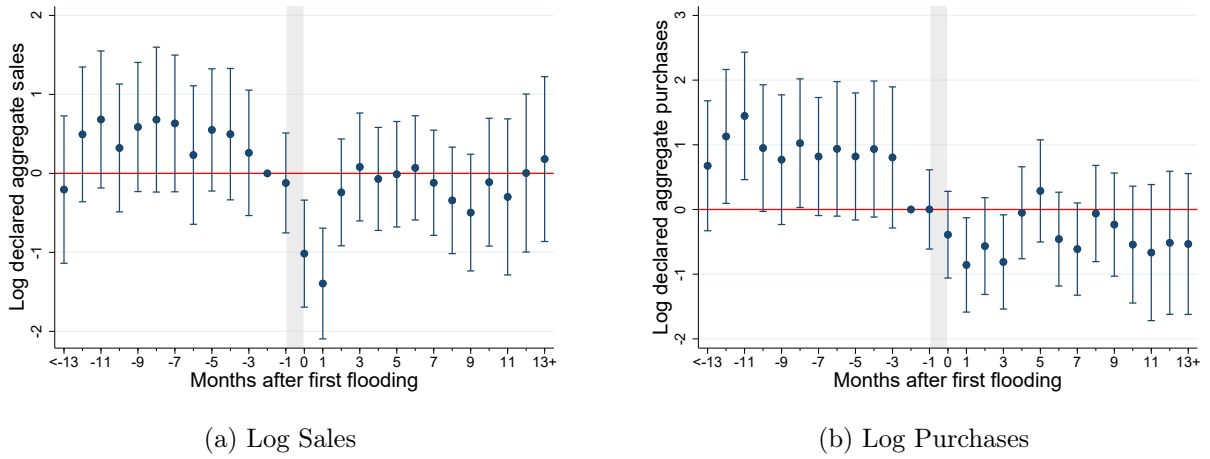
Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are all firm-year-months for which the 2011 and 2019 addresses are known, $\leq 10\text{km}$ apart and which are never treated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

F.2 Results excluding electricity and gas producers

We examine how far the results are affected by industries for which supply disruptions of the nature considered in the analysis may not be pertinent. The first of these robustness checks excludes from the sample the 1% of firms, accounting for 14% of aggregate sales, with two-digit industry identifiers corresponding to electricity, gas and extraction of crude petroleum.¹⁷ This accounts for the fact that, while firms purchase these inputs regularly, these are monopolies that firms are unable to substitute away from. The results in this case are very similar to the baseline results.

F.2.1 Impact of flooding on firm sales and purchases

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



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

¹⁷The two-digit industry code corresponding to electricity, gas and extraction of crude petroleum also includes steam and air conditioning suppliers.

F.2.2 Firm location

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

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	2.487*** (0.847)	3.108*** (0.917)	-197.0* (113.3)	-30.60 (45.79)
District FE	Yes		Yes	
District $\times$ Fathom 1 in 100 FE			Yes	Yes
R^2	0.033	0.054	0.101	0.447
N	43,526	43,131	7,386	7,243

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

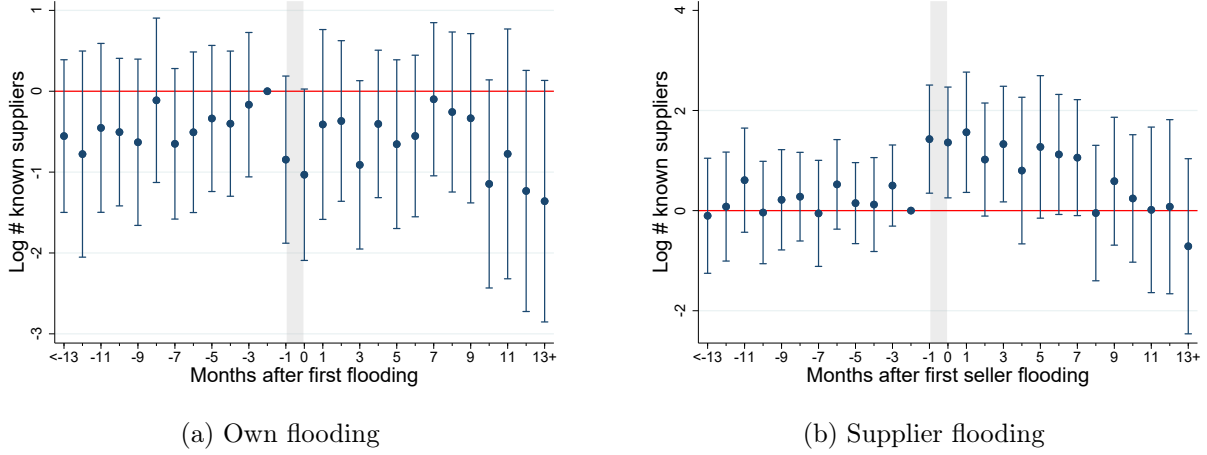
Table F.2. Impact of destination flood history on relocation flows (excl. electricity and gas)

	Number of Firms Moved
Dest. flooded 12mo prior	-1.060*** (0.246)
Origin $\times$ Destination FE	Yes
Origin $\times$ Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10 km
N	1,575

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

F.2.3 Supplier diversification

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



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

F.2.4 Supplier choice

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	3.079 (4.104)	-1.909 (3.086)	7.419 (5.018)
Suppliers' max flood extent	-60.93*** (15.34)	-63.71*** (16.10)	-74.37*** (18.10)
Average effect of mean flooded supplier buffer in cm	-0.932	-0.975	-1.138
Average effect of 10% flooded supplier buffer in cm	-6.093	-6.371	-7.437
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0087	0.0237	0.0550
N	132,534	131,779	127,742

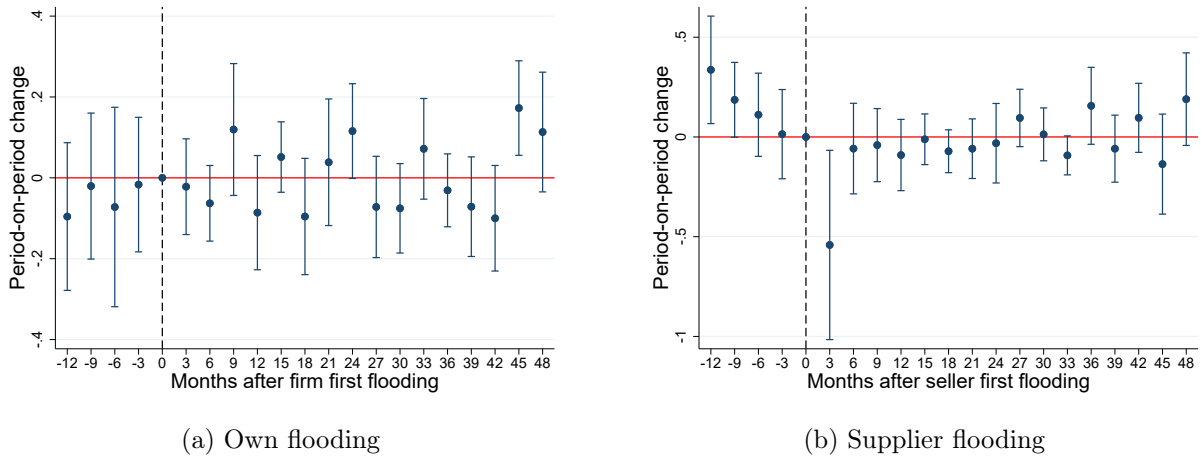
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	1.152 (3.472)	0.0620 (2.882)	3.902 (5.243)
Suppliers' max flood extent	-19.79*** (6.090)	-21.37*** (6.469)	-20.06*** (6.288)
Average effect of mean flooded supplier buffer in cm	-0.303	-0.327	-0.307
Average effect of 10% flooded supplier buffer in cm	-1.979	-2.137	-2.006
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0059	0.0209	0.0522
N	132,372	131,617	127,593

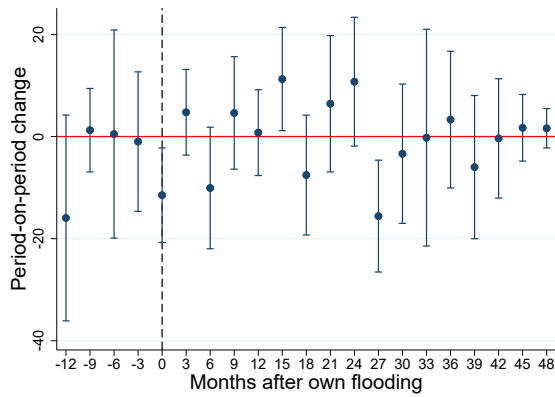
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

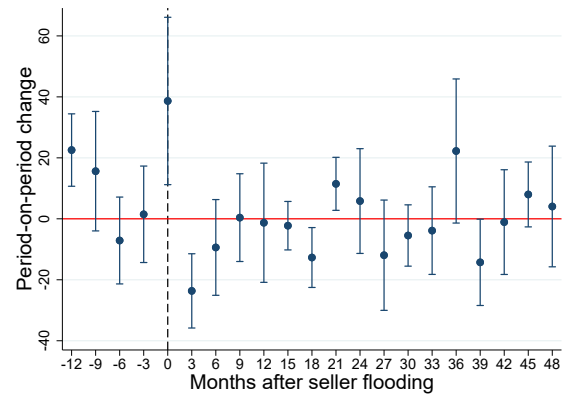


Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). We exclude electricity and gas producers from buyers and sellers. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10 km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure F.22. Dynamic impact of supplier and own flooding on flood risk of $\leq 5\%$ flooded suppliers (excl. electricity and gas)



(a) Own flooding



(b) Supplier flooding

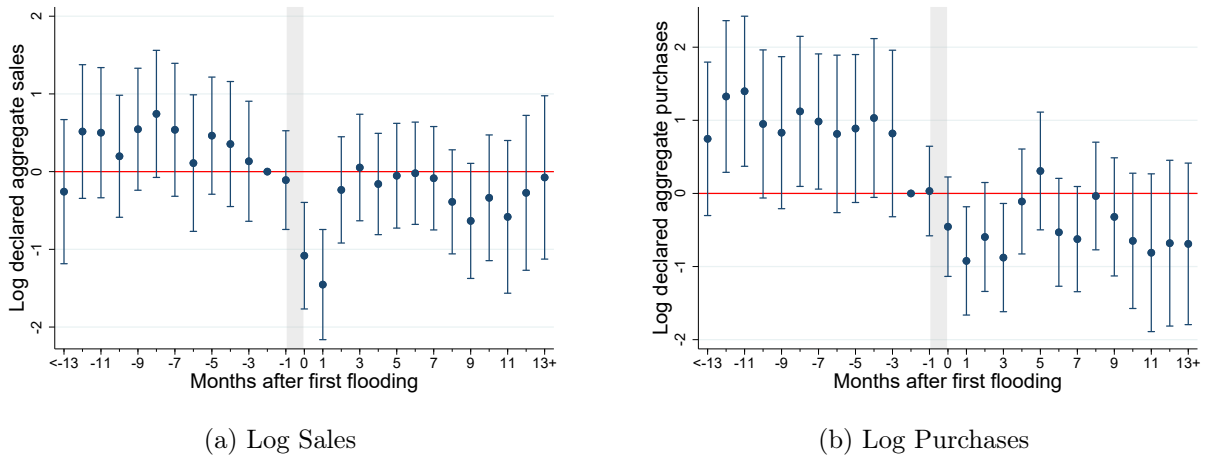
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). We exclude electricity and gas producers from buyers and sellers. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

F.3 Results excluding capital purchases

We next consider the robustness of results to excluding transactions involving capital goods, given that lumpy capital purchases are likely to be infrequent and may be less prone to flood-induced supply disruptions. To do so, we remove all transactions in which either the buyer or the seller has a primary product code which maps to a capital good, identified using Part I of the Fifth Schedule of the Customs Act ([Federal Board of Revenue of Pakistan, 2015](https://www.fbr.gov.pk/categ/customs-tariff/51149/70853/131188)).¹⁸

F.3.1 Impact of flooding on firm sales and purchases

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

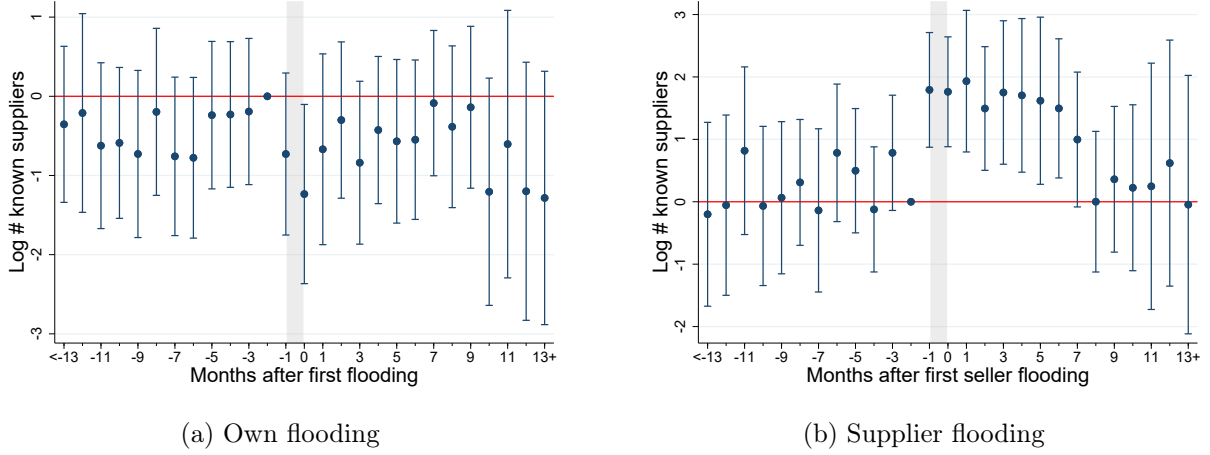


Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Observations are firm-month-years excluding firms transacting primarily in capital goods. The 95% confidence intervals rely on standard errors clustered at the firm-level.

¹⁸<https://www.fbr.gov.pk/categ/customs-tariff/51149/70853/131188>

F.3.2 Supplier diversification

Figure F.24. Impact of flooding on log number of suppliers (excl. capital purchases)



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

F.3.3 Supplier choice

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-9.747 (11.08)	-7.858 (8.936)	-16.55 (13.75)
Suppliers' max flood extent	-49.92*** (13.69)	-50.81*** (14.31)	-58.42*** (15.73)
Average effect of mean flooded supplier buffer in cm	-0.765	-0.778	-0.895
Average effect of 10% flooded supplier buffer in cm	-4.992	-5.081	-5.842
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0116	0.0323	0.0684
N	119,349	118,559	114,431

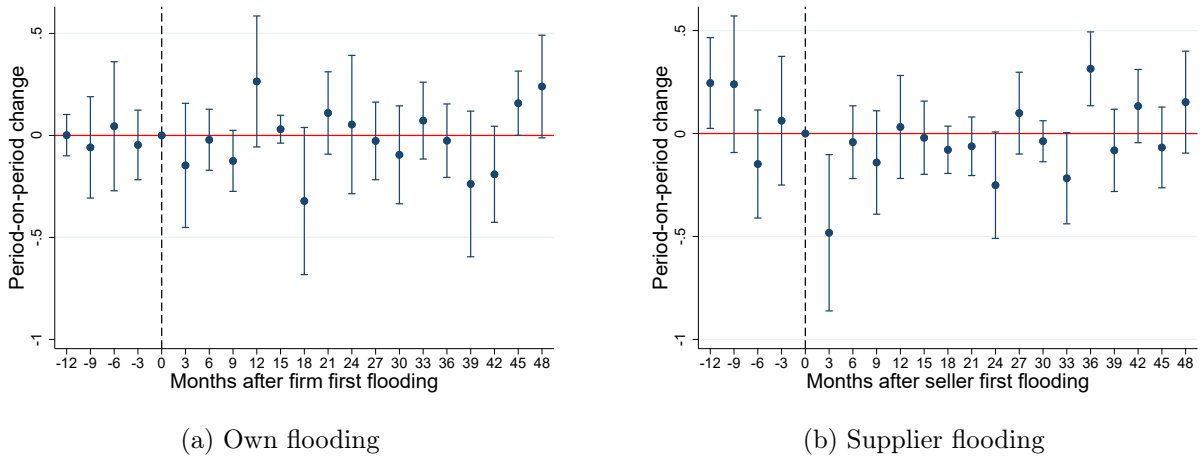
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-14.48 (11.49)	-10.40 (8.815)	-20.64 (14.16)
Suppliers' max flood extent	-19.49*** (7.540)	-17.14** (8.013)	-16.25* (9.386)
Average effect of mean flooded supplier buffer in cm	-0.299	-0.263	-0.249
Average effect of 10% flooded supplier buffer in cm	-1.949	-1.714	-1.625
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0105	0.0329	0.0693
N	119,218	118,428	114,308

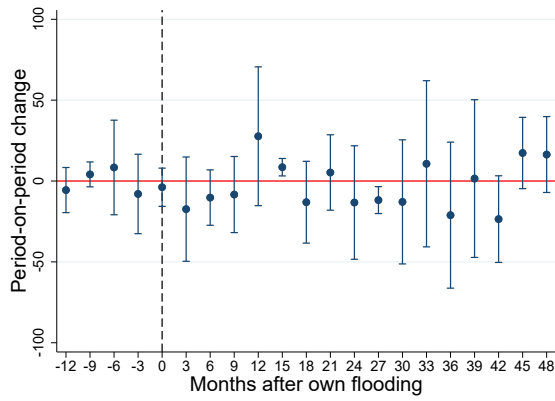
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

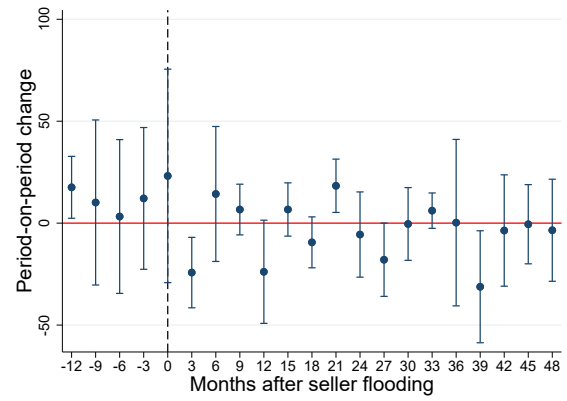


Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). We exclude firms primarily transacting in capital goods from buyers and sellers. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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



(a) Own flooding



(b) Supplier flooding

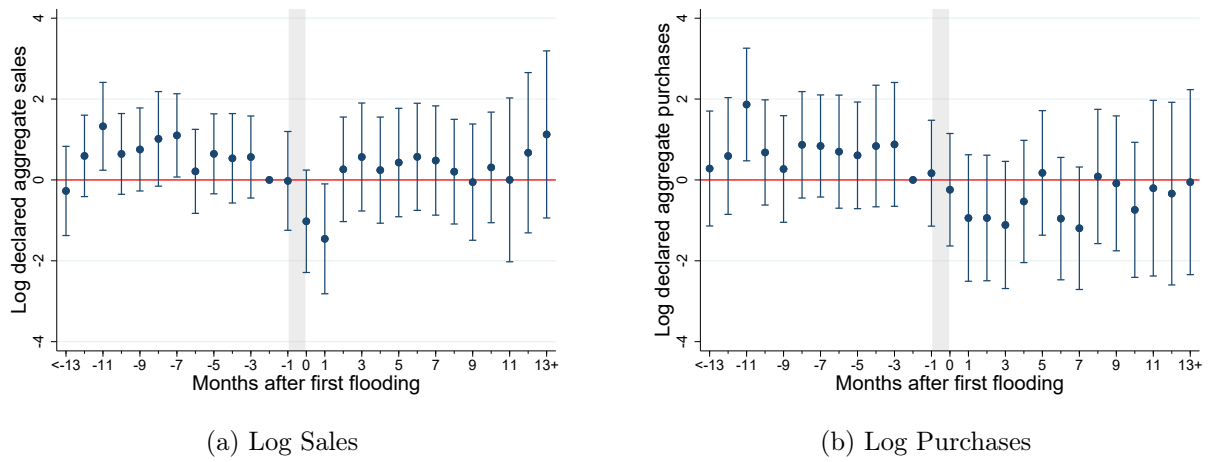
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). We exclude firms primarily transacting in capital goods from buyers and sellers. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

F.4 Results using manufacturing firms

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

F.4.1 Impact of flooding on firm sales and purchases

Figure F.27. Impact of flooding on firm sales and purchases (manufacturing sample)



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

F.4.2 Firm location

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

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	2.840** (1.199)	3.482*** (1.025)	-129.4 (91.77)	-11.48 (48.74)
District FE	Yes		Yes	
District $\times$ Fathom 1 in 100 FE			Yes	
R^2	0.040	0.061	0.114	0.438
N	17,425	17,124	3,516	3,414

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

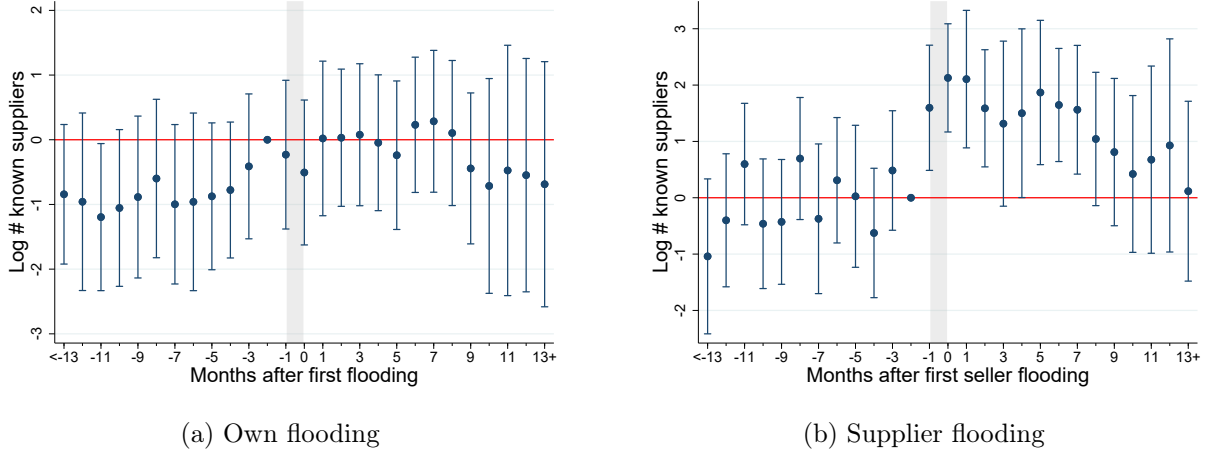
Table F.8. Impact of destination flood history on relocation flows (manufacturing)

	Number of Firms Moved
Dest. flooded 12mo prior	-1.120*** (0.318)
Origin $\times$ Destination FE	Yes
Origin $\times$ Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10 km
N	872

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

F.4.3 Supplier diversification

Figure F.28. Impact of flooding on log number of suppliers (manufacturing sample)



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

F.4.4 Supplier choice

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	14.56*** (5.473)	12.62** (5.523)	16.87** (7.863)
Suppliers' max flood extent	-67.78*** (12.53)	-67.86*** (13.03)	-67.03*** (12.61)
Average effect of mean flooded supplier buffer in cm	-1.177	-1.179	-1.164
Average effect of 10% flooded supplier buffer in cm	-6.778	-6.786	-6.703
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0178	0.0469	0.0676
N	50,148	49,701	48,837

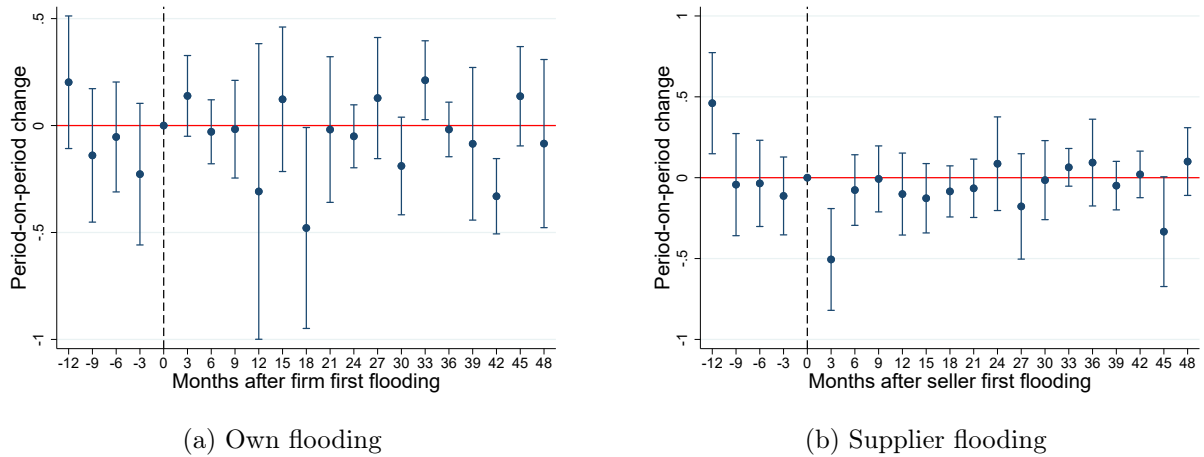
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. Standard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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	9.266 (7.421)	7.603 (7.951)	10.75 (9.109)
Suppliers' max flood extent	-20.64** (9.616)	-19.63** (9.508)	-18.72** (8.851)
Average effect of mean flooded supplier buffer in cm	-0.359	-0.341	-0.325
Average effect of 10% flooded supplier buffer in cm	-2.064	-1.963	-1.872
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0142	0.0436	0.0632
N	50,039	49,593	48,728

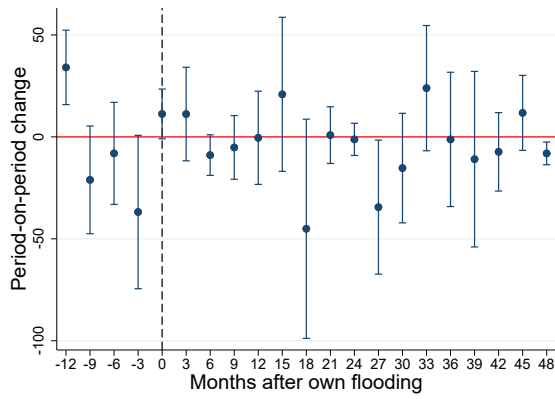
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

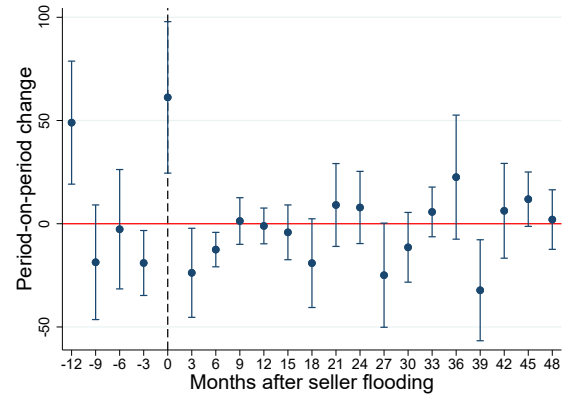


Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). We restrict buyers and sellers to manufacturing firms. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10 km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure F.30. Dynamic impact of supplier and own flooding on flood risk of $\leq 5\%$ flooded suppliers (manufacturing)



(a) Own flooding



(b) Supplier flooding

Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). We restrict buyers and sellers to manufacturing firms. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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

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

To the extent that buyer and seller reports of the same monthly-level transactions reflect strategic misreporting rather than random error, we expect the two parties to have conflicting incentives to misreport: while sellers will wish to understate their sales to reduce their VAT liability, the converse is true for buyers who will wish to overstate their purchases. Using the fact that we observe independent reports of pair-level monthly transactions from the buyer and seller, we can investigate the potential importance of such biases. In this robustness specification, we take an extremely stringent approach to ruling this out by restricting attention to cases where buyer and seller reports match exactly and as such where misreporting is highly unlikely.

F.5.1 Supplier choice

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	3.679 (9.845)	-3.610 (13.82)	6.065 (9.854)
Suppliers' max flood extent	-91.98*** (20.32)	-89.57*** (20.88)	-89.53*** (21.80)
Average effect of mean flooded supplier buffer in cm	-1.293	-1.260	-1.259
Average effect of 10% flooded supplier buffer in cm	-9.198	-8.957	-8.953
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0108	0.0307	0.0615
N	82,610	82,004	79,567

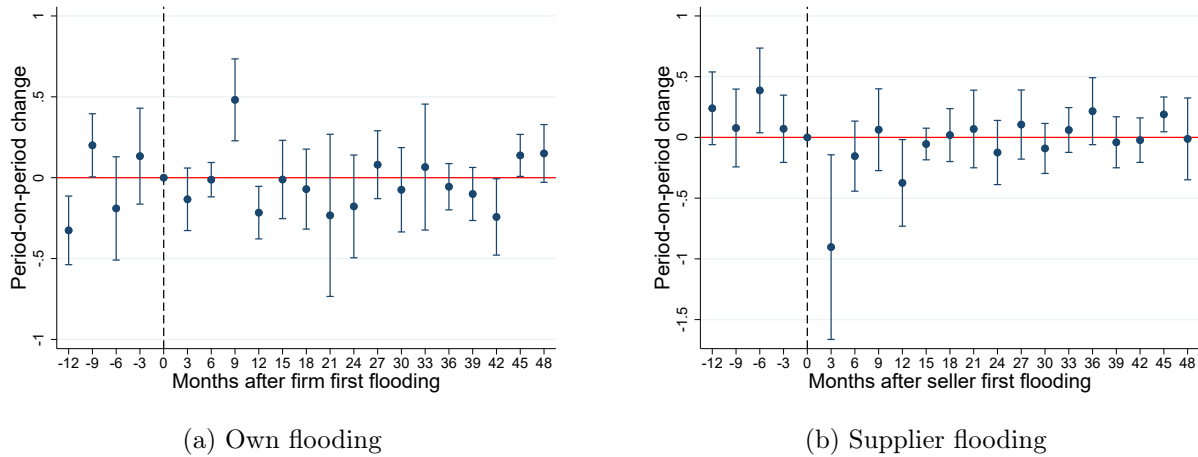
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	3.807 (7.603)	0.595 (10.84)	4.396 (8.596)
Suppliers' max flood extent	-37.96*** (10.70)	-34.77*** (10.88)	-34.20*** (11.16)
Average effect of mean flooded supplier buffer in cm	-0.534	-0.489	-0.481
Average effect of 10% flooded supplier buffer in cm	-3.796	-3.477	-3.420
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0079	0.0287	0.0597
N	82,484	81,879	79,446

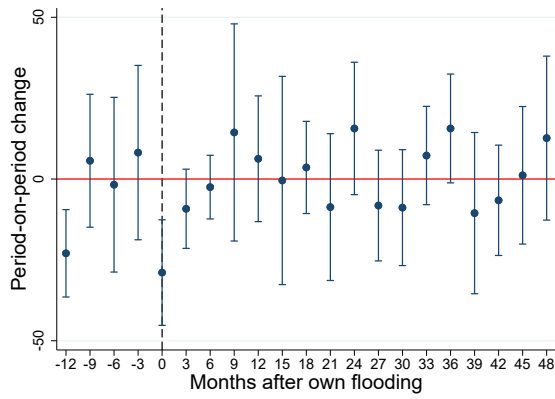
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

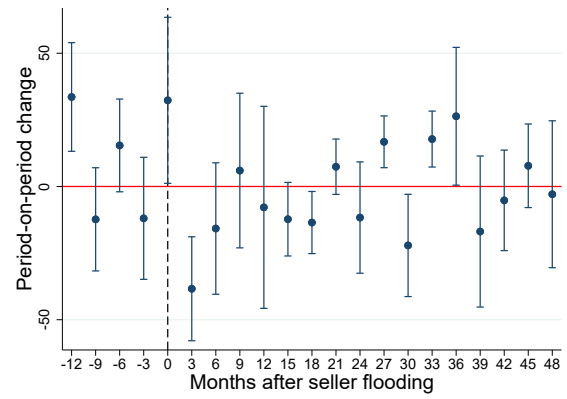


Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). We restrict attention to transactions for which buyer and seller reports coincide precisely. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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



(a) Own flooding



(b) Supplier flooding

Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). We restrict attention to transactions for which buyer and seller reports coincide precisely. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

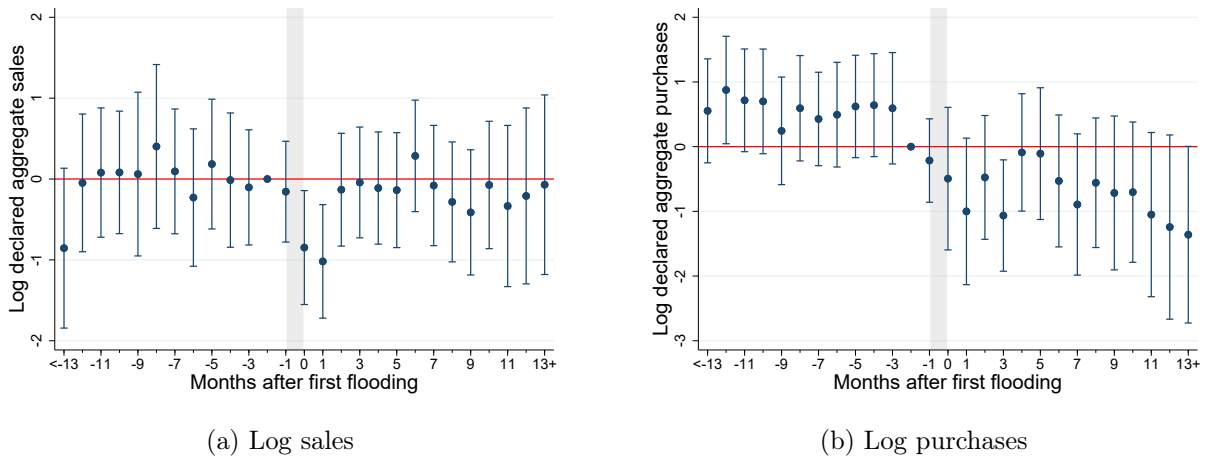
F.6 Firm buffers with 1km and 3km radii

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

F.6.1 Impact of flooding on firm sales and purchases

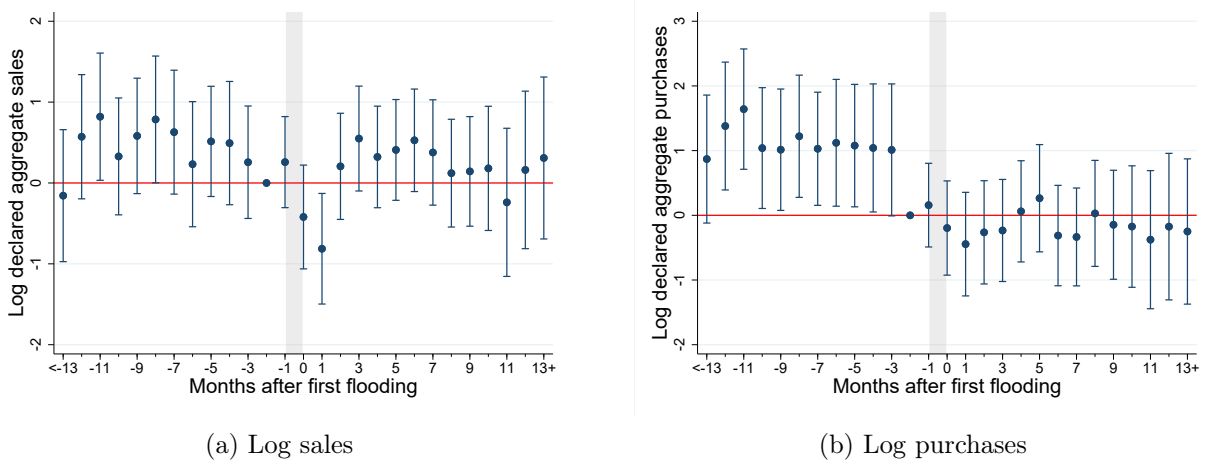
F.6.2 Impact of flooding on firm sales and purchases

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



Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Here, we use a 1km buffer around the firm to define the treatment (share of firm buffer flooded) instead of the standard 2km buffer. The unit of observation is a firm-month-year. The 95% confidence intervals rely on standard errors clustered at the firm-level.

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



Notes: The panels plot OLS estimates of the effect of flooding on log declared sales and purchases as specified in equation (1). Here, we use a 3km buffer around the firm to define the treatment (share of firm buffer flooded) instead of the standard 2km buffer. The unit of observation is a firm-month-year. The 95% confidence intervals rely on standard errors clustered at the firm-level.

F.6.3 Firm location

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

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 1km buffer flooded	3.410*** (0.829)	4.005*** (0.848)	-104.1** (41.23)	-48.21** (22.35)
District FE	Yes		Yes	
District $\times$ Fathom 1 in 100 FE			Yes	Yes
R^2	0.034	0.052	0.082	0.446
N	43,847	43,419	7,474	7,330

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

Table F.14. Impact of destination flood history on relocation flows (1km buffer)

	Number of Firms Moved
Dest. flooded 12mo prior	-1.158*** (0.340)
Origin $\times$ Destination FE	Yes
Origin $\times$ Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10 km
N	1,074

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

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

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 3km buffer flooded	2.930*** (0.950)	3.477*** (0.933)	-247.6 (158.1)	-43.98 (40.20)
District FE	Yes		Yes	
District $\times$ Fathom 1 in 100 FE			Yes	Yes
R^2	0.033	0.053	0.101	0.451
N	43,847	43,554	7,474	7,343

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

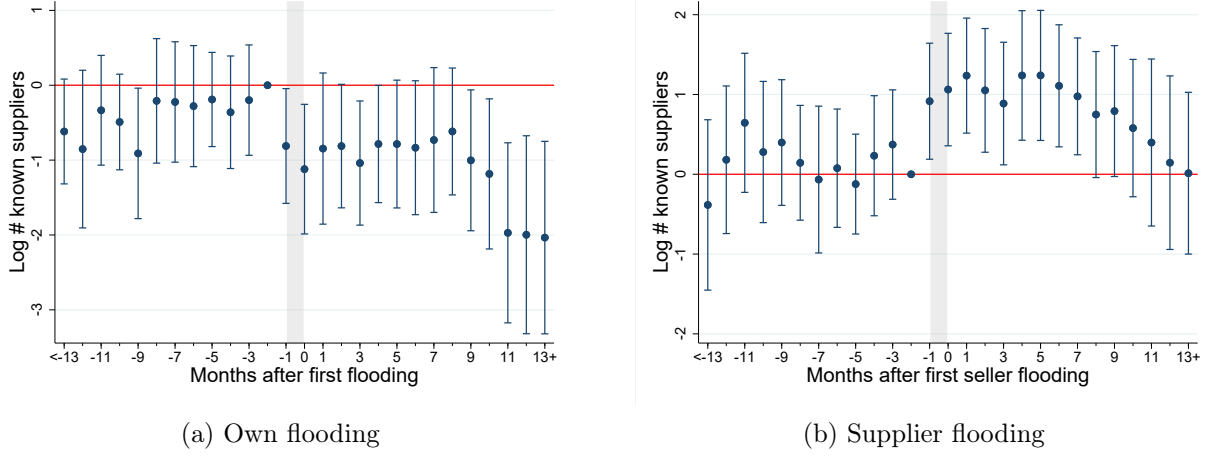
Table F.16. Impact of destination flood history on relocation flows (3km buffer)

	Number of Firms Moved
Dest. flooded 12mo prior	-0.938*** (0.266)
Origin $\times$ Destination FE	Yes
Origin $\times$ Flood Event (month) FE	Yes
Flood Event of Destination FE	Yes
Move Distance Restriction	>10 km
N	1,946

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

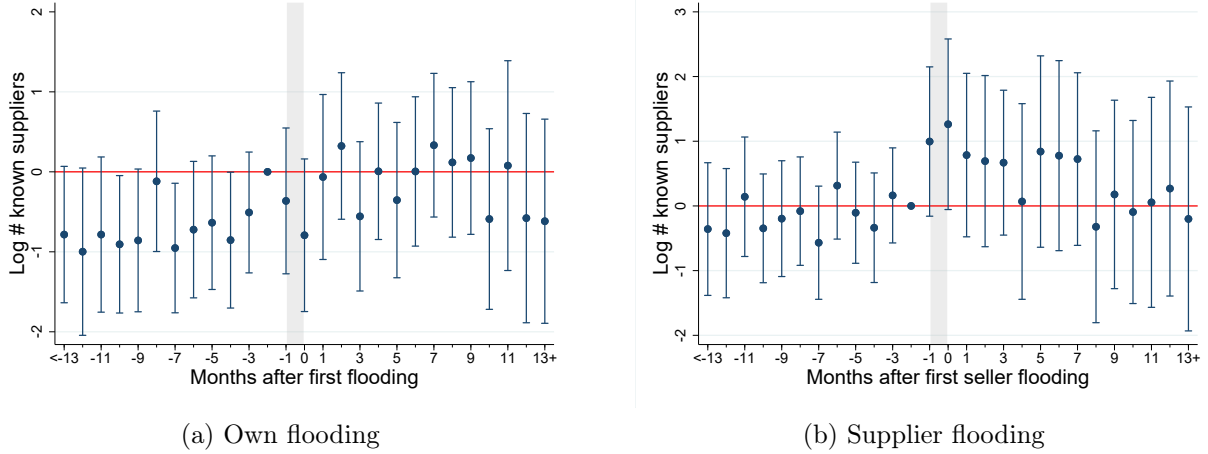
F.6.4 Supplier diversification

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



Notes: Panels (a) and (b) plot OLS estimates of the effect of own flooding and supplier flooding on the log number of suppliers following equations (6) and (7), respectively. Here, we use a 1km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. Observations are firm-month-years whose 2011 and 2019 addresses are known and ≤ 10 km apart. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

Figure F.36. Supplier Diversification: Impact of flooding on log number of suppliers (3km buffer)



Notes: Panels (a) and (b) plot OLS estimates of the effect of own flooding and supplier flooding on the log number of suppliers following equations (6) and (7), respectively. Here, we use a 3km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. Observations are firm-month-years whose 2011 and 2019 addresses are known and ≤ 10 km apart. We restrict attention to transactions for which buyer and seller reports coincide precisely. The 95% confidence intervals rely on standard errors clustered at the firm-level.

F.6.5 Supplier choice

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-2.922 (7.011)	-3.473 (7.819)	-4.099 (7.855)
Suppliers' max flood extent	-30.88*** (6.854)	-32.92*** (6.291)	-39.94*** (6.314)
Average effect of mean flooded supplier buffer in cm	-0.587	-0.626	-0.760
Average effect of 10% flooded supplier buffer in cm	-3.088	-3.292	-3.994
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0113	0.0313	0.0661
N	137,957	137,175	132,854

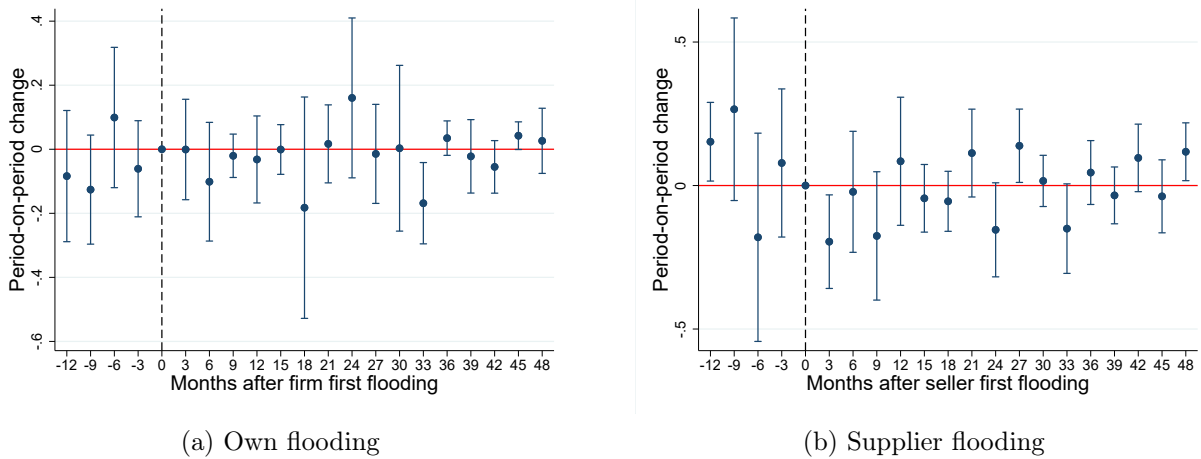
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-7.725 (8.049)	-9.178 (8.338)	-8.186 (8.161)
Suppliers' max flood extent	-9.546 (7.374)	-10.36 (7.639)	-7.595 (7.863)
Average effect of mean flooded supplier buffer in cm	-0.182	-0.197	-0.144
Average effect of 10% flooded supplier buffer in cm	-0.955	-1.036	-0.759
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0102	0.0304	0.0639
N	137,879	137,098	132,781

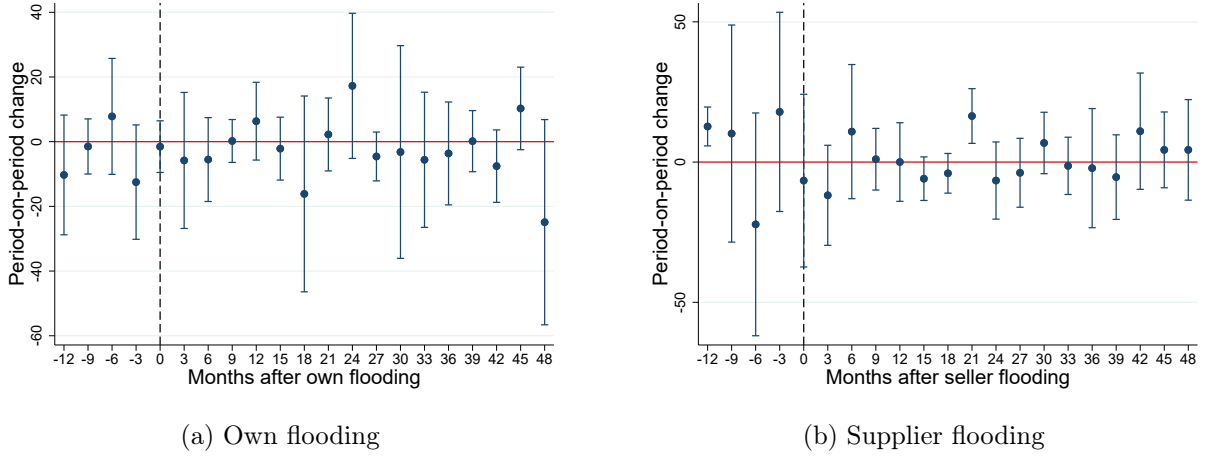
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 1km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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



Notes: The panel plots OLS estimates of the effect of supplier flooding on the change in suppliers' sales-weighted average flood risk following equation (10). Here, we use a 1km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. Observations are all firm-year-months for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure F.38. Dynamic impact of supplier and own flooding on flood risk of $\leq 5\%$ flooded suppliers (1km buffer)



Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). Here, we use a 1km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-4.625 (10.44)	-11.08 (8.462)	-5.953 (13.12)
Suppliers' max flood extent	-73.76*** (24.69)	-75.47*** (25.75)	-87.82*** (28.76)
Average effect of mean flooded supplier buffer in cm	-0.800	-0.819	-0.953
Average effect of 10% flooded supplier buffer in cm	-7.376	-7.547	-8.782
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0113	0.0254	0.0594
N	137,957	137,232	132,854

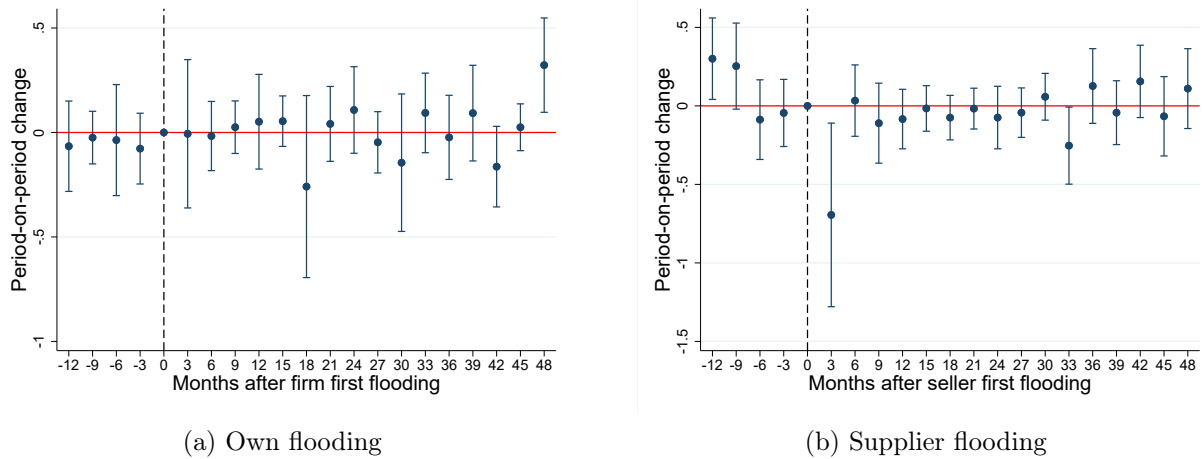
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. Standard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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-10.81 (9.748)	-14.49 (8.842)	-12.62 (11.65)
Suppliers' max flood extent	-41.70*** (10.49)	-40.74*** (10.47)	-42.09*** (11.65)
Average effect of mean flooded supplier buffer in cm	-0.452	-0.442	-0.457
Average effect of 10% flooded supplier buffer in cm	-4.170	-4.074	-4.209
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0089	0.0242	0.0575
N	137,728	137,003	132,628

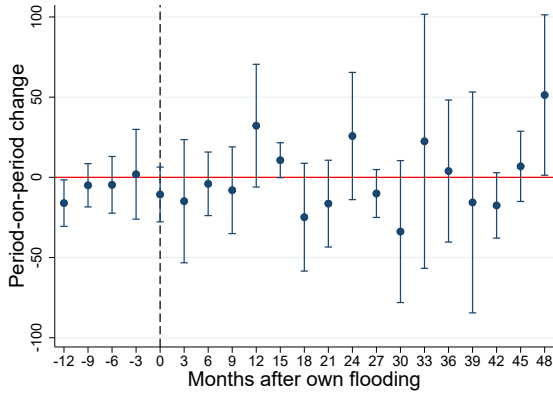
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 3km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

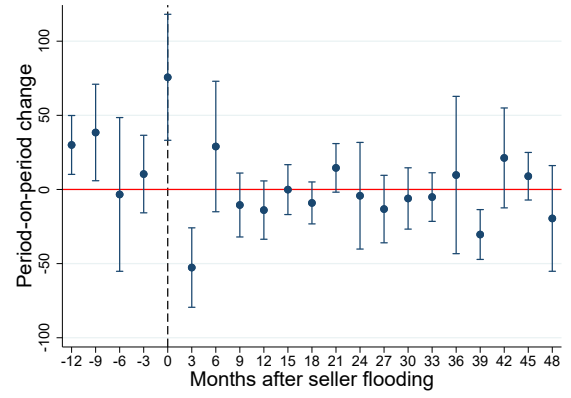


Notes: The panel plots OLS estimates of the effect of supplier flooding on the change in suppliers' sales-weighted average flood risk following equation (10). Here, we use a 3km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. Observations are all firm-year-months for which the 2011 and 2019 addresses are known and ≤ 10 km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

Figure F.40. Dynamic impact of supplier and own flooding on flood risk of $\leq 5\%$ flooded suppliers (3km buffer)



(a) Own flooding



(b) Supplier flooding

Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). Here, we use a 3km buffer around the firm to define the treatment (share of firm own/supplier buffer flooded) instead of the standard 2km buffer. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

F.7 Floods with return periods of 1 in 10 years and 1 in 50 years

Our central results relating to flood risk consider the combined fluvial and pluvial flood risk, measured as the expected flood depth in each location associated with a 1 in 100 year flood. This represents the most expansive definition of flood risk captured by the Fathom flood risk data, as can be seen by comparing Panel (c) of Figure 1 with both panels in Figure A.3. In this section we demonstrate the robustness of results to measuring flood risk in relation to 1 in 10 year floods or 1 in 50 year floods.

F.7.1 Firm location

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

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	2.504*** (0.845)	2.612*** (0.682)	-140.6 (99.37)	-30.71 (54.19)
District FE	Yes		Yes	
District $\times$ Fathom 1 in 10 FE			Yes	
R^2	0.033	0.050	0.055	0.397
N	43,847	43,676	7,474	7,413

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

Table F.22. Impact of flooding on firm relocation and location flood risk (1 in 50 year return period)

	Move Dummy		Δ Flood Risk (cm)	
	(1)	(2)	(3)	(4)
Max share of 2km buffer flooded	2.504*** (0.845)	2.835** (1.196)	-184.1 (112.7)	-38.20 (56.42)
District FE	Yes		Yes	
District $\times$ Fathom 1 in 50 FE		Yes		Yes
R^2	0.033	0.054	0.086	0.432
N	43,847	43,549	7,474	7,329

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

F.7.2 Supplier choice

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-4.288 (6.030)	-3.398 (5.753)	-5.049 (7.647)
Suppliers' max flood extent	-39.98*** (15.15)	-41.64*** (15.67)	-48.11*** (18.10)
Average effect of mean flooded supplier buffer in cm	-0.592	-0.617	-0.713
Average effect of 10% flooded supplier buffer in cm	-3.998	-4.164	-4.811
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE		Yes	
Time $\times$ District $\times$ Industry FE			Yes
R^2	0.0075	0.0163	0.0570
N	137,957	137,660	132,854

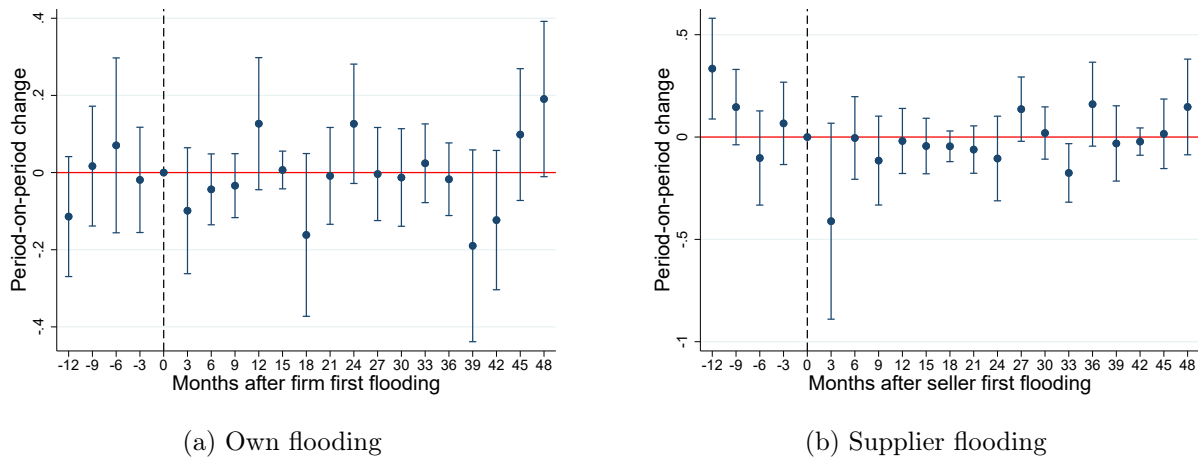
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-8.094 (5.723)	-5.232 (5.299)	-9.156 (6.980)
Suppliers' max flood extent	-22.73*** (7.364)	-23.32*** (7.245)	-23.38*** (7.945)
Average effect of mean flooded supplier buffer in cm	-0.337	-0.346	-0.346
Average effect of 10% flooded supplier buffer in cm	-2.273	-2.332	-2.338
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0063	0.0151	0.0572
N	137,822	137,522	132,724

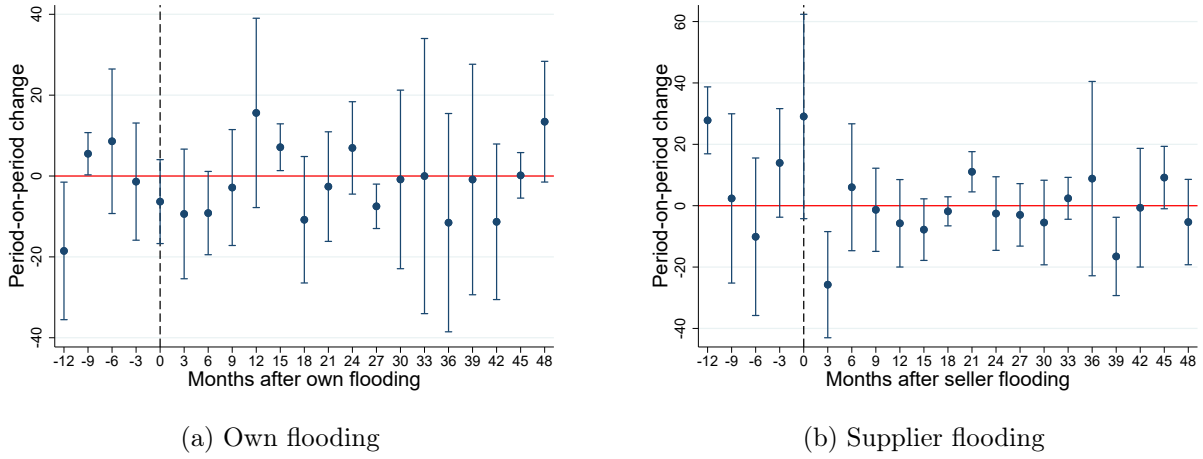
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 10 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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



Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Here, flood risk is measured for a 1 in 10 instead of a 1 in 100 year return period. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10 km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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



Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). Here, flood risk is measured for a 1 in 10 instead of a 1 in 100 year return period. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-7.761 (8.867)	-7.652 (7.328)	-11.11 (10.98)
Suppliers' max flood extent	-53.18*** (16.25)	-55.87*** (16.96)	-63.85*** (19.04)
Average effect of mean flooded supplier buffer in cm	-0.788	-0.828	-0.946
Average effect of 10% flooded supplier buffer in cm	-5.318	-5.587	-6.385
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0101	0.0269	0.0595
N	137,957	137,237	132,854

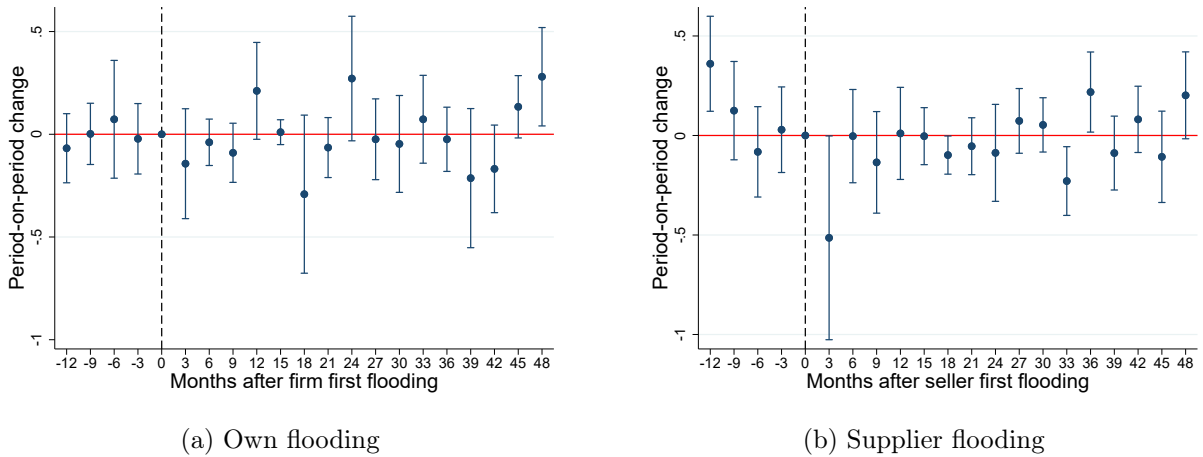
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. Standard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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-12.90 (8.993)	-10.22 (7.233)	-16.81 (11.11)
Suppliers' max flood extent	-24.01*** (8.955)	-25.26*** (8.620)	-22.93** (9.747)
Average effect of mean flooded supplier buffer in cm	-0.356	-0.374	-0.340
Average effect of 10% flooded supplier buffer in cm	-2.401	-2.526	-2.293
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0081	0.0259	0.0586
N	137,822	137,105	132,724

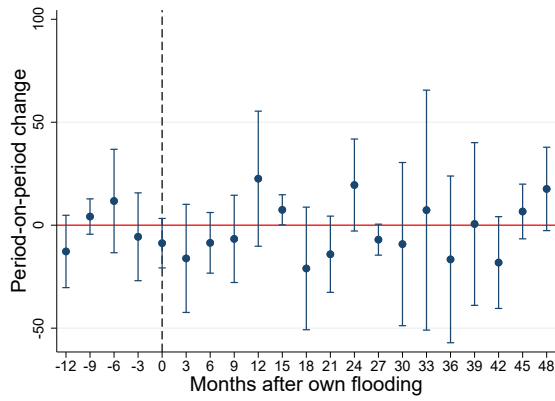
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 50 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

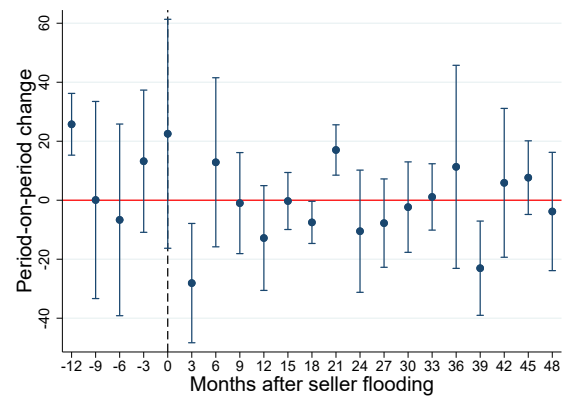


Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Here, flood risk is measured for a 1 in 50 instead of a 1 in 100 year return period. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10 km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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



(a) Own flooding



(b) Supplier flooding

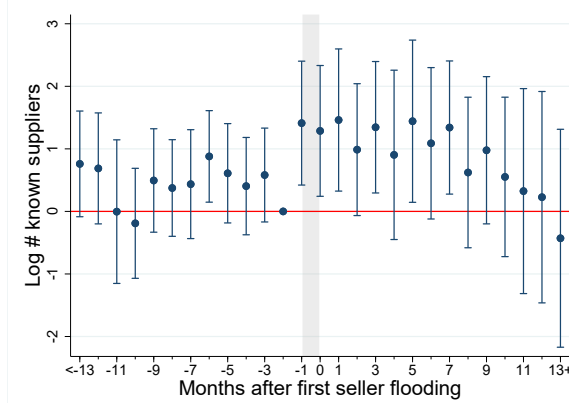
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). Here, flood risk is measured for a 1 in 50 instead of a 1 in 100 year return period. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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

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

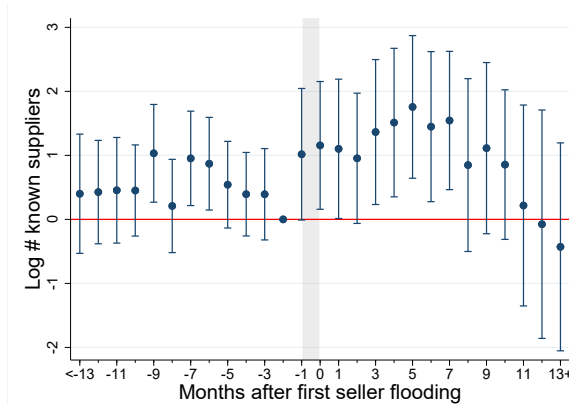
F.8.1 Supplier diversification

Figure F.45. Impact of supplier flooding on log number of suppliers (6-month window)



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

Figure F.46. Impact of supplier flooding on log number of suppliers (12-month window)



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

F.8.2 Supplier choice

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-0.608 (8.239)	-6.471 (7.047)	-3.749 (10.16)
Suppliers' max flood extent	-60.95*** (13.17)	-62.54*** (13.61)	-70.85*** (14.78)
Average effect of mean flooded supplier buffer in cm	-0.919	-0.944	-1.069
Average effect of 10% flooded supplier buffer in cm	-6.095	-6.254	-7.085
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0108	0.0290	0.0568
N	148,108	147,329	142,686

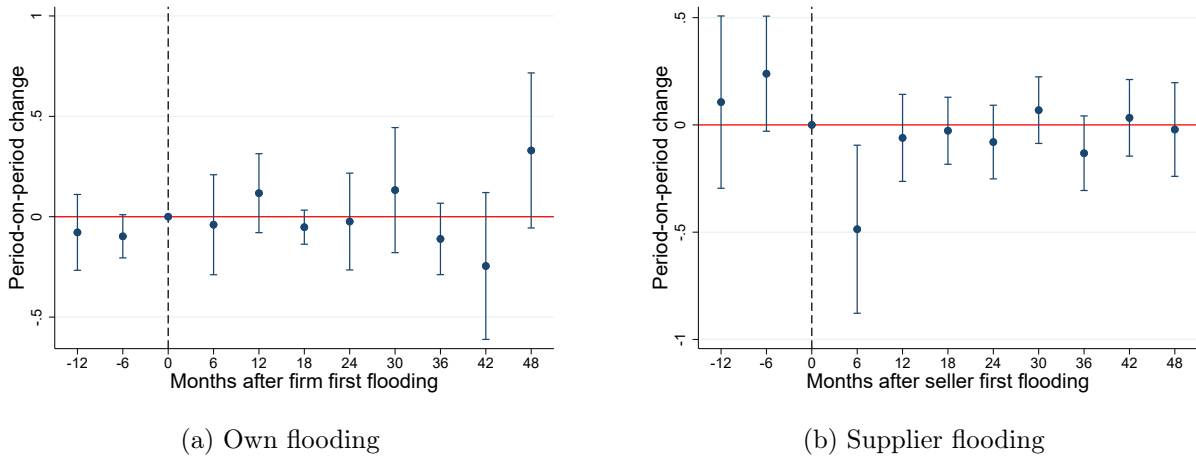
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-7.147 (8.712)	-5.614 (7.989)	-8.937 (11.36)
Suppliers' max flood extent	-28.26*** (9.152)	-27.41*** (9.044)	-29.32*** (9.554)
Average effect of mean flooded supplier buffer in cm	-0.426	-0.413	-0.442
Average effect of 10% flooded supplier buffer in cm	-2.826	-2.741	-2.932
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0085	0.0280	0.0552
N	147,984	147,205	142,568

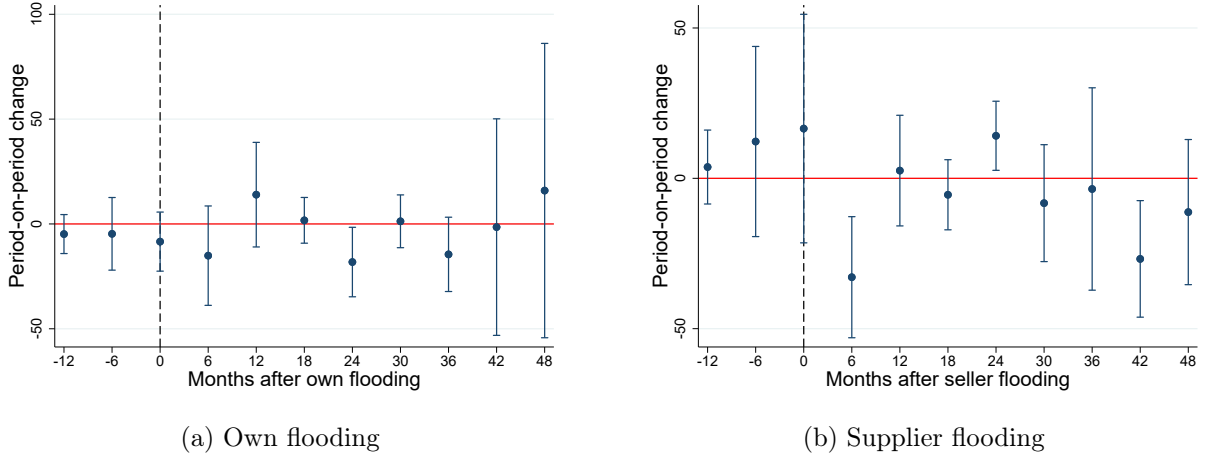
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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



Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Here, we use a 6 instead of a 3-month window to define suppliers. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10 km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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



Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). Here, we use a 6 instead of a 3-month window to define suppliers. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	2.248 (6.632)	-5.583 (5.361)	2.066 (7.389)
Suppliers' max flood extent	-58.21*** (11.25)	-60.89*** (11.59)	-69.07*** (12.87)
Average effect of mean flooded supplier buffer in cm	-0.862	-0.901	-1.023
Average effect of 10% flooded supplier buffer in cm	-5.821	-6.089	-6.907
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0107	0.0274	0.0563
N	157,166	156,383	151,470

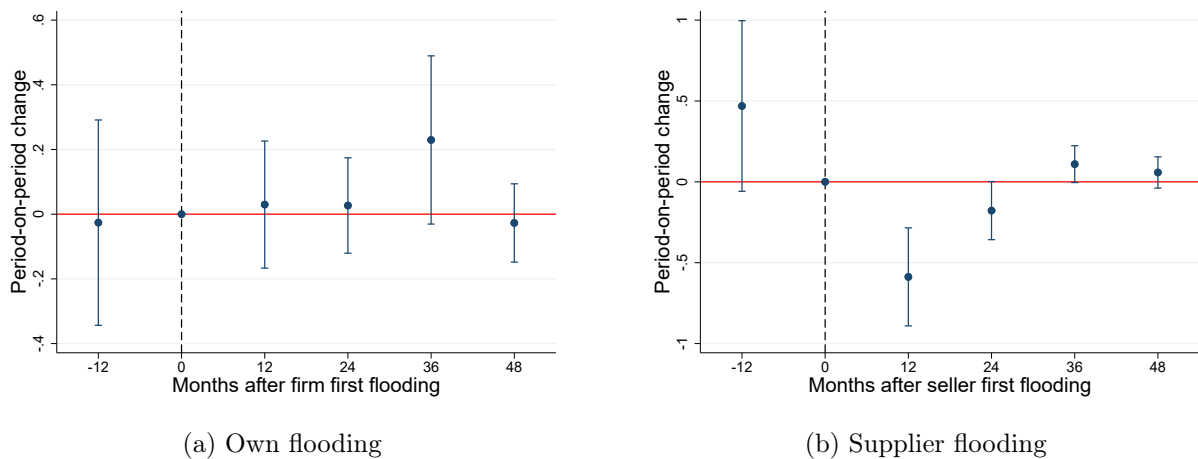
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. Standard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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-15.71** (6.958)	-20.58*** (7.076)	-17.98** (8.833)
Suppliers' max flood extent	-42.86*** (8.464)	-45.00*** (8.575)	-45.13*** (8.769)
Average effect of mean flooded supplier buffer in cm	-0.613	-0.643	-0.645
Average effect of 10% flooded supplier buffer in cm	-4.286	-4.500	-4.513
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0084	0.0265	0.0569
N	124,944	124,193	119,893

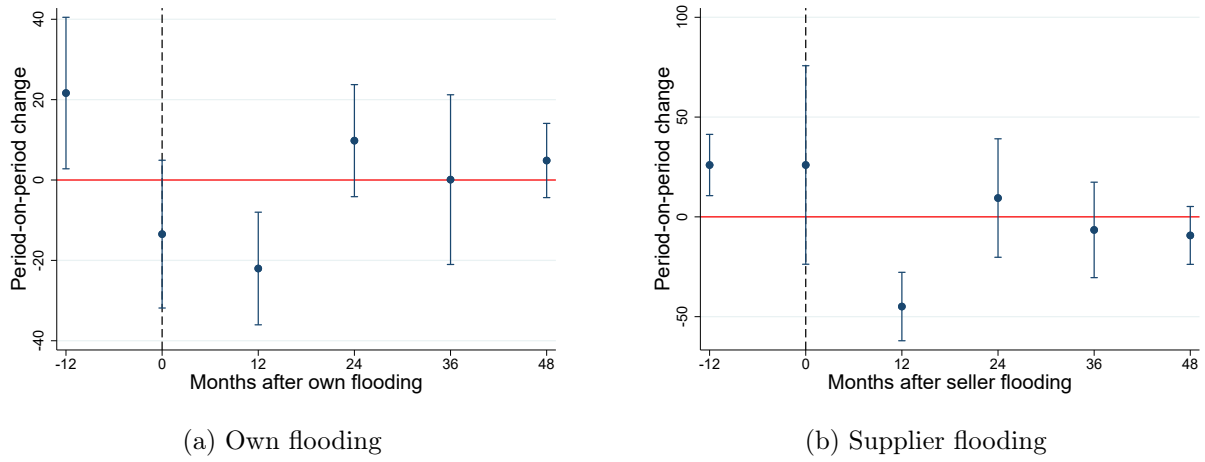
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known and ≤ 10 km apart. We exclude all firms which are flooded or have any supplier flooded in a different event during the flood risk windows. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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



Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Here, we use a 12 instead of a 3-month window to define suppliers. Observations are firm-year-month pairs for which the 2011 and 2019 addresses are known and ≤ 10 km apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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



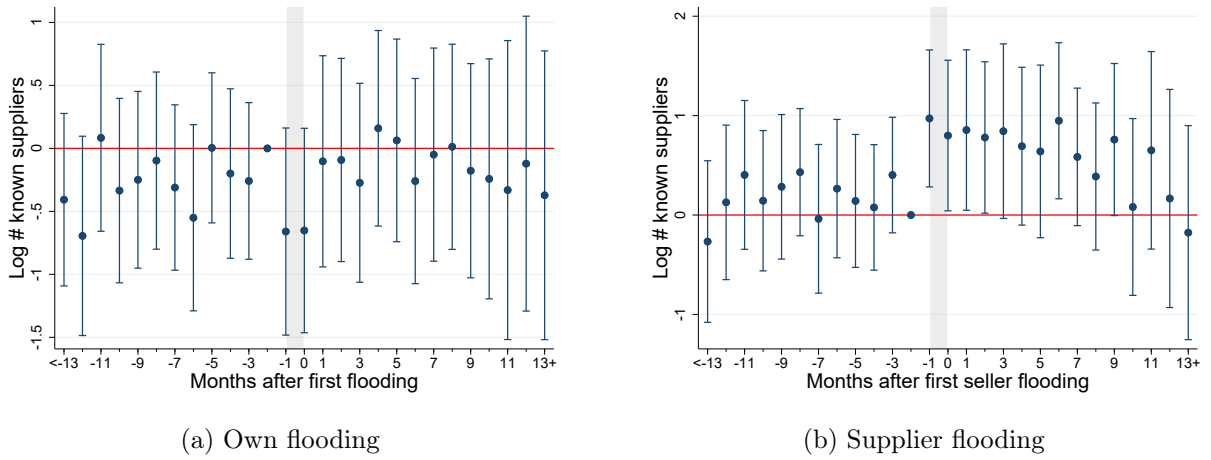
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). Here, we use a 12 instead of a 3-month window to define suppliers. Observations are firm-by-flood-year-month pairs for which the 2011 and 2019 addresses are known and $\leq 10\text{km}$ apart. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

F.9 Results including moving firms

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

F.9.1 Supplier diversification

Figure F.51. Supplier Diversification: Impact of flooding on log number of suppliers (incl. movers)



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

F.9.2 Supplier choice

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-4.178 (4.381)	-6.571 (4.029)	-3.092 (4.662)
Suppliers' max flood extent	-50.38*** (14.27)	-51.44*** (14.58)	-62.80*** (15.53)
Average effect of mean flooded supplier buffer in cm	-0.756	-0.772	-0.942
Average effect of 10% flooded supplier buffer in cm	-5.038	-5.144	-6.280
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0094	0.0267	0.0540
N	217,306	216,561	209,002

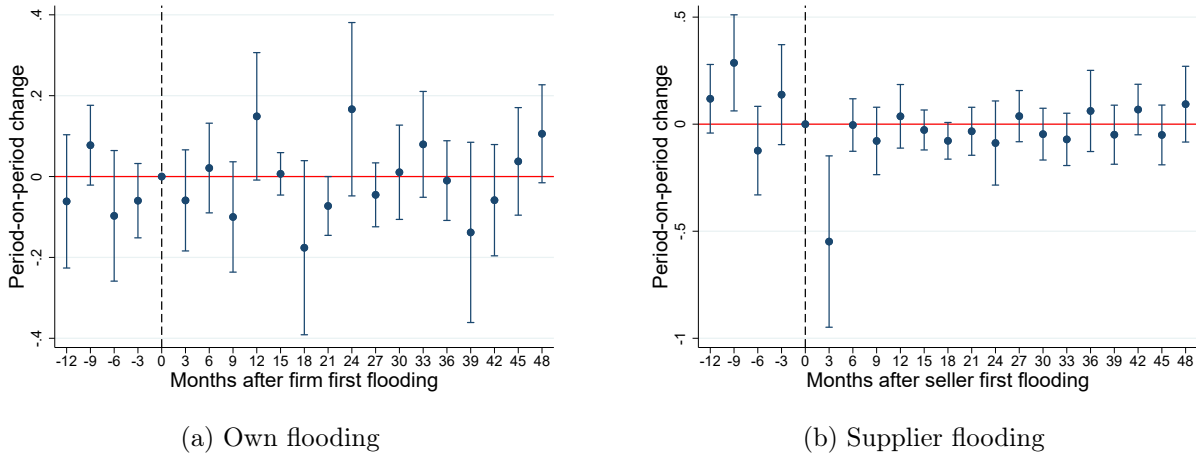
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among all suppliers. Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known. Standard errors (in parentheses) are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

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

	Δ Supplier Flood Risk (cm)		
	(1)	(2)	(3)
Own max flood extent	-4.958 (4.620)	-6.530 (4.106)	-4.191 (4.910)
Suppliers' max flood extent	-22.29*** (7.518)	-22.11*** (7.252)	-24.70*** (7.565)
Average effect of mean flooded supplier buffer in cm	-0.334	-0.332	-0.371
Average effect of 10% flooded supplier buffer in cm	-2.229	-2.211	-2.470
Time $\times$ District FE	Yes		
Time $\times$ District $\times$ Risk decile FE	Yes		
Time $\times$ District $\times$ Industry FE	Yes		
R^2	0.0078	0.0268	0.0534
N	217,034	216,296	208,735

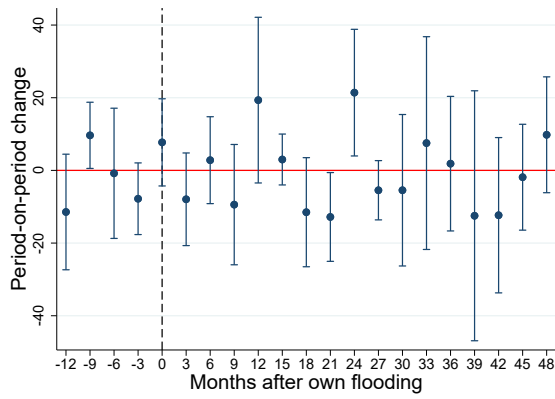
Notes: The table reports OLS estimates following equation (8) of the effects of supplier and own flooding on the change in sales-weighted average flood risk among suppliers that are not flooded (defined as $\leq 5\%$ overlap of the 2km buffer and the flood polygon). Observations are firm-by-flood-year-month pairs whose 2011 and 2019 addresses are known. Standard errors (in parentheses) are clustered at the time $\times$ district level. Effect of mean (10%) flooded supplier buffer refers to the estimated effect of a firm experiencing average, across treated firms in the estimation sample, (10%) supplier flooding. Risk decile indicates the decile of a firms's own flood risk for a 1 in 100 year return period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

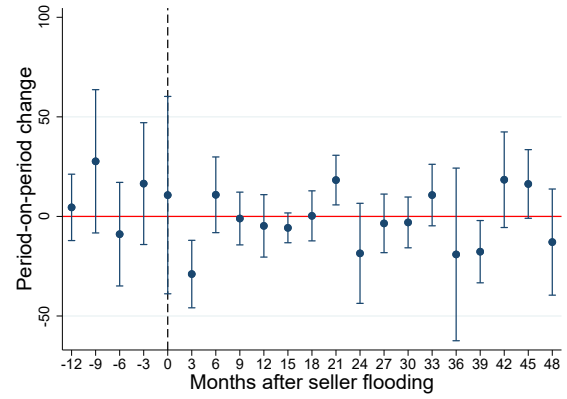


Notes: The panel plots estimates of the effect of supplier flooding on the change in sales-weighted average flood risk among all suppliers following equation (10). Observations are firm-year-month pairs. Here, this includes relocating firms. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

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



(a) Own flooding



(b) Supplier flooding

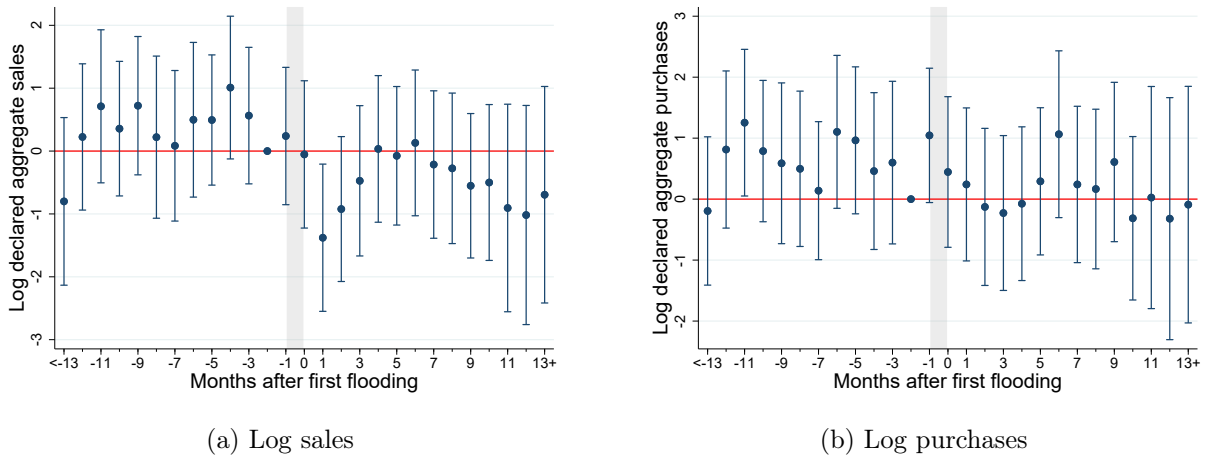
Notes: plots OLS estimates of a sequence of separate regressions examining the impact of supplier and own flooding on the sales-weighted average flood risk among suppliers flooded by $\leq 5\%$ following equation (2). Observations are firm-by-flood-year-month pairs. Here, this includes relocating firms. The 95% confidence intervals rely on standard errors clustered at the time $\times$ district level.

F.10 Results excluding repeated exposures

In the standard event studies, we consider a firm treated at the intensity of its first treatment in all periods following this first treatment. Given that treatment in a subsequent flood event could affect estimates for later treatment lags, in this section we present event study results restricting attention to firms which are either never treated or treated only in one flood event. For the two-month flood events (Aug-Sep 2011 and Jul-Aug 2015), we define event time relative to the first month of the event.

F.10.1 Impact of flooding on firm sales and purchases

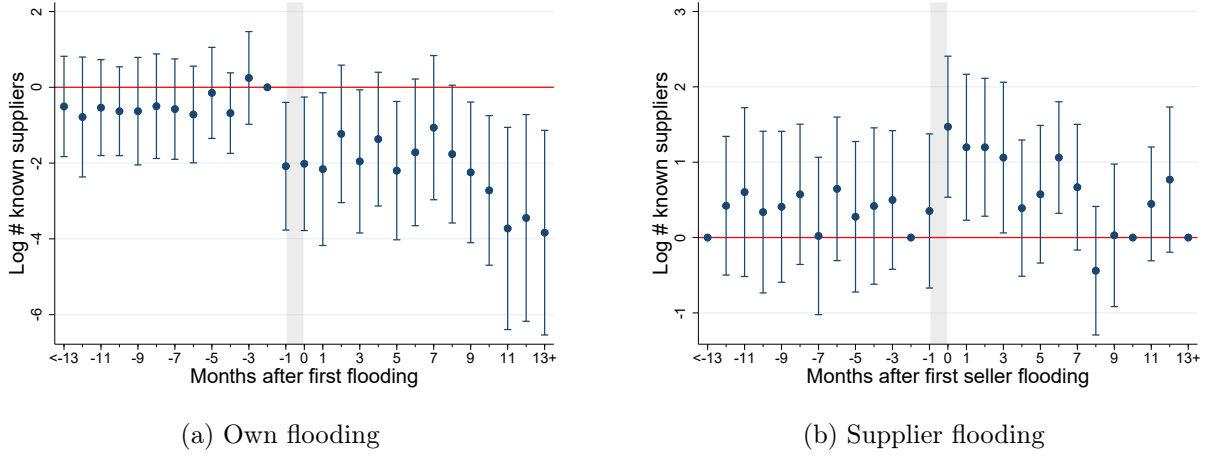
Figure F.54. Impact of flooding on firm sales and purchases (excl. repeated exposures)



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

F.10.2 Supplier diversification

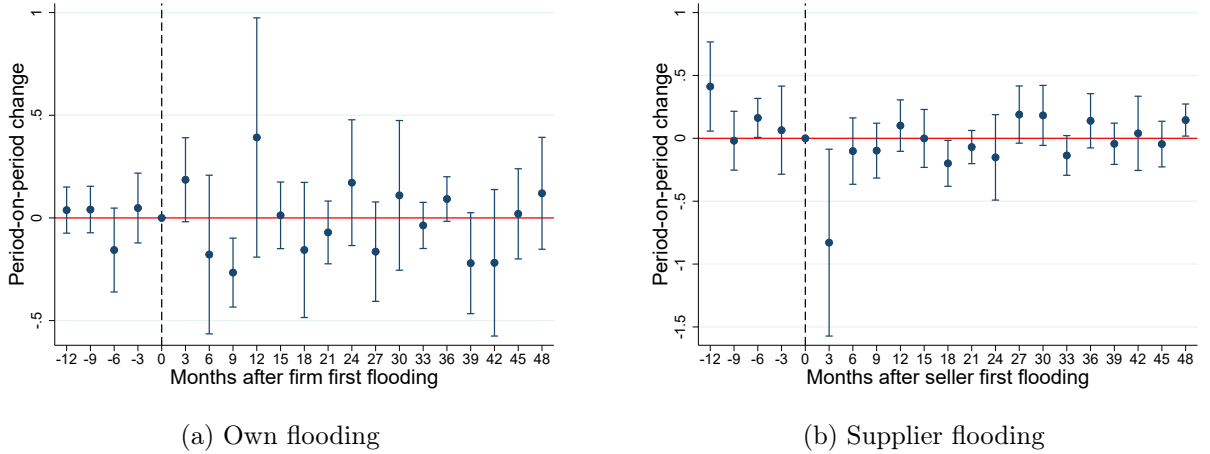
Figure F.55. Supplier Diversification: Impact of flooding on log number of suppliers (excl. repeated exposures)



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

F.10.3 Supplier choice

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



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

F.11 Robustness of route-level flooding impacts

Table F.33. Impact of route-level flooding on probability of relationship being active

	Dependent variable: $\mathbf{1}(\text{Sales}_{bst})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$(\text{Shortest Path Flooded})_{bst} \times \text{Post}_t$	-0.008*** (0.001)	-0.010*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.006*** (0.001)	-0.010*** (0.002)	-0.007*** (0.002)
Years since first sale FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seller-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-Seller FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Baseline	NonMan	Cap	CV Only	Mov	2015 Only	1 Exposure
N	10,023,417	30,709,619	9,743,633	9,221,869	26,889,233	10,023,417	7,194,920
R^2	0.547	0.559	0.553	0.508	0.536	0.547	0.563

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

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