Erin Grela

Beyond Local Exposure: Network-Driven Impacts of Floods in Informal Economies

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My research lies at the intersection of development and environmental economics, with a particular interest in how the structure of developing economies shapes the incidence of climate shocks and the possibilities for adaptation. My main dissertation project studies the propagation of flood shocks through informal economic networks in Indonesia. A large literature has shown that shocks can propagate through production networks in formal economies. In developing economies, however, the networks that matter for propagation may be quite different. Firms are often household enterprises, so a decline in one household's income can reduce its consumption at other household firms, generating further rounds of income and demand losses. At the same time, households insure one another through informal financial and social networks. The economic incidence of a shock therefore depends jointly on the demand network through which losses propagate and the risk-sharing network through which they are absorbed.

I study these mechanisms using a novel dataset that I have constructed through a partnership with one of Indonesia's largest digital payments platforms. To answer this question, I have worked directly with the firm to construct a few types of spatial linkages from their payments data: a geocoded consumer–merchant demand network; links between individuals' household consumption accounts and the small firms they operate; and a geocoded peer-to-peer transfer network capturing informal financial transfers. The resulting data cover tens of millions of consumers and millions of microenterprises and allow me to observe, in the same setting, both the network through which shocks propagate and the network through which households insure them. I combine these data with high-frequency, geolocated flood exposure to estimate these mechanisms and develop a model of propagation and informal risk sharing.

This project is part of a broader research agenda on climate adaptation in developing economies. In related work, I study how repeated climate shocks deplete the financial coping capacity of subsistence households; how gender-based distortions in agricultural production shape vulnerability to climate change; and how migration and urbanization can provide an important margin of adaptation when rural livelihoods become increasingly exposed. Across these projects, I am interested in how pre-existing economic structures mediate climate damages and constrain or enable adaptation.

This workshop would be particularly valuable to me because many of the questions I am working through are questions in empirical network economics. Having constructed the network data and established the main reduced-form patterns, I am now tackling how best to: identify economically meaningful link strength from observed interactions; distinguish direct from higher-order network exposure; characterize interactions between multiple networks; and understand how network formation may respond endogenously as the distribution of shocks changes. I would particularly value feedback at this stage as I move from reduced-form evidence toward estimation of the network model and its counterfactuals. More broadly, I would benefit from learning how researchers at the frontier of empirical network economics approach related identification and measurement problems in development.

Erin Grela

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Education

Massachusetts Institute of Technology Expected June 2028
Economics PhD candidate
Fields: development economics, environmental economics
Advisors: David Atkin, Esther Duflo, Ben Olken, Rob Townsend

Massachusetts Institute of Technology June 2020
Double Major in Chemistry and Economics
Thesis: "The Effect of Unified Enrollment on School Access" (advised by Josh Angrist)

PhD Courses Completed

14.771, 14.772 - Graduate development economics (micro and macro)
14.661, 14.662 - Graduate labor economics
14.125 - Graduate market design
14.121/2, 14.123/4 - Graduate microeconomic theory
14.271 - Graduate IO
14.380/1, 14.382, 14.385 - Graduate econometrics, graduate nonlinear econometrics
14.451/2 - Graduate macroeconomics
14.471, 14.472 - Graduate PF

Research and Work Experience

MIT Economics, Professor David Atkin, *Research Assistant*	2024-2026
MIT Economics, Professor Rob Townsend, *Research Assistant*	2024-2026
World Bank, Enterprise Analysis Unit, *Short Term Consultant*	2023-2024
MIT Economics, Professor Nina Roussille, *Research Assistant*	2023
MIT Economics, Professors David Atkin, Esther Duflo, *Predoctoral Research Fellow*	2020-2022
MIT Economics, Professor Esther Duflo, *Undergraduate Researcher*	2018-2020
MIT Economics, Professor Heidi Williams, *Undergraduate Researcher*	2017
Singapore-MIT Alliance for Research and Technology, Singapore, *Undergraduate Researcher*	2017

Fellowships, Honors, Awards, and Grants

J-PAL Jameel Graduate Fellowship	2026-2027
George and Obie Shultz Fund Grant (x3)	2024, 2025
J-PAL Inclusive Financial Innovation Initiative pilot grant (75k, with Rob Townsend)	2025
J-PAL Inclusive Financial Innovation Initiative development grant (10k, with Rob Townsend)	2024
Emma Castle Krob Fellowship, MIT Economics	2022-2024
Phi Beta Kappa, MIT	2020
Certificate of Excellence for Outstanding Scholarship, Royal Society of Chemistry	2020
Best Undergraduate Paper, MIT Economics	2020
Grant for Independent Undergraduate Research, MIT Economics	2019
Burchard Scholar, for excellence in the Humanities, Arts and Social Sciences, MIT	2018

Teaching

14.73: The Challenge of World Poverty (Undergrad, MIT), *Head TA*	2021, 2024, 2025
14.75: Political Economy and Economic Development (Undergrad, MIT), *TA*	2026

Presentations

London School of Economics, Environmental Camp: "Adaptation to Repeated Weather Shocks"	2024

Activities and Service

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MIT Next House, *Undergraduate Residence Advisor* 2025-present
MIT English as a Second Language Program, *Volunteer Night-shift Tutor* 2017-2023

Research In Progress

Beyond Local Exposure: Network-Driven Impacts of Floods in Informal Economies

Adaptation to Repeated Weather Shocks: Evidence from Nigerian Microdata

Urban Structure and Climate Adaptation (with David Atkin and Keelan Beirne)

Digital Financial Insurance for Urban MSMEs: A Randomized Experiment (with Rob Townsend and Budi Gandasoebrata)

Digital Finance for Weather Insurance: An RCT for Smallholder Farmers (with Rob Townsend and Budi Gandasoebrata)

Gender and Climate Change: The Adaptive Costs of Household Production Inefficiency

Estimating Climate Damages in a Non-Stationary World (with Luke Heeney, Christopher Knittel, Robert Pindyck, Ali Sarhadi, and Catherine Wolfram)

Economics Publications

Depression and Loneliness Among the Elderly in Low- and Middle-Income Countries with Abhijit Banerjee, Esther Duflo, Madeline McKelway, Frank Schilbach, Garima Sharma, and Girija Vaidyanathan. 2023. Journal of Economic Perspectives, 37 (2): 179-202.

Effects of Cognitive Behavioral Therapy and Cash Transfers on Older Persons Living Alone in India with Madeline McKelway, Abhijit Banerjee, Frank Schilbach, Garima Sharma, Miriam Sequeira, Girija Vaidyanathan, and Esther Duflo. 2023. Annals of Internal Medicine, 176 (5): 632–641.

Chemistry Publications

Weak Acids as an Alternative for Anti-Microbial Therapy with Binu Kundukad, Gayathri Udayakumar, Dhamanpreet Kaur, Scott Rice, Staffan Kjelleberg, and Patrick Doyle. 2020. Biofilm 2, 100019.

On-Demand Manufacturing of Direct Compressible Tablets: Can Formulation be Simplified? with Mohammad Azad, Juan Osorio, Allison Wang, David Klee, Mary Eccles, Rebecca Sloan, Gregory Hammersmith, Kersten Rapp, and David Brancasio. 2019. Pharmaceutical Research 36, 167.

Extended Abstract: Beyond Local Exposure: Climate Propagation and Insurance in Informal Economies

Erin Grela (MIT)

Motivation

Climate change poses a growing threat to economic activity in low- and middle-income countries. A large literature documents the direct effects of climate shocks on agricultural productivity, labor supply, income, and household welfare. A parallel literature on production networks shows that localized shocks need not remain local: in formal economies, disruptions can propagate through supply chains and generate aggregate losses well beyond the firms or places initially affected (Acemoglu et al. 2012; Barrot and Sauvagnat 2016; Carvalho et al. 2021). Much less is known about how shocks propagate in developing economies, where economic activity is predominantly informal and the networks linking households and firms look very different from formal production networks.

In informal economies, households and firms are often effectively the same economic unit. A street vendor or small shop earns household income through the firm and finances consumption from that income. A shock that reduces one household's income can therefore reduce its spending at other household firms, lowering their revenues and generating further rounds of income and consumption losses. The natural propagation network is thus not only a supply chain, but a consumer demand network linking household income to spending and firm revenue. At the same time, households insure one another through informal social and financial relationships. Transfers can absorb part of an income loss before it reaches consumption, damping the same demand propagation. The economic incidence of a disaster therefore depends on the joint structure of the demand network that propagates losses and the informal insurance network that offsets them.

These two networks may become especially important as the distribution of climate risk changes. Informal risk-sharing works when shocks differ across linked households, but provides little protection when both sides of a link are hit together. More spatially correlated shocks can therefore both generate broader contractions in household demand and weaken the informal insurance arrangements that would otherwise absorb them. Where a disaster is economically most damaging, who is most vulnerable, and how damages change as climate shocks grow more correlated depend on the interaction between these two networks rather than on physical exposure alone.

I study these mechanisms in Indonesia using transaction-level records from a large digital payments platform. Consumer–merchant transactions identify where households spend and therefore the demand network; peer-to-peer transfers identify informal financial relationships; and accounts that operate as both consumers and merchants link firm revenue to the household that owns the firm. I combine these data with high-frequency satellite-derived flood extent. I first estimate how floods affect household spending, transfers, and merchant activity, and how losses travel through the observed economic networks. I then develop a framework in which climate losses pass through informal insurance, household consumption, and the demand network, allowing me to quantify total damages, the extent to which informal insurance attenuates propagation, and how both change as

the spatial distribution of flood risk changes.

Setting and data

Indonesia is a useful setting because both informality and flood exposure are widespread. Fifty-nine percent of the workforce is informal, and roughly half of informal workers are in MSMEs. Floods are the country's most common natural disaster: BNPB recorded 3,062 flood reports over 2022–2025 across much of the archipelago (Figure 1).

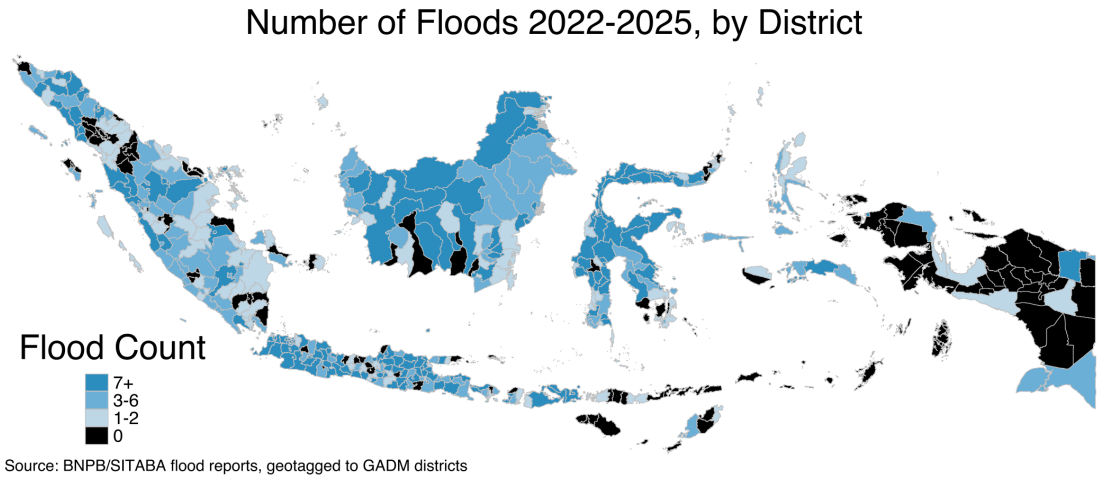


Figure 1: Flood prevalence, 2022–2025

I use transaction-level records from a large Indonesian digital payments platform covering both consumers and merchants (Table 1). KYC consumers are observed at GID-4, approximately the village or urban-village level, together with demographics and transactions. Merchants are observed at their own coordinates with sector and business structure. Three features of the data are especially useful. Consumer–merchant transactions identify the demand network. Peer-to-peer transfers identify the informal insurance network. Finally, 5.9 million accounts transact as both a merchant and a consumer, 3.8 million of them as consumers in the last year, which links firm revenue to the spending and resources of the household that owns the firm.

Table 1: Data structure

Account type	All time	Transacted last year	Data available
KYC users	46.6 M	19.1 M	GID-4 location, occupation, birthplace, age, marital status, gender; transactions: MSME, P2P, deposits/withdrawals
MSMEs	7.9 M	636 k	Sector, name, long/lat, business structure, transactions
MSMEs w/ itemized receipts	820 k	47 k	Price, quantity, item description

The main merchant sample contains 591,390 geolocated firms that transacted for at least two months over 2022–2025 with geolocated consumers. These are overwhelmingly small household

businesses: 97.8% are individual rather than corporate establishments and 70.7% are in food and restaurants. This is the part of the economy in which the distinction between firm revenue and household income is especially thin.

Platform coverage is broad but incomplete. The KYC consumer sample contains about 17% of the national population. Conditional on use, platform spending is about 12% of demographic-matched consumption in SUSENAS; the median user records 5% of matched consumption on the platform and the 75th-percentile user 20% (Figure 2). Users are younger and more urban than the SAKERNAS working-age population, with agriculture under-represented. I address partial coverage using national survey outcomes, heterogeneity by the share of consumption observed on platform, and merchant POS records that include transactions of all types rather than only platform-mediated payments.

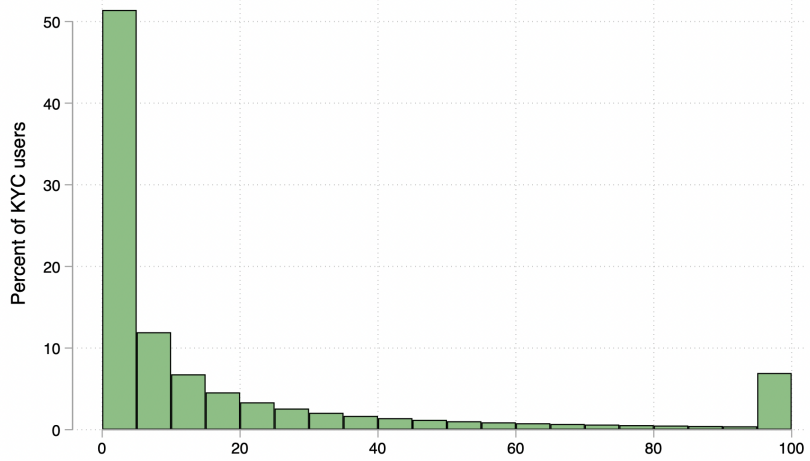


Figure 2: Platform spending as a percent of matched per-capita expenditure

Flood extent comes from Sentinel-1 radar change detection, using VV < -4 dB and VH < -2.5 dB relative to a 90–30 day baseline and removing permanent water and slopes $\geq 5°$. Events are sourced from the BNPB/SITABA monitoring dashboard. The resulting data contain 2,651 events with detected water over 2022–2025, covering 14,721 desa. I treat water as present from seven days before to seven days after each report.

The spatial resolution of the flood measure matters. Earlier versions vectorised the 10 m flood mask onto a 100 m grid, which promoted isolated detections to full 100 m cells and inflated exported polygon area by a median factor of 3.2 relative to the raster-measured water. Re-exporting at 10 m brings the polygon-to-raster area ratio to a median of 1.0000 while leaving the underlying flood classification unchanged. This makes it possible to distinguish a merchant whose own coordinate is under water from a merchant located in a desa in which some water is detected. Only 6.3% of merchant-weeks in a flooded desa have the merchant itself in the water. I therefore use point exposure for merchants where possible and desa-level exposure for consumers, who are not observed more finely.

Network structure

Let the demand network be the share of firm i's revenue coming from consumer location j,

$$A_{ij} = \frac{\overline{x_{ji}}}{\sum_k \overline{x_{ki}}},$$

and let the insurance network be bilateral P2P flow scaled by household income,

$$G_{ij} = \frac{\overline{t_{ij}} + \overline{t_{ji}}}{\overline{y_i}}, \qquad g_i = \sum_j G_{ij}, \qquad \omega_{ij}^G = \frac{G_{ij}}{g_i}.$$

The corresponding network exposures are

$$E_i^A = \sum_j A_{ij} s_j, \qquad E_i^G = \sum_j \omega_{ij}^G s_j,$$

where E_i^A is the exposure of a firm's customers and E_i^G is the exposure of a household's insurance partners.

The two networks have two features that are useful for the analysis. First, neither is especially local, and the insurance network is more geographically dispersed than the demand network. Only one quarter of merchant revenue comes from consumers in the same GID-4 area and one fifth of P2P inflows come from the same area; even at the province level, nearly one third of merchant revenue and more than 40% of transfers cross the boundary (Table 2). Geographic concentration also varies substantially across regencies (Figure 3), so the same physical flood can map into very different network exposure depending on where it occurs.

Table 2: Consumer demand networks are spatially disaggregated; informal insurance networks even more so

	Average share of inflows from same geolevel, across GID-4 areas	
Geolevel	Merchant revenue	Peer-to-peer transfers
GID-4 (village)	0.25	0.20
GID-3 (subdistrict)	0.38	0.28
GID-2 (district)	0.53	0.40
GID-1 (province)	0.69	0.58

Some merchants are not geographically diversified at all: 11% of MSMEs have consumer bases entirely within their own GID-4.

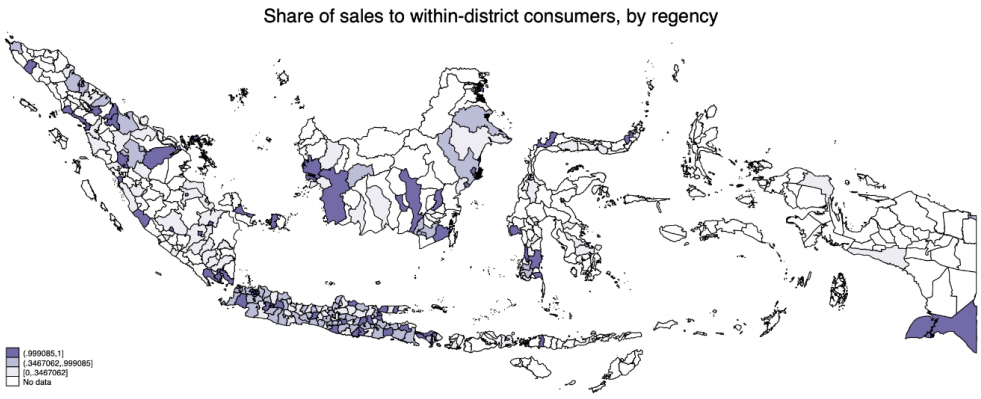


Figure 3: Geographic concentration of merchant–consumer linkages

Second, the two networks overlap in the raw data but much of that overlap is geographic. The bilateral correlation between insurance shares and revenue shares is 0.613. With origin and destination fixed effects, distance controls, and self-pairs removed, it falls to 0.084 at the subdistrict level and −0.012 at the village level (Table 3). The insurance network is therefore not simply the demand network under another name; conditional on geography, the same shock can load differently on the two.

Table 3: Correlation between consumer demand links and insurance links

	Bilateral revenue share			
	(1)	(2)	(3)	(4)
Bilateral insurance share	0.613	0.084	0.086	−0.012
	(0.015)	(0.007)	(0.008)	(0.001)
Observations	42,679,835	42,673,375	5,862,293	19,283,926
Level	GID-3	GID-3	GID-3	GID-4
Origin, destination FEs	Yes	Yes	Yes	Yes
Distance control	No	Yes	Yes	Yes
Exclude self-pairs	No	Yes	Yes	Yes
Sample	Full	Full	Union	Union

Reduced-form findings

(1) Floods reduce consumer spending on both margins. At the desa level over the full KYC population, a flood week reduces the number of spenders by 0.7%, spending per spender by 1.0%, and total spending by 1.5% (Table 5). At the subdistrict-month level, a flood in the preceding 60 days reduces aggregate consumption by 6.1% (s.e. 1.5). The response becomes weaker when the sample is restricted to the most continuously active users, because that screen removes the marginal spenders whose participation responds to the flood.

(2) Informal transfers respond to relative flood exposure. Regressing bilateral P2P inflows on the receiver's flood exposure minus the sender's gives a positive and precisely estimated

coefficient that survives directed-pair fixed effects (Table 4). Conditional on pair identity, transfers move toward the end of the link that is more exposed in a given month. This is the reduced-form counterpart of a risk-sharing rule in which transfers depend on loss differentials rather than the level of either household's loss. It also implies that transfer responses weaken as the two ends of a link become jointly exposed.

Table 4: Bilateral peer transfers between subdistrict pairs, monthly

	ln(informal insurance inflow)	
	(1)	(2)
$Flood_{\text{receiver}} - Flood_{\text{sender}}$	0.006	0.007
	(0.001)	(0.001)
N	77,279,639	73,073,517
Fixed effects	Sender, receiver	Directed-pair
Month FE	Yes	Yes

(3) Merchant losses run almost entirely through the extensive margin. When a merchant's own coordinate is under water, the probability of transacting falls 1.4 percentage points, revenue conditional on transacting does not move, and unconditional revenue falls 3.1% (Figure 4 and Table 5). The effect is sharper among merchants that normally transact every week, consistent with the outcome being a participation margin. Floods with reported depth of at least 50 cm or at least 100 houses flooded produce effects on the probability of transacting roughly three times the average. Controlling for own-desa rainfall and its lag from CHIRPS leaves the estimates essentially unchanged, while rainfall entered without the flood measure does little.

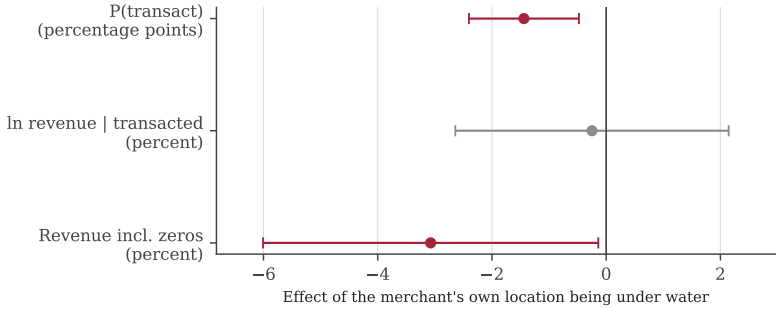


Figure 4: Merchant revenue falls on the extensive margin

The point exposure measure matters quantitatively. Moving from desa-level flood exposure to whether the merchant's own coordinate is under water roughly doubles the estimated effect on the probability of transacting and on unconditional revenue, holding the merchant sample, weeks, and outcomes fixed (Figure 5).

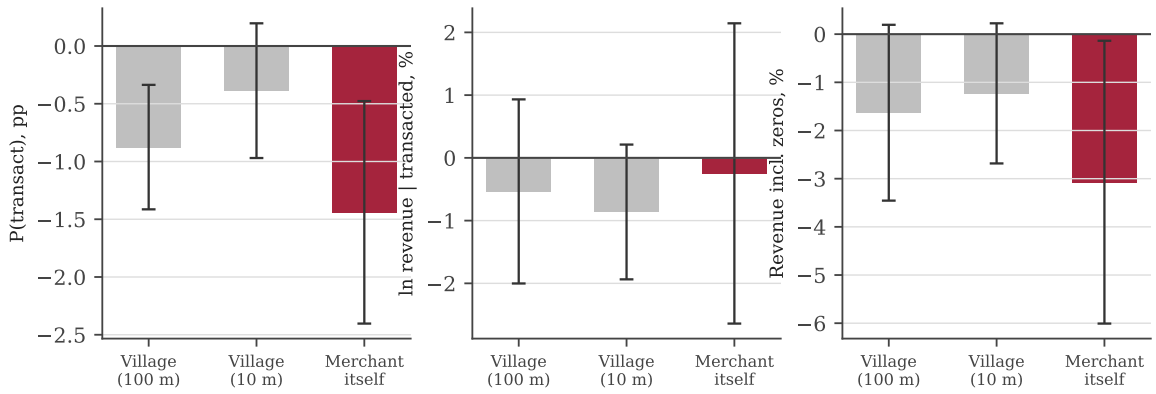


Figure 5: The attenuation ladder: desa-level exposure understates the merchant effect by about half

Table 5: Main effects of a week with flood water up

	Coef.	(SE)
Merchants, own coordinate under water		
P(transact), percentage points	−1.44	(0.49)
ln revenue | transacted, percent	−0.25	(1.22)
Revenue including zeros, percent	−3.07	(1.50)
Consumers, desa flooded, aggregate		
Spender count, percent	−0.68	(0.15)
ln spend per spender, percent	−0.97	(0.31)
Total desa spending, percent	−1.49	(0.39)

Merchant rows: merchant and kabupaten × week fixed effects, clustered on desa, top 10% continuity stratum, 16.7m merchant-weeks. Consumer rows: desa and kabupaten × period fixed effects over the full KYC population (49,232 desa), clustered on desa.

(4) Consumer and merchant losses have different spatial footprints. Entering mutually exclusive distance rings jointly against units with no flood active within 30 km, the merchant effect is confined to shops in the water and within roughly 500 m. Consumer spending falls by 2–3% in desa one to two kilometres from the water, about as much as at the water's edge, and decays only over several kilometres (Figure 6). The locator, distance rings, weeks, and flood windows are the same across the two series; only the outcome population differs.

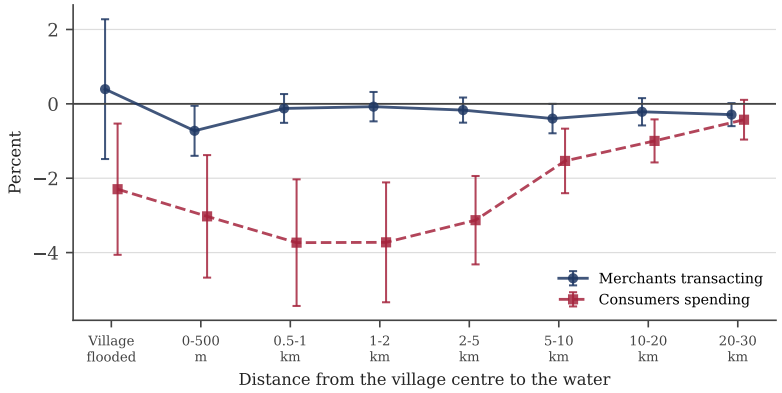


Figure 6: Households cut spending when a flood is nearby; shops lose revenue only when the water reaches them

This wedge is the central reduced-form fact. A flood destroys purchasing power over a larger area than the area in which it prevents firms from operating. The spending lost in the outer rings must therefore fall on merchants elsewhere, wherever the affected households normally shop. A merchant's physical location is informative about whether the shop can open, but not about whether its customers were hit.

The usual fixed-effect structure can absorb part of this propagation. With kabupaten × week fixed effects, control merchants share a kabupaten-week with directly exposed merchants, so kabupaten-wide consequences of the flood are differenced out. Moving to province × week fixed effects leaves the innermost effect roughly stable while shifting the outer rings. A separate kabupaten-wide exposure term also points toward spillovers: merchant revenue falls with the share of the merchant's kabupaten under water, −0.72 (s.e. 0.30), although the quintile dose-response is not monotone, so I treat this evidence as suggestive.

(5) Preliminary estimates using the demand network point in the same direction. Replacing geographic distance with consumer-weighted flood exposure, $E_{it}^{A} = \sum_j A_{ij} Flood_{jt}$, gives a much larger response to customers' exposure than to the firm's own subdistrict exposure in a preliminary subdistrict-month specification (Table 6). The estimate uses the earlier 100 m flood geometry, predates merchant-level exposure, and does not control for flood size, so I do not treat it as a main finding. Its role here is to show that the network exposure object is measurable and moves in the direction implied by the spatial evidence; the merchant-week specification on corrected flood outlines is the next step.

Table 6: Preliminary: subdistrict-level revenue, monthly

	(1) Share open	(2) ln(Rev)	(3) ln(Rev) if open
Flood in subdistrict, last 60 days	0.003	−0.021	−0.018
	(0.002)	(0.130)	(0.059)
Consumer-weighted flood, last 60 days	−0.014	−0.592	−0.306
	(0.006)	(0.280)	(0.157)
N	153,309	153,309	113,030
p-value (direct)	0.206	0.874	0.766
p-value (consumer-weighted)	0.029	0.035	0.051
GID FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes

Taken together, the reduced forms imply that local flood exposure is not a sufficient statistic for economic incidence. Floods reduce consumption over a wider area than they directly disrupt merchants, and transfers respond to the distribution of exposure within the insurance network. Quantifying total damages therefore requires following the shock through insurance, consumption, firm revenue, and back into household income.

Model

I use a simple framework to organize these channels. Flood losses first pass through a predetermined informal insurance network G. The residual loss changes consumption according to the household's marginal propensity to consume. Consumption losses then reduce firm revenue through the observed demand network A; because firms are owned by households, this creates a new household income loss and closes the loop.

Household block and the insurance operator

Households $i = 1, \ldots, N$ have common preferences u with $u' > 0$, $u'' < 0$, and $u''' > 0$, and hold liquid assets with gross return R subject to a borrowing limit. Floods s_t generate losses $d_{it} = d_i(s_t) \geq 0$ that are spatially correlated within a month. Let $G = (V, E)$ be the undirected network of transfer relationships, with incidence matrix B, so that $[B\tau]_i$ is household i's net transfer inflow. Each edge has strength $K_e > 0$, the inverse of a transfer friction, with cost $\tau_e^2/2K_e$. I take G and K as predetermined with respect to the current flood and current saving choice; an event study of network topology around floods provides a direct test of this assumption.

Within a month, floods realize and give pre-transfer cash on hand $x_{it} = Ra_{it} + y_{it}^0 - d_{it}$; transfers execute; households then choose consumption and saving out of post-transfer cash on hand $m_{it} = x_{it} + [B\tau_t^*]_i$. Transfers solve

$$\tau_t^* = \arg\max_{\tau} \sum_i v\big(x_{it} + [B\tau]_i\big) - \sum_e \frac{\tau_e^2}{2K_e}.$$

Expanding around the no-shock reference $x_{it}^0 = Ra_{it} + y_{it}^0$, where $B'v'(x^0) = 0$, and writing $\bar{D} \equiv$

$-v''(x^0) > 0$ for local curvature gives

$$\tau^* = \left(\bar{D}B'B + K^{-1}\right)^{-1}\bar{D}B'd.$$

Residual post-transfer losses $\ell = d - B\tau^*$ can therefore be written

$$\ell = H(G,K)d, \qquad H(G,K) = \left[\mathbf{I} + \bar{D}BKB'\right]^{-1} = \left[\mathbf{I} + \bar{D}L_K(G)\right]^{-1},$$

where $L_K(G) = BKB'$ is the weighted graph Laplacian.

Two properties do most of the work. First, $H\mathbf{1} = \mathbf{1}$: because $[L_K d]_i = \sum_j K_{ij}(d_i - d_j)$, a shock common to all members of the network generates no transfer response. Insurance therefore absorbs relative shocks but not the common component. Second, H_{ij} can be non-zero when i and j are not directly linked, because a loss changes transfers along chains of relationships. The full operator therefore allows for indirect adjustment that a pairwise approximation misses.

For an isolated pair with $K_{ij} = K$, the transfer rule simplifies to

$$\tau_{ij} = \phi_{ij}(d_i - d_j), \qquad \phi_{ij} = \frac{\bar{D}K}{2\bar{D}K + 1} \in \left[0, \tfrac{1}{2}\right].$$

The dyadic transfer response identifies ϕ_{ij} directly, and $\bar{D}K_{ij} = \phi_{ij}/(1 - 2\phi_{ij})$ then maps the pairwise estimate into H.

Consumption responds to post-transfer resources at a common local marginal propensity to consume μ,

$$\Delta c = -\mu H d.$$

Demand propagation and equilibrium

Let X^0_{fj} be pre-period spending by household j at firm f, let $c^0_j = \sum_f X^0_{fj}$, and let $D_c = \mathrm{diag}(c^0_j)$. Holding merchant shares fixed, a consumption loss $q_{jt} \equiv -\Delta c_{jt}$ reduces revenue at firm f by $X^0_{fj}q_{jt}/c^0_j$, so firm revenue losses are $r_t = X^0 D_c^{-1} q_t$. With P the firm-to-owner mapping from the linked merchant-consumer accounts, demand-induced household income losses are

$$d^A_t = B_A q_t, \qquad B_A \equiv PX^0 D_c^{-1}.$$

Total losses are $d_t = d^0_t + B_A q_t$, where d^0_t are direct climate-induced income losses. Substituting into the household block gives

$$q_t = \left[\mathbf{I} - \mu H B_A\right]^{-1} \mu H d^0_t = \sum_{k=0}^{\infty} (\mu H B_A)^k \mu H d^0_t, \qquad \rho(\mu H B_A) < 1.$$

The sequence is income loss → post-insurance loss → consumption loss → demand-induced income loss. The multiplier $[\mathbf{I} - \mu H B_A]^{-1}$ is the central object: H determines how much of a shock survives insurance, μ determines how much of that reaches spending, and B_A determines where the spending loss lands.

Writing $\mathcal{L} = [\mathbf{I} - \mu H B_A]^{-1}$, the row sums of $\mathcal{L}\mu H$ give a household-level measure of vulnerability to shocks elsewhere in the economy, while the column sums give the aggregate consumption effect of a shock at each node. The interaction between A and G can be summarized in several ways.

Bilateral edge overlap measures whether the same pair is connected through demand and insurance; centrality overlap measures whether households that are important in the demand network are also central in the insurance network; and shock-exposure overlap measures whether a firm's customers and those customers' insurance partners are flooded together. A compact local statistic is

$$\Omega_i = \sum_j A_{ij}\omega_{ij}^G,$$

which is high when the same locations matter for both demand and insurance. These objects are observed rather than imposed by geography.

From model to estimation

Each structural object maps to a distinct source of variation.

- **Damages d.** A first stage maps flood intensity, extent, and duration into rupiah income and revenue losses,

  $$Y_{it} = \alpha_i + \delta_t + \delta' Flood_{it} + \varepsilon_{it}.$$

  The severity gradient in the reduced forms supplies the identifying variation. Applying the fitted mapping to historical CHIRPS/ERA5 and hazard data gives the spatial loss covariance Σ_d; applying it to projected flood risk gives Σ_d^{future}.

- **Insurance strength and H.** Persistent pre-period P2P links define G. A Townsend-style specification decomposes losses into relative exposure and network-common exposure,

  $$\Delta c_{it} = -\beta_I(d_{it} - E_{it}^G) - \beta_G E_{it}^G + \alpha_i + \delta_t + \varepsilon_{it},$$

  while the dyadic regression

  $$t_{ji,t} = \alpha_{ij} + \gamma(d_{it} - d_{jt}) + \delta_t + \varepsilon_{ijt}$$

  identifies the shock-responsive component of transfers. Pair fixed effects remove routine bilateral exchange. Fitted $\hat{\phi}_{ij}$ map to $\bar{D}K_{ij}$ and build $\widehat{H}$. Adding the donor's exposure through other partners tests whether pairwise adjustment is sufficient or whether the full network operator is needed.

- **The MPC μ.** Realized transfers cannot be used directly because they respond to unobserved need. Instead, the fitted insurance operator generates predicted residual losses $\hat{\ell}_t = \widehat{H}\hat{d}_t$. Regressing consumption changes on predicted residual losses recovers the common local MPC μ.

- **Demand propagation.** The demand matrix A is observed directly. At the reduced-form level I estimate

  $$Y_{it} = \alpha_i + \delta_t + \beta_0 d_{it} + \beta_A E_{it}^A + \beta_{AG} E_{it}^{AG} + \varepsilon_{it},$$

  where

  $$E_{it}^A = \sum_j A_{ij} d_{jt}, \qquad E_{it}^{AG} = \sum_j A_{ij} \sum_k \omega_{jk}^G d_{kt}.$$

β_A captures losses arriving through customers, while β_{AG} measures whether those losses are larger when customers' insurance partners are also exposed. The specification is estimated at the merchant-week level using the corrected flood outlines and a fixed-effect structure that does not difference out the spillovers of interest.

- **Revenue-to-income pass-through and overidentification.** The linked household-firm accounts identify the mapping P and the share of firm revenue that becomes owner income, with itemized merchant records used for validation. Combining $\hat{\mu}$, $\widehat{H}$, A, and P gives predicted district-level consumption and revenue responses that can be compared with freely estimated reduced forms. The structural pipeline is therefore required to reproduce moments that were not used to fit it.

Two supporting exercises discipline the interpretation. An event study of network topology around routine floods tests whether flows respond while links remain fixed, with rewiring after tail events interpreted as evidence of belief updating. Regressing estimated $\hat{\phi}_{ij}$ and link formation on the historical spatial correlation of shocks, distance, social similarity, and A_{ij} tests whether the existing insurance network is itself climate-diversifying and provides the inputs for the endogenous-network extension.

Quantities and counterfactuals

The framework delivers three main quantities. First, it decomposes total damages into direct losses, losses absorbed by transfers and saving, and losses propagated through consumer demand. The value of the insurance network is the difference between total consumption damages at the estimated H and at $H = \mathbf{I}$,

$$\mathbf{1}'\big[\mathbf{I} - \mu B_A\big]^{-1}\mu d^0 - \mathbf{1}'\big[\mathbf{I} - \mu H B_A\big]^{-1}\mu H d^0.$$

This provides a direct estimate of how much conventional local-exposure measures miss once demand propagation and informal insurance are allowed for.

Second, for $d \sim (0, \Sigma_d)$, the household-level insurable share is

$$IS_i = 1 - \frac{e_i' H \Sigma_d H' e_i}{e_i' \Sigma_d e_i},$$

the fraction of household i's climate risk removed by its observed transfer network. I compute this under both historical and projected flood covariance. Because H is disciplined by observed transfer behavior rather than by geography or link volume alone, this evaluates the existing multi-purpose network specifically against climate risk.

Third, the model gives policy and adaptation counterfactuals. I compare relief targeted on direct geographic exposure with relief targeted on network vulnerability or systemic importance. I then evaluate welfare as the distribution of extreme events becomes more frequent, severe, and spatially correlated. The first counterfactual holds behavior and networks fixed. The second allows savings to re-optimize with G fixed. The final extension endogenizes G by valuing a link at the net present value of its future insurance services under projected climate risk, with link costs determined by distance, the existing network, and historical climate (Morten 2019). The difference between the fixed-network and endogenous-network cases measures the adaptive capacity of informal insurance.

The broader point is that a flood's economic footprint and its physical footprint are different objects. The reduced forms show household spending falling outside the narrow area in which merchants are directly disrupted. The model uses the observed demand and insurance networks to measure where those losses go, how much informal insurance absorbs, and how both margins change when flood risk becomes more spatially correlated.

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