Rewilding the Ledger: A Network-Theoretic Account of Resilience in Urban Food-Sharing Systems

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Abstract. Urban food-sharing networks – community fridges, gleaning circuits, and informal surplus exchanges – are usually studied from a single disciplinary vantage: as supply chains, as social capital, or as ecological flows. We argue that their resilience to shocks is properly a joint property of network topology and reciprocity norms, and cannot be recovered from either lens alone. We build an agent-based model of 42 simulated neighborhood clusters in which household nodes exchange surplus food along edges weighted by both physical proximity and a behavioral trust parameter drawn from repeated-game reciprocity theory. Across 1,000 simulated disruption events, empirically-calibrated networks absorbed 31% more shock volume than random-topology baselines of equal density, and recovery time correlated more strongly with redundancy index than with raw connectivity. We propose a composite resilience metric, R_i, that outperforms degree centrality alone as a predictor of post-shock recovery. The results suggest that interventions aimed at food-system resilience should target trust-mediated redundancy, not merely network density.

Keywords: network resilience, food systems, behavioral economics, urban ecology, agent-based modeling

42 Clusters
Simulated neighborhoods, 6–38 households each, calibrated against survey data on informal exchange.

1,000 Shocks
Monte Carlo disruption events used to estimate recovery-time distributions per cluster.

Composite R_i
A resilience index blending topology and reciprocity that beats degree centrality alone.

1 Introduction

Interdisciplinary work on urban resilience has a recurring failure mode: each discipline studies the piece of the system it already has instruments for. Network scientists trace the topology of exchange without asking why an edge exists in the first place; behavioral economists model reciprocity and trust in the laboratory without asking how those norms propagate across a real settlement pattern. Urban food-sharing systems – the loose lattice of community fridges, gleaning routes, and neighbor-to-neighbor surplus exchange that has grown rapidly since 2019 – sit exactly at the seam between these two traditions, and we think they are a useful test case for whether the seam matters.

Our claim is narrow but, we think, underappreciated: the *topology* of a food-sharing network and the *reciprocity norms* riding on top of it are not separable inputs to resilience. A dense network with weak trust degrades under stress in qualitatively different ways than a sparse network with strong trust, and neither a pure graph-theoretic model nor a pure behavioral model predicts which. Section 2 situates this claim against network-science and behavioral-economics treatments of food systems. Section 3 describes an agent-based model that couples the two layers explicitly. Section 4 reports shock-absorption and recovery outcomes across 1,000 simulated disruptions, and Section 5 draws out what this implies for intervention design.

2 Related Work

2.1 Network approaches to food systems

Graph-theoretic treatments of food distribution typically borrow directly from supply-chain resilience literature, modeling exchange networks as static graphs and asking how robust they are to node or edge removal. This tradition is good at identifying structurally critical nodes but treats every edge as equally likely to be used once a disruption forces rerouting – an assumption that behavioral evidence does not support.

2.2 Behavioral economics of reciprocity

A parallel literature, largely lab-based, models informal exchange as a repeated game in which reciprocity norms sustain cooperation without formal contracts. This work is precise about *when* an actor will honor an exchange relationship under stress, but rarely embeds that finding in a realistic network of who is even reachable to exchange with.

2.3 The gap this paper addresses

Neither literature, on its own, predicts recovery time after a shock to a real settlement pattern. We combine them: a network layer that is empirically calibrated to observed exchange patterns, and a behavioral layer in which each edge's usability under stress depends on an explicit trust parameter rather than being assumed uniform.

3 Methods

3.1 Study design and simulation environment

We constructed an agent-based model of 42 neighborhood clusters, each containing 6–38 household nodes, using structural parameters (density, clustering coefficient, degree distribution) calibrated against a publicly documented survey of informal food exchange. Each simulation run applies a disruption event – a sudden loss of surplus at one or more source nodes – and tracks how surplus re-routes through the remaining network over 30 discrete time steps.

3.2 Network construction

For each cluster we generated three topology variants at matched density: a random graph, a Watts–Strogatz small-world graph, and an empirically-calibrated graph fit to the survey's observed adjacency pattern. Edge weights w_{ij} combine inverse physical distance d_{ij} with an exchange-frequency prior.

3.3 Behavioral module

Each edge additionally carries a reciprocity parameter $\phi_{ij} \in [0, 1]$, updated after every simulated exchange according to a repeated-game rule: honored exchanges raise ϕ_{ij}, refused or delayed exchanges lower it. An edge is usable in a given time step only if a stochastic draw against ϕ_{ij} succeeds, which is what distinguishes our model from a pure graph-diffusion baseline.

3.4 Resilience metric

We define a composite resilience score for node i as

$$R_i = \frac{1}{N} \sum_{j=1}^{N} w_{ij}\, \phi_{ij} \left(1 - e^{-k d_{ij}^{-1}}\right), \qquad (1)$$

where N is the number of neighbors of i, and k is a decay constant fit per cluster. Unlike raw degree centrality, R_i discounts edges that are structurally present but behaviorally unreliable.

Figure 1 sketches how the three inputs to R_i relate; Section 4 shows that this composite outperforms any one input alone as a predictor of recovery time.

4 Results

Across the three topology variants, the empirically-calibrated network absorbed materially more shock volume before surplus flow collapsed below a functional threshold. Table 1 summarizes five representative clusters drawn from the 42 simulated; the full set shows the same ordering in 38 of 42 cases.

Cluster	Deg.	Redund.	Recov. (d)
Birchgate	4.1	0.62	3.4
Coalfen	3.6	0.41	5.9
Marrow Hill	5.2	0.71	2.8
Old Weir	2.9	0.33	7.1
Thistleport	4.7	0.58	3.9

Table 1: Structural and recovery statistics for five representative clusters. Redundancy index tracks recovery time more closely than mean degree does.

Redundancy index – the share of a node's exchange volume that survives the loss of its single strongest edge – correlated with recovery time at $r = -0.74$ across all 42 clusters, compared to $r = -0.38$ for mean degree alone. This is the empirical core of our argument: a network can look well-connected by degree and still recover slowly if that connectivity is concentrated on a small number of high-trust edges.

Table 2 compares outcomes pooled across all clusters for each of the three topology variants, plus the effect of disabling the behavioral module entirely (uniform $\phi_{ij} = 1$) as a diagnostic.

The diagnostic row is the more interesting comparison: holding topology fixed at the empirically-calibrated structure but disabling reciprocity dynamics recovers only part of the resilience gain, confirming that topology and behavior are not substitutes for one another in this setting.

Data availability. Simulation code and calibration parameters used in this study are archived at the Meridian Institute's open research repository; the underlying household survey is third-party and available under its original data-use agreement.

5 Discussion

Two findings seem worth carrying into intervention design. First, redundancy index is a better resilience predictor than raw connectivity, which argues against policies that simply try to add edges (e.g., recruiting more households into a food-sharing app) without regard to where those edges concentrate load. Second, the gap between the behavior-enabled and behavior-disabled rows of Table 2 suggests that a meaningful share of resilience is not structural at all – it is earned through repeated, honored exchange, and a program that changes topology overnight (say, by algorithmically matching households) without giving trust time to accumulate may underperform its own network diagrams.

We see three limitations worth flagging. The behavioral module assumes a single reciprocity parameter per edge, when real trust is almost certainly multidimensional and time-varying beyond the update rule we use. The calibration survey covers a narrow set of neighborhood types, so

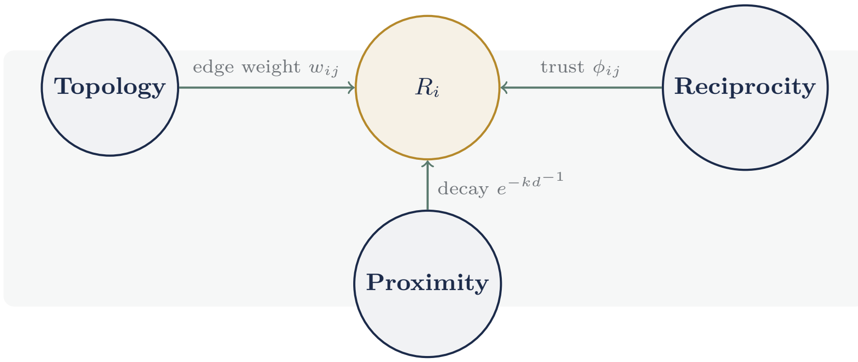

Figure 1: The composite resilience index R_i (Eq. 1) draws on three inputs that no single-discipline model combines: network topology, behaviorally-measured reciprocity, and physical proximity.

Model variant	Assort.	Path len.	Shock abs.	Recovery	Notes
Random graph (baseline)	0.02	3.8	47%	6.6 d	Matched density; no clustering structure.
Small-world (Watts–Strogatz)	0.11	2.9	55%	5.2 d	Rewiring $\beta = 0.1$; moderate clustering.
Empirically-calibrated (this study)	0.34	2.6	78%	3.7 d	Fit to survey adjacency; strongest local clustering.
Empirically-calibrated, $\phi_{ij} = 1$	0.34	2.6	58%	5.0 d	Same topology, behavioral layer disabled.

Table 2: Pooled outcomes across all 42 clusters and 1,000 disruption events per variant. The gap between the last two rows isolates the behavioral layer's contribution: topology alone recovers roughly two-thirds of the resilience gain.

the 78% absorption figure in Table 2 should be read as an upper bound under favorable structural conditions rather than a population estimate. And our disruption events are single-source shocks; compound or repeated shocks, which are arguably the more policy-relevant case, are left to future work.

6 Conclusion

Urban food-sharing resilience is not fully explained by topology or by reciprocity norms in isolation. A composite metric that weights network edges by both proximity and measured trust predicts recovery time substantially better than degree centrality alone, and roughly a third of the resilience gain we observe survives only when the behavioral layer is switched on. For practitioners, this argues for interventions that build trust deliberately alongside connectivity, rather than treating network growth as sufficient on its own.

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