Firm Networks, Credit Access, and Resilience to Shocks Among Small Firms in Tanzania

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Abstract

Small nonfarm firms without access to formal financial institutions in developing countries often rely on their relationships with other local firms to access credit, in addition to other benefits such as operational support and information. We examine the role of these firm networks in helping firms cope with shocks using novel data that we collected in rural Tanzania. We use both directly elicited firm-to-firm relationships and aggregate relational data (ARD), which we use to estimate broader village networks, to study how important firms' positions in these networks are for coping with shocks. We find that network position is strongly associated with access to credit after a shock and greater resilience to it. A one standard deviation increase in the number of connections a firm has is associated with a 4.5–5.3 percentage-point increase in the probability of obtaining credit from another firm after a shock and a 3.0–3.9 percentage-point decrease in the probability of temporarily closing after a major shock. More connected firms are also more likely to take wage work, especially nearby wage work, as a coping response to a shock.

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1 Introduction

Nonfarm firms are a driving force of the rural economy in developing countries. In Africa, 42 percent of rural households operate a nonfarm enterprise, most of which are informal and small (Christiaensen and Demery, 2018). Many of these firms face obstacles to accessing credit, as formal financial institutions are often inaccessible due to stringent eligibility criteria, collateral requirements, or limited lending capacity. As a result, even short-run liquidity shocks can force firms to reduce inventories, cut back operations, or exit temporarily. In the absence of well-functioning formal credit and insurance markets, entrepreneurs often rely on relationships with suppliers, customers, and other nearby firms to access informal credit (Fafchamps and Lund, 2003; McMillan and Woodruff 1999; Ghani and Reed, 2022; Rudder and Dillon, 2024). These network-based credit arrangements allow firms to acquire inputs, maintain inventories, and continue operating when they experience shocks.

Credit through business networks has two features that distinguish it from formal credit and make it especially relevant for small informal firms. First, repeated transactions give suppliers, customers, and other connected firms a monitoring advantage. Through regular interactions, firms can learn about a borrower's reliability, business performance, and likelihood of repayment in ways that banks can only acquire at higher cost (Smith, 1987; McMillan and Woodruff, 1999). Second, network-based credit often takes the form of trade credit or other in-kind support, which reduces the lender's risk. When credit is extended as inputs or inventory rather than cash, it is harder for borrowers to divert funds to other uses, and default may threaten access to future supplies or support from the same network (Burkart and Ellingsen, 2004; Petersen and Rajan, 1997).

These features allow firm networks to substitute for missing formal credit markets by reducing the information and enforcement frictions that constrain lending to small firms.

This paper studies whether local firm networks improve access to credit and strengthen the resilience of small firms in Tanzania. Our central hypothesis is not only that networks provide a source of informal credit, but that a firm's position within these networks determines how much support it can access after a shock. Firms with more connections, or those occupying more central positions in local business networks, may be better able to draw on relationships with suppliers, customers, and other firms when facing shocks. Existing work shows that informal networks help households smooth shocks through loans and transfers, and that interfirm credit depends on reputation and business relationships (Fafchamps and Lund, 2003; Kinnan and Townsend, 2012; McMillan and Woodruff, 1999; Rudder and Dillon, 2024). Less is known, however, about how credit flows through local firm networks after shocks, and whether a firm's position in these networks affects its ability to cope with shocks.

We test our hypothesis using novel firm network data collected in the Kagera region of Tanzania. Kagera is a predominantly rural region where smallholder agriculture remains central to household livelihoods, but where nonfarm enterprises are also important in towns and local market centers. Our baseline survey covers 743 nonfarm firms, concentrated in retail, food and beverage, personal services, and transport services. These include general stores, fruits and vegetables sellers, restaurants, boda-boda motorcycle taxis, tailors, clothing stores, salons, and barbershops, along with a long tail of smaller service and specialized retail activities. Most of these businesses are small, with the median firm having no full-time employees.

Among these firms, we document a rich network of relationships and credit links within their villages. Most firms report only a small number of direct business connections, with the median firm having six links, but connectedness is highly skewed, with firms in the top decile having at least fourteen links. These relationships include trading and credit ties with firms they buy from, sell to, borrow from, lend to, or transact with on credit. They also include operational and informational support links, such as firms they turn to for shopkeeping help, breaking large bills, price information, or business advice. These data allow us to examine whether more connected and central firms are better able to access credit when facing shocks.

A common challenge in studying networks is that directly elicited links may capture only a subset of the relationships that connect firms in a local economy. Respondents may omit some relationships, and a survey of a subset of firms may miss links involving firms outside the sample. To address this, we supplement the conventional network data with aggregate relational data (ARD) (Breza et al., 2020). Before the baseline survey, we conducted a census of roughly 9,000 firms across 100 villages, recording basic firm characteristics and the number of firms of each type in each community. Our baseline respondents are a subsample of this census, and we asked them ARD-style questions of the form "How many other firms do you know that..." with specific characteristics such as having employees, being operated by a woman, having a visible sign, or operating in the same sector. We combine these counts with the census data to estimate a network formation model and simulate the broader village-level firm network.

Firms in our sample face frequent shocks. In the baseline survey, conducted around June 2023, firms were asked whether they had experienced shocks over the previous year. The most common shocks were a sudden decrease in customers, reported by 60 percent of firms, an increase in input prices, reported by 57 percent, and an increase in household food prices, reported by 39 percent. Firms also reported household illness, theft, supplier disruptions, drought-related crop losses, and unexpected expenditures. Because we observe both directly elicited firm-to-firm links and a broader ARD-estimated village network, we can examine whether firms that are more connected or central in these networks respond differently to shocks.

We find that network position is strongly associated with credit access after a shock in both types of network. Among firms that experienced a shock, more connected and central firms are more likely to obtain credit from another firm. In the directly elicited network, a one standard deviation increase in degree centrality, which captures the number of direct within-village links a firm has, is associated with a 5.3 percentage-point increase in the probability of obtaining credit from another firm after a shock. Betweenness centrality and supported degree, which capture whether a firm bridges different parts of the village network and the number of its relationships backed by mutual contacts, are also positively associated with post-shock credit access. Community size, which captures the size of the local network cluster a firm belongs to, has a positive but statistically insignificant coefficient in this specification.

We also find that network position is associated with other post-shock business and coping outcomes. In the directly elicited network, a one standard deviation increase in degree centrality is associated with a 3.9 percentage-point decrease in the probability that a firm temporarily closes in response to the shock that most affected it. Betweenness centrality shows a similar negative association, suggesting that firms that are more connected or better positioned as bridges in the village network are less likely to close after major shocks. At the same time, more connected firms are more likely to take wage work as a coping response. A one standard deviation increase in degree centrality is associated with a 3.4 percentage-point increase in the probability of taking wage work after a major shock, and this response is concentrated in nearby wage work. This suggests that networks may help firms not only by improving access to credit, but also by expanding access to short-term local coping opportunities while keeping the business alive.

A concern with these results is that some reported shocks may themselves be related to firm characteristics or performance. For example, a sudden decline in customers or the loss of a key supplier may partly reflect the firm's own business conditions, which could also be correlated with its network position. To address this concern, we repeat the analysis using only responses attached to plausibly exogenous shocks: drought or low rainfall affecting crops, crop flooding, livestock loss, flooding or road damage limiting market access, illness of a household member, increases in the price of business supplies, and increases in household food prices. The results remain broadly similar, suggesting that the main patterns are not driven solely by shocks that are more likely to reflect firms' own characteristics or performance.

In the ARD-estimated network, which is constructed from respondents' answers to ARD questions rather than direct reports of firm-to-firm links, we find broadly similar patterns. A one standard deviation increase in ARD-estimated degree centrality is associated with a 4.5 percentage-point increase in the probability of obtaining credit from another firm after a shock. Supported degree and community size are also positively and statistically significantly associated with post-shock credit access, while betweenness centrality is positive but not statistically significant. As in the directly elicited network, we find a negative association between connectedness and temporary closure after a shock and a positive association between connectedness and wage work, concentrated in nearby wage work. A one standard deviation increase in ARD-estimated degree centrality is associated with a 3.0 percentage-point decrease in the probability of temporary closure after a major shock. It is also associated with increases of 4.3 percentage points in the probability of taking wage work and 3.9 percentage points in nearby wage work after a major shock, both significant at the 1 percent level.

These ARD results use posterior mean network measures constructed from 1,000 simulated networks. To assess whether the results are sensitive to uncertainty in the ARD-estimated network, we also rerun the ARD regressions separately for each of the 1,000 posterior draws and examine the resulting distribution of coefficient estimates. This follows the broader idea that ARD can be used to simulate a distribution of plausible networks and study the implied distribution of network statistics and functions of those statistics, including regression coefficients (Breza et al., 2023). The posterior-draw results support the main ARD findings. For credit access after shocks, the degree-centrality coefficient distribution is centered around 0.032, and all draw-specific estimates are positive. For wage work after a major shock, the distribution is centered around 0.031, with all estimates positive and the central 95 percent between 0.021 and 0.042. For temporary closure after a major shock, the distribution is centered around -0.021, with 99.6 percent of estimates negative. Overall, this supports the ARD evidence for credit access, wage work coping, and temporary closure across simulated networks, although the estimated magnitudes are generally smaller in the draw-specific regressions than in the regressions using posterior mean network measures.

The rest of the paper is organized as follows. Section 2 describes the data and shows descriptive statistics. Section 3 outlines the construction of network measures, ARD estimation, and the empirical strategy. Section 4 shows the results using directly elicited and ARD-estimated networks, along with robustness checks. The Appendix provides additional results and network graphs.

2 Data

We use firm-level survey data collected in the Kagera region of Tanzania. The data come from two linked surveys. First, we conducted a census of about 9,000 nonfarm firms across 100 villages, recording basic firm characteristics and village-level business activity. Second, from this census, we selected a sample of 743 firms to participate in a detailed baseline survey. This survey collected information on firm characteristics, business relationships, credit and support links with other firms, and shocks experienced over the previous year.

Firms in these villages are mostly small, informal, and owner-operated. The remainder of this section describes the direct network elicitation, firm shocks, sectoral composition, and descriptive features of the directly elicited networks.

2.1 Direct Network Elicitation

The baseline survey directly elicited firm-to-firm relationships within each village. Respondents were asked to name other firms with which they interacted in the course of operating their business. They were shown a list of potential partners from the village firm census and were also allowed to name firms not appearing on the list. This approach allows us to recover direct business relationships among surveyed firms while also allowing respondents to report relevant links outside the pre-listed set.

The network questions cover four types of business relationships, summarized in Table 1. Credit links include cash loans and purchases or sales on credit. Trade links include purchases and sales for business or household use. Information links include advice and price information. Operational support and trust links include shopkeeping help, breaking large bills, and other forms of day-to-day support. Together, these questions capture the main business, credit, information, and support links through which firms may access resources and respond to shocks.

Table 1: Relationship Types Used to Construct the Directly Elicited Network

Relationship Type	**Elicited Links**
Credit	Firms from which the respondent borrowed cash, firms to which the respondent lent cash, firms from which the respondent bought goods on credit, and firms to which the respondent sold goods on credit.
Trade	Firms from which the respondent made purchases for the business or household, and firms that made purchases from the respondent for business or household use.
Information	Firms the respondent would ask for business advice, firms that would ask the respondent for advice, and firms the respondent would ask for input or output price information.
Operational Support and Trust	Firms the respondent would ask to watch the shop, firms that would ask the respondent to watch their shop, and firms the respondent would ask for change when breaking a large bill.

The directly elicited network is constructed from reported firm-to-firm links within each village. Credit questions separately elicited small and large cash loans, as well as purchases and sales on credit above and below survey-specific value thresholds.

2.2 Firm Shocks

In addition to eliciting firm networks, the baseline survey asked firms whether they had experienced different types of shocks over the previous year. Shocks were common among surveyed firms: 90.7 percent of firms reported experiencing at least one shock, and the average firm reported 2.2 shocks. The median firm experienced two shocks, with the number of reported shocks ranging from zero to eight.

The most common shocks were demand-side and price-related. A sudden decrease in customers was reported by 59.9 percent of firms, while 56.5 percent reported an increase in input prices and 38.6 percent reported an increase in household food prices. Household and crime-related shocks were also common: 14.9 percent of firms reported illness of a household member, and 14.1 percent reported theft. Supply-side and agricultural shocks were less frequent, with 11.0 percent of firms reporting supplier disruptions and 7.1 percent reporting drought or crop failure.

Other shocks, such as fraud, flooding that limited market access, and fire or flooding at the business premises, were relatively rare.

2.3 Sectoral Composition

Table 2 shows the sectoral composition of firms in the baseline survey. Firms are classified into 41 detailed subsectors, which we group into 10 broader sector categories for descriptive purposes. Retail is the largest sector group, accounting for 34.3 percent of firms, followed by food and beverage businesses at 28.1 percent. Personal services and transport services account for 15.2 and 10.6 percent of firms, respectively. The remaining sectors are much smaller, with construction and home services, professional services, finance, agriculture, energy, and manufacturing together accounting for 11.7 percent of firms.

Table 2: Sectoral Composition of Firms

Sector Group	**Share**	**Subsectors**
Retail	34.3%	General store, kioski, vessel, clothing, electronics, spare parts
Food and Beverage	28.1%	Restaurant, drinks, cereals, fish, fruits and vegetables, maize mill, meat
Personal Services	15.2%	Beauty, salon, shoemaker, tailor, entertainment
Transport Services	10.6%	Bike, bike mechanic, boda boda, car mechanic, motorbike mechanic, petrol
Construction and Home Services	5.1%	Carpenter, construction, decorating, welding, stove maker
Professional Services	3.9%	Electronics repairs, phone services, photocopy, pharmacy
Finance	1.6%	Wakala, financial institution
Agriculture	0.5%	Agrovet, tree garden, livestock
Energy	0.3%	Charcoal
Manufacturing	0.3%	Scrap metal, brickmaking

Shares are calculated among the 743 firms in the baseline survey. Sector groups are used for descriptive purposes and aggregate the more detailed subsector classifications collected in the survey. Shares may not sum to 100 percent because of rounding.

2.4 Descriptive Statistics

Table 3 shows village-level summary statistics for the directly elicited networks in 28 villages. The average village network contains 99 firms and 147 distinct firm-to-firm connections, with the number of firms ranging from 5 to 404. Network density is generally low, averaging 0.056 and ranging from 0.007 to 0.400.

Despite this variation in network size, the average number of direct links per firm is relatively similar across villages. The mean village-level average degree is 2.75, with a standard deviation of 0.64. However, the maximum degree in a village averages 15.4 and ranges from 2 to 35. This suggests that most firms maintain a small number of direct links, while a smaller number occupy much more connected positions. This right skewness in degree is consistent with evidence from risk-sharing networks. For example, Henderson and Alam (2022) find evidence of *preferential attachment* in the Tanzanian village of Nyakatoke, whereby households who have more existing partners are more likely to acquire new partners.

Village networks also differ in their community structure. The number of communities detected separately within each village using the Louvain algorithm (Blondel et al., 2008) ranges from 2 to 18, with a mean of 9 and a median of 8. Larger villages tend to contain more communities. The mean within-village global clustering coefficient is 0.142. This means that, on average across villages, about 14 percent of pairs of firms connected to the same firm are also connected to each other. This is about 2.6 times the average random network benchmark of 0.056 for networks with the same sizes and average degrees (Watts, 1999).[1] The average village contains 3.8 reciprocal pairs, where both interviewed firms name each other.

[1] For village v, the independent random linking benchmark is $p_v = k_v/(n_v - 1)$, which is the village network density, where k_v is average degree and n_v is the number of firms. We average these benchmarks across villages.

Appendix Figure A.1 illustrates the directly elicited firm networks for selected villages, showing variation in network size, density, and connectedness across the sample.

Table 3: Village-Level Network Summary Statistics

Statistic	**Mean**	**Median**	**SD**	**Min**	**Max**
Number of firms	98.9	67.5	85.5	5	404
Number of connections	147.0	85.0	139.4	4	558
Network density	0.056	0.042	0.074	0.007	0.400
Average degree	2.75	2.62	0.64	1.38	4.25
Maximum degree	15.4	14.5	7.5	2	35
Number of communities	9.0	8.0	3.6	2	18
Global clustering	0.142	0.109	0.183	0.000	1.000
Reciprocal pairs (both interviewed)	3.8	3.0	3.0	0	11

Network statistics are calculated across 28 villages. Nodes include baseline respondents and their named partners, including respondents with no recorded links. Connections are distinct undirected firm pairs. Density is the number of connections divided by $n(n-1)/2$. Louvain communities are detected separately within each village. Global clustering is calculated among villages with at least one connected triplet. Reciprocal pairs require both firms to have been interviewed and to have named each other.

3 Methodology

3.1 Network Construction and Measures

We construct directed firm networks at the village level from the directly elicited network questions. Each node is a firm, and a directed edge from firm i to firm j is created when firm i names firm j in response to any of the network questions. Named partners include other surveyed firms, non-surveyed firms from the census, and firms outside the census that respondents identified.

The data include the type of relationship reported between each pair of firms, including credit, trade, information, and operational support links. A firm may name the same partner across multiple relationship types. For the main network measures used below, we collapse these data into an indicator for whether any relationship exists between the pair. We then use the resulting village-level networks to construct four main measures of network position and embeddedness: degree centrality, betweenness centrality, supported degree, and community size.

Degree centrality captures the number of direct within-village links a firm has. Betweenness centrality captures the extent to which a firm lies on shortest paths between other firms and therefore its potential to serve as a bridge between different parts of the village network. Such bridging positions can facilitate exchange across groups (Stovel and Shaw, 2012). Supported degree counts the number of a firm's connections that are embedded in at least one triangle, meaning that the firm and its partner share at least one common neighbor. Supported links can be interpreted as relationships backed by social collateral (Jackson, Rodriguez-Barraquer, and Tan, 2012). Mutual contacts may help monitor behavior and transmit information about defaults or broken obligations, making these relationships more able to sustain informal credit and favor exchange. Community size measures the size of the local village network cluster to which the firm belongs (Pons and Latapy, 2006).

3.2 Aggregate Relational Data (ARD)

The directly elicited network captures relationships reported by firms in the survey, but it may represent only a subset of the links that connect firms in the local economy. Respondents may omit some relationships, and dense parts of the village network may be missed if few or none of the firms in those areas were surveyed. To address this limitation, we complement the directly elicited network with aggregate relational data (ARD), which we use to simulate broader village-level firm networks (Breza et al., 2020).

ARD questions ask respondents to report the number of firms they know with particular characteristics, rather than asking them to name each firm individually. In our setting, respondents were asked questions of the form "How many other firms do you know that..." followed by characteristics observed in the firm census, such as having employees, being operated by a woman, having a visible sign, or belonging to specific subsectors. Since the census records the distribution of these characteristics within each village, the ARD responses provide information about how each respondent is connected to different types of firms in the broader village network.

We use the ARD responses together with the village firm census to estimate a network formation model and simulate plausible village-level firm networks. The simulated networks place each surveyed firm in a broader local network that includes firms beyond those directly named in the network survey. For each simulated network, we compute the same measures of network position used in the directly elicited network.

Our main ARD specifications use the posterior mean of each network measure across 1,000 simulated networks. These posterior mean measures are standardized before entering the regressions, making the ARD estimates directly comparable to the results from the directly elicited network. As a robustness check, we also rerun the ARD regressions separately for each posterior draw and examine the resulting distribution of coefficient estimates.

3.2.1 Details about Network Estimation

In our data, we observe a population of n_v firms in each of the $V = 31$ villages in our sample. Within each village, we survey a subset of m_v firms. Each respondent i answers $K = 19$ ARD questions of the form "How many other firms do you know that have trait k?" The traits comprise six firm- or owner-level attributes and thirteen subsector indicators. The six firm- or owner-level attributes are whether the firm has at least one employee, has been in operation for at least 10 years, is woman-operated, has an owner with tertiary education, uses a smartphone, and has visible signage. The thirteen subsector indicators are from the detailed subsector classifications shown in Table 2. For each of the n_v firms in the village census, we observe the same K traits.

We follow the ARD network estimation approach of Breza et al. (2020). Each firm i is characterized by a log-degree parameter α_i, which captures its overall propensity to form links, and a latent position z_i on the unit sphere S^{p-1}, with $p = 3$. Each trait k is characterized by a log-prevalence parameter β_k, a latent center $\mu_k \in S^{p-1}$, and a concentration parameter η_k. A scalar η captures overall homophily in the network. The latent-space edge formation model implies that links are more likely between firms with higher degree parameters and more similar latent positions:

$$\Pr(g_{ij} = 1 \mid \alpha_i, \alpha_j, \eta, z_i, z_j) \propto \exp\left(\alpha_i + \alpha_j + \eta z_i^\top z_j\right). \tag{1}$$

Thus, conditional on degree heterogeneity, the probability of a link is increasing in the inner product $z_i^\top z_j$, or equivalently decreasing in the distance between firms on the latent sphere.

The ARD responses identify this latent structure by aggregating over firms with each trait. Let y_{ik} denote respondent i's answer to the ARD question for trait k. This response is modeled as a count drawn from a Poisson distribution:

$$y_{ik} \mid \alpha_i, \beta_k, \eta, \eta_k, z_i, \mu_k \sim \text{Poisson}(\lambda_{ik}), \tag{2}$$

where λ_{ik} is the expected number of firm i's contacts who have trait k. The expected count depends on firm i's overall connectedness, the prevalence of trait k, and the distance between firm i's latent position and the trait-specific center:

$$\lambda_{ik} = \exp(\alpha_i + \beta_k) \cdot C_p(\eta) \cdot \frac{C_p(\eta_k)}{C_p(0) C_p\left(\sqrt{\eta^2 + \eta_k^2 + 2\eta\eta_k z_i^\top \mu_k}\right)}. \tag{3}$$

Here $C_p(\cdot)$ is the von Mises-Fisher normalizing constant on S^{p-1}. Intuitively, respondents with higher α_i know more firms overall, traits with higher β_k are more common in the village, and respondents located closer to a trait center μ_k are expected to know more firms with that trait.

The model is estimated separately by village. Since ARD responses are observed only for surveyed firms, we extend the estimated latent positions and degree parameters to non-surveyed census firms using a nearest-neighbor procedure in covariate space. For each non-surveyed firm, we identify up to five nearby surveyed firms using pre-treatment firm and owner characteristics, including location, owner demographics, firm age, number of competitors, number of employees, and electricity access. We then impute the non-surveyed firm's latent position and normalized degree as weighted averages of its nearest surveyed neighbors. The ARD trait variables themselves are excluded from this distance calculation so that the imputation does not mechanically reproduce the ARD responses.

For each posterior draw, we then simulate a village-level adjacency matrix from the estimated edge formation model. Specifically, edges are drawn independently according to

$$g_{ij}^{(s)} \sim \text{Bernoulli}\left(\min\left\{c^{(s)} \exp\left(g_i^{(s)} + g_j^{(s)} + \eta^{(s)} z_i^{(s)\top} z_j^{(s)}\right), 1\right\}\right), \tag{4}$$

where s indexes posterior draws, $g_i^{(s)}$ is the normalized log-degree for firm i, and $c^{(s)}$ is a normalizing constant chosen using the expected total degree among ARD respondents. This produces a posterior distribution over village-level firm networks. We use this graph posterior to construct ARD-based measures of firms' positions in the broader village network. The main ARD specifications use posterior mean measures, while the posterior-draw robustness checks use the full distribution of simulated networks.

3.3 Empirical Strategy

We examine how network position is associated with firms' responses to shocks. Coping responses were elicited only from firms that reported a shock in the past year, so our analysis is conditional on experiencing a shock. We estimate the following specification:

$$Y_{ivs} = \beta \,\text{NetworkMeasure}_{ivs} + \delta \,\text{Employees}_{ivs} + \alpha_s + \gamma_v + \varepsilon_{ivs}, \tag{5}$$

where Y_{ivs} is an outcome for firm i in village v and subsector s. Depending on the specification, the outcome is an indicator for whether the firm obtained credit from another firm after a shock, temporarily closed in response to a major shock, or used another coping response such as wage work. $\text{NetworkMeasure}_{ivs}$ is one of the four standardized measures of network position defined above. The coefficient β can be interpreted as the change in the probability of the outcome associated with a one standard deviation increase in the network measure. Employees_{ivs} controls for firm size, measured as the total number of full-time and part-time employees. We include subsector fixed effects α_s and village fixed effects γ_v, which control for all time-invariant subsector-specific and village-specific characteristics. Standard errors are clustered at the subsector level.

4 Results

4.1 Connectedness and Response to Shocks

Directly Elicited Network

We begin with results using the directly elicited firm network, constructed from firms' reported business links within the village. We later compare these results with analogous measures estimated from aggregate relational data. Table 4 estimates equation (5) using credit access after a shock as the outcome. Credit access is defined as an indicator equal to one if the firm reported obtaining a loan from another business or buying goods on credit from another business in response to a shock. The coefficients on degree centrality, betweenness centrality, and supported degree are positive and statistically significant. A one standard deviation increase in degree centrality is associated with a 5.3 percentage-point increase in the probability of obtaining credit from another firm after a shock, significant at the 1 percent level. The corresponding effects for betweenness centrality and supported degree are 5.2 and 2.7 percentage points, significant at the 10 and 5 percent levels, respectively. Community size is not statistically significantly associated with credit access.

Next, we regress other post-shock business and coping outcomes on these directly elicited network measures. Table 5 uses an indicator for whether the firm temporarily closed in response to the shock that most affected it. The coefficients on degree centrality and betweenness centrality are negative and statistically significant, indicating that more connected and central firms are less likely to temporarily close. A one standard deviation increase in degree centrality is associated with a 3.9 percentage-point decrease in the probability of temporary closure, significant at the 5 percent level.

Table 4: Firm Connectedness and Credit Access After Shocks: Directly Elicited Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0535***	0.0516*	0.0274**	0.00118
	(0.0189)	(0.0275)	(0.0110)	(0.0148)
Observations	620	620	620	620
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for obtaining credit from another firm after a shock.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** p<0.01; ** p<0.05; * p<0.10

The corresponding effect for betweenness centrality is a 2.8 percentage-point decrease, significant at the 10 percent level. The coefficients on supported degree and community size are also negative but are not statistically significant. Appendix Table A.1 shows that these results also hold when responses to any ranked shock are considered.

Table 6 estimates the same specification using an indicator for whether the firm owner took wage work in response to the shock that most affected the firm. A one standard deviation increase in degree centrality is associated with a 3.4 percentage-point increase in the probability of taking wage work after this shock, significant at the 5 percent level. This effect appears to be concentrated in nearby wage work, as shown in Table 7. Supported degree and community size are also positively associated with wage work, but neither is statistically significant for nearby wage work. Appendix Tables A.2 and A.3 show the corresponding results using responses to any ranked shock.

Taking wage work may be a coping response to a shock, but it does not necessarily imply that entrepreneurs who do so are worse off than those who do not. Informal self-employment in devel-

Table 5: Firm Connectedness and Temporary Closure After a Major Shock: Directly Elicited Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	-0.0390**	-0.0275*	-0.0183	-0.0101
	(0.0154)	(0.0142)	(0.0135)	(0.0174)
Observations	620	620	620	620
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for temporarily closing in response to the shock that most affected the firm.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** $p<0.01$; ** $p<0.05$; * $p<0.10$

oping country settings is often precarious, and households frequently combine self-employment with casual labor and other activities to supplement income (Falco and Haywood, 2016). In this context, the fact that more connected firms are less likely to close but more likely to take wage work suggests that wage work may reflect access to an additional coping option. Entrepreneurs without such opportunities may instead have to absorb the shock without an additional source of short-term income. This is supported by the fact that the wage work response is concentrated in nearby wage work, suggesting that connected firms are not necessarily exiting the village economy or abandoning their business. Instead, more connected entrepreneurs may be better able to find short-term local work while keeping the business alive. These results suggest that firm networks may also help entrepreneurs cope with shocks by improving access to nearby economic opportunities.

Table 6: Firm Connectedness and Wage Work After a Major Shock: Directly Elicited Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0338**	0.00816	0.0212*	0.0311**
	(0.0131)	(0.00692)	(0.0116)	(0.0113)
Observations	620	620	620	620
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for taking wage work in response to the shock that most affected the firm.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** p<0.01; ** p<0.05; * p<0.10

Table 7: Firm Connectedness and Nearby Wage Work After a Major Shock: Directly Elicited Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0299***	0.0212	0.0163	0.0134
	(0.00800)	(0.0157)	(0.0104)	(0.00849)
Observations	620	620	620	620
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for taking nearby wage work in response to the shock that most affected the firm.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** p<0.01; ** p<0.05; * p<0.10

Robustness: Plausibly Exogenous Shocks

A concern with the results above is that some reported shocks may themselves be related to firm characteristics or performance. For example, a sudden decline in customers, the loss of a key supplier, or the departure of an important employee may partly reflect the firm's own business conditions, owner decisions, or capabilities. Conditioning on responses to these shocks could bias the estimates if the same underlying characteristics are also correlated with firm connectedness. To address this concern, we repeat the analysis using only responses attached to plausibly exogenous shocks. These include drought or low rainfall affecting crops, crop flooding, livestock loss, flooding or road damage limiting market access, illness of a household member, increases in the price of business supplies, and increases in household food prices.

Table 8 below, and Tables A.7, A.8, and A.9 in the Appendix show results from the same four sets of regressions as in the previous subsection, but using only responses attached to plausibly exogenous shocks. The credit access results remain broadly similar: the coefficients on degree centrality and supported degree are positive and statistically significant, although the coefficient on degree centrality is smaller and less statistically significant than in the earlier result. The temporary closure results actually strengthen when restricting to plausibly exogenous shocks, with coefficients on degree centrality, betweenness centrality, and supported degree being negatively and statistically significant. Finally, degree centrality remains positively and statistically significantly associated with taking wage work and nearby wage work, and supported degree and community size are also positively associated with wage work after a major plausibly exogenous shock. Overall, these results suggest that the earlier results are not driven solely by shocks that are more likely to reflect firms' own characteristics or performance.

ARD-Estimated Network

We next rerun the same regressions using network measures from the ARD-estimated network. Unlike the directly elicited network, these measures are constructed from respondents' answers

Table 8: Firm Connectedness and Credit Access After Plausibly Exogenous Shocks: Directly Elicited Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0314*	0.0298	0.0260**	0.00933
	(0.0158)	(0.0229)	(0.0104)	(0.0188)
Observations	509	509	509	509
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for obtaining credit from another firm after a plausibly exogenous ranked shock.
Plausibly exogenous shocks include agricultural and health shocks, input price increases, and household food price increases.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms that experienced at least one plausibly exogenous shock in the past year.
Standard errors are clustered at the subsector level.
*** p<0.01; ** p<0.05; * p<0.10

to ARD questions, as described above. This approach allows us to situate each firm in a broader village-level network rather than relying only on the links that respondents directly report. The ARD-estimated network therefore helps address limitations of the directly elicited network data, including the possibility that respondents omit some relationships and the fact that it is not feasible to directly observe every link among firms in each village.

Table 9 shows analogous estimates using credit access after a shock as the outcome. The coefficients on degree centrality, supported degree, and community size are all positive and statistically significant. A one standard deviation increase in ARD-estimated degree centrality is associated with a 4.5 percentage-point increase in the probability of obtaining credit from another firm after a shock. The corresponding effects for supported degree and community size are 4.4 and 72.2 percentage points, respectively. These results are consistent with those found using directly elicited networks.

Table 9: Firm Connectedness and Credit Access After Shocks: ARD-Estimated Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0449**	0.0296	0.0440**	0.722***
	(0.0195)	(0.0199)	(0.0192)	(0.237)
Observations	600	600	600	600
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for obtaining credit from another firm after a shock.
The main independent variable is the ARD-estimated standardized network measure indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** $p<0.01$; ** $p<0.05$; * $p<0.10$

Next, we examine whether the ARD-estimated network measures show similar relationships with other post-shock business and coping outcomes. Table 10 uses temporary closure in response to the shock that most affected the firm as the outcome. A one standard deviation increase in degree centrality is associated with a 3.0 percentage-point decrease in temporary closure, while the corresponding effect for supported degree is a 2.8 percentage-point decrease. Both coefficients are significant at the 10 percent level. Community size also has a negative coefficient significant at the 10 percent level. Thus, all four coefficients have consistent signs across the two networks, although the effect on degree centrality has weaker statistical support. Appendix Table A.4 shows that these results also hold when responses to any ranked shock are considered.

Tables 11 and 12 show the estimated effects of connectedness in the ARD-estimated network on wage work and nearby wage work. The effects are more consistently statistically significant

Table 10: Firm Connectedness and Temporary Closure After a Major Shock: ARD-Estimated Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	-0.0295*	-0.0215	-0.0281*	-0.742*
	(0.0149)	(0.0140)	(0.0147)	(0.388)
Observations	600	600	600	600
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for temporarily closing in response to the shock that most affected the firm.
The main independent variable is the ARD-estimated standardized network measure indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** $p<0.01$; ** $p<0.05$; * $p<0.10$

across network measures than in the directly elicited network. A one standard deviation increase in degree centrality is associated with increases of 4.3 percentage points in wage work and 3.9 percentage points in nearby wage work. The corresponding effects for supported degree are 4.3 and 4.0 percentage points. All four of these coefficients are significant at the 1 percent level. Betweenness centrality is also positive and significant at the 5 percent level in both tables, while community size is positive and significant at the 1 percent level for both outcomes.

As discussed earlier, this suggests that networks give more connected firms access to wage work as a coping response, helping them absorb shocks while keeping their businesses alive. The support results further suggest that these coping opportunities may be easier to access when firms' relationships are supported by mutual contacts. Appendix Tables A.5 and A.6 show that the positive degree and supported-degree effects also hold when responses to any ranked shock are considered.

Table 11: Firm Connectedness and Wage Work After a Major Shock: ARD-Estimated Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0426***	0.0177**	0.0427***	0.560***
	(0.0108)	(0.00788)	(0.0108)	(0.175)
Observations	600	600	600	600
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for taking wage work in response to the shock that most affected the firm.
The main independent variable is the ARD-estimated standardized network measure indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** $p<0.01$; ** $p<0.05$; * $p<0.10$

Table 12: Firm Connectedness and Nearby Wage Work After a Major Shock: ARD-Estimated Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0393***	0.0150**	0.0400***	0.383***
	(0.00759)	(0.00690)	(0.00765)	(0.108)
Observations	600	600	600	600
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for taking nearby wage work in response to the shock that most affected the firm.
The main independent variable is the ARD-estimated standardized network measure indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** $p<0.01$; ** $p<0.05$; * $p<0.10$

Robustness: Posterior Draws of the ARD Network

The ARD results above use posterior mean network measures constructed from 1,000 simulated networks. This makes the ARD estimates directly comparable to the directly elicited network regressions, but it treats the posterior mean network measure as fixed. As an additional robustness check, we rerun the ARD regressions separately for each of the 1,000 posterior draws of the simulated network and examine the resulting distribution of coefficient estimates. This follows the broader idea that ARD can be used to simulate a distribution of plausible networks and study the implied distributions of network statistics and functions of those statistics, including regression coefficients (Breza et al., 2023).

Figure 1 plots these distributions for degree centrality. The grey densities show the distribution of coefficients across posterior network draws, while the blue solid line shows the corresponding estimate from the regression using posterior mean ARD degree centrality. The posterior-draw distributions are tight relative to the confidence intervals from the posterior-mean regressions, indicating that the coefficient estimates are not very sensitive to which plausible ARD network draw is used. This suggests that uncertainty in the estimates comes mainly from sampling uncertainty in the regression rather than from uncertainty in the ARD-estimated network.

The draw-specific coefficient averages 0.032 for credit access, 0.031 for wage work, and -0.021 for temporary closure. All 1,000 credit access and wage work estimates are positive and 99.6 percent of temporary closure estimates are negative. The central 95 percent of draw-specific coefficients ranges from 0.019 to 0.045 for credit access, from 0.021 to 0.042 for wage work, and from -0.035 to -0.007 for temporary closure.

Overall, this exercise supports the main findings that, across almost all simulated networks, firm connectedness is positively associated with credit access and wage work after a shock and negatively associated with temporary closure. The estimated magnitudes are, however, generally smaller in the draw-specific regressions.

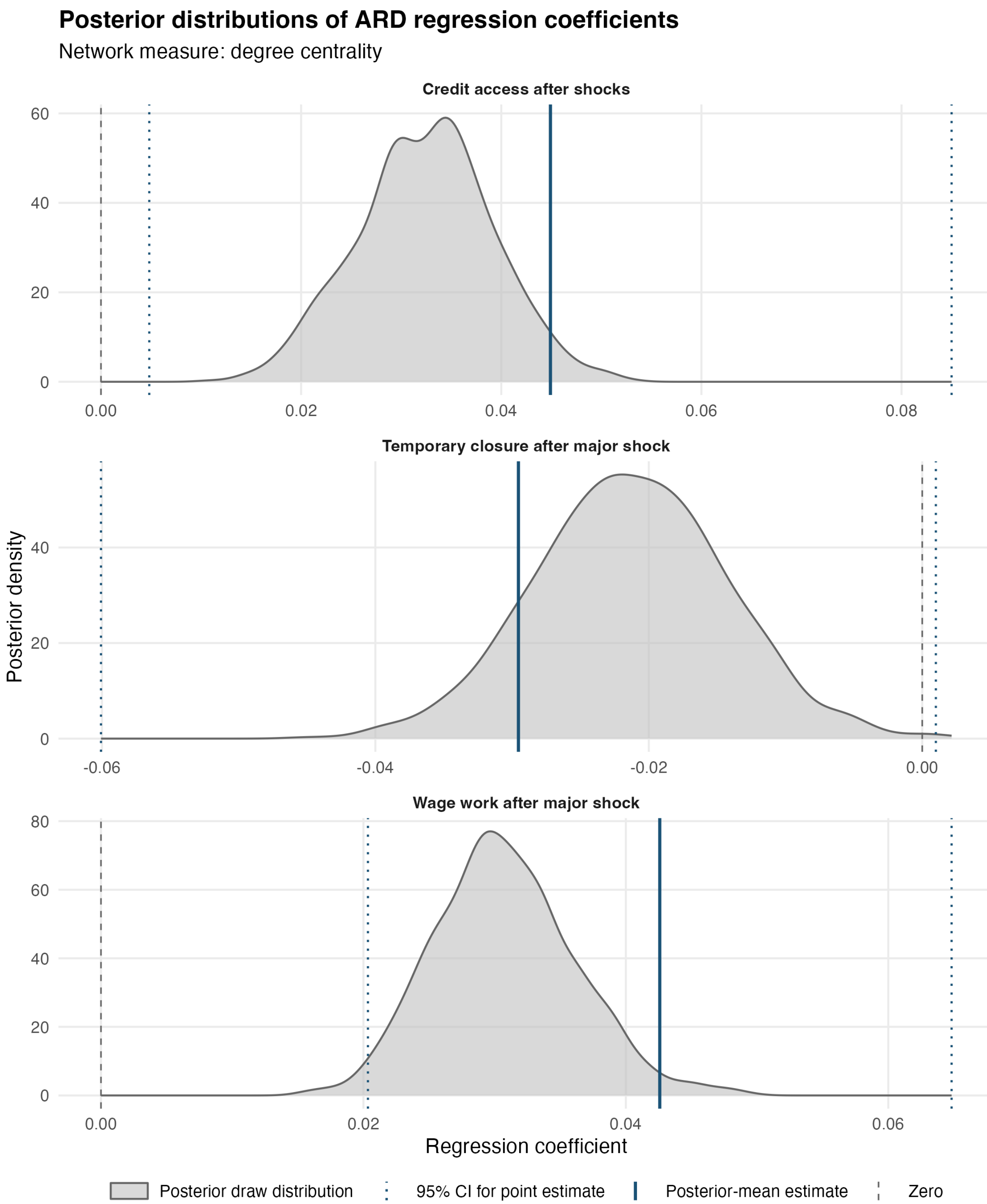

Figure 1: Posterior Distributions of ARD Degree-Centrality Coefficients

A Appendix: Figures and Tables

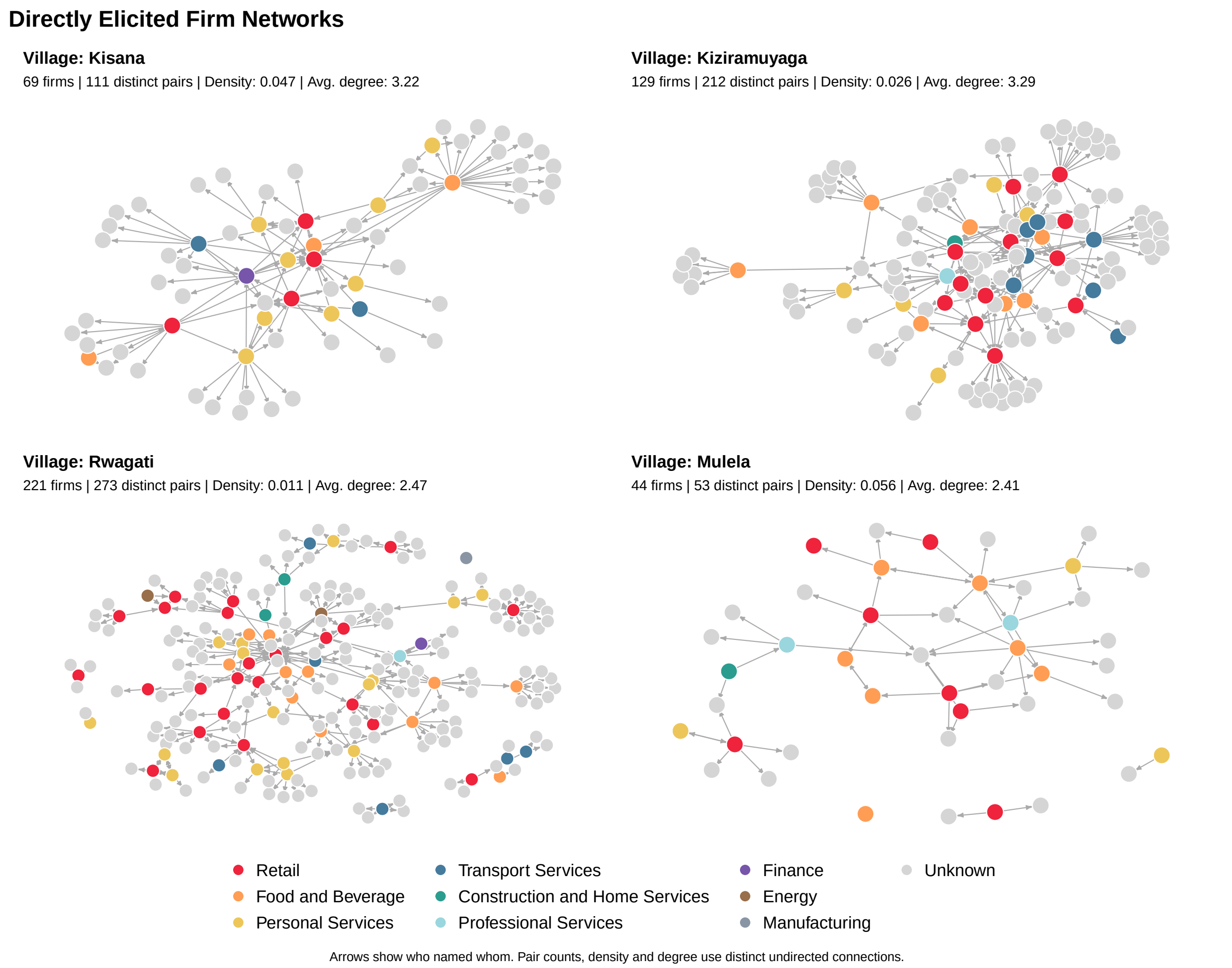

Figure A.1: Directly Elicited Firm Networks in Selected Villages

Notes: Each node represents a firm, and each directed edge indicates that one firm named another firm in response to at least one network question. Node colors indicate broad sector groups, while gray nodes indicate named partner firms for which sector information is not available.

Table A.1: Firm Connectedness and Temporary Closure After Shocks: Directly Elicited Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	-0.0380*	-0.0283*	-0.0211	0.0229
	(0.0204)	(0.0161)	(0.0183)	(0.0159)
Observations	620	620	620	620
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for temporarily closing in response to any of the firm's ranked shocks.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** $p<0.01$; ** $p<0.05$; * $p<0.10$

Table A.2: Firm Connectedness and Wage Work After Shocks: Directly Elicited Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0444**	0.0216	0.0293**	0.0294**
	(0.0164)	(0.0174)	(0.0122)	(0.0114)
Observations	620	620	620	620
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for taking wage work in response to a shock.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** $p<0.01$; ** $p<0.05$; * $p<0.10$

Table A.3: Firm Connectedness and Nearby Wage Work After Shocks: Directly Elicited Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0432***	0.0279*	0.0287*	0.0162
	(0.00995)	(0.0153)	(0.0165)	(0.0121)
Observations	620	620	620	620
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for taking nearby wage work in response to a shock.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** $p<0.01$; ** $p<0.05$; * $p<0.10$

Table A.4: Firm Connectedness and Temporary Closure After Shocks: ARD-Estimated Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	-0.0389**	-0.0272	-0.0368**	-0.745*
	(0.0179)	(0.0168)	(0.0175)	(0.428)
Observations	600	600	600	600
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for temporarily closing in response to any of the firm's ranked shocks.
The main independent variable is the ARD-estimated standardized network measure indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** $p<0.01$; ** $p<0.05$; * $p<0.10$

Table A.5: Firm Connectedness and Wage Work After Shocks: ARD-Estimated Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0486***	0.0224**	0.0488***	0.716***
	(0.0122)	(0.0106)	(0.0121)	(0.192)
Observations	600	600	600	600
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for taking wage work in response to a shock.
The main independent variable is the ARD-estimated standardized network measure indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** p<0.01; ** p<0.05; * p<0.10

Table A.6: Firm Connectedness and Nearby Wage Work After Shocks: ARD-Estimated Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0552***	0.0215*	0.0555***	0.569***
	(0.0115)	(0.0107)	(0.0114)	(0.179)
Observations	600	600	600	600
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for taking nearby wage work in response to a shock.
The main independent variable is the ARD-estimated standardized network measure indicated in each column.
Sample is restricted to firms that experienced at least one shock in the past year.
Standard errors are clustered at the subsector level.
*** p<0.01; ** p<0.05; * p<0.10

Table A.7: Firm Connectedness and Temporary Closure After a Major Plausibly Exogenous Shock: Directly Elicited Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	-0.0597**	-0.0602**	-0.0299*	-0.0327
	(0.0274)	(0.0216)	(0.0169)	(0.0334)
Observations	282	282	282	282
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for temporarily closing in response to the plausibly exogenous shock that most affected the firm.
Plausibly exogenous shocks include agricultural and health shocks, input price increases, and household food price increases.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms whose shock that most affected them was plausibly exogenous.
Standard errors are clustered at the subsector level.
*** p<0.01; ** p<0.05; * p<0.10

Table A.8: Firm Connectedness and Wage Work After a Major Plausibly Exogenous Shock: Directly Elicited Network

	(1) Degree	(2) Betweenness	(3) Supported degree	(4) Community size
Network measure	0.0309**	0.00738	0.0160**	0.0366*
	(0.0124)	(0.00770)	(0.00765)	(0.0199)
Observations	282	282	282	282
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for taking wage work in response to the plausibly exogenous shock that most affected the firm.
Plausibly exogenous shocks include agricultural and health shocks, input price increases, and household food price increases.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms whose shock that most affected them was plausibly exogenous.
Standard errors are clustered at the subsector level.
*** p<0.01; ** p<0.05; * p<0.10

Table A.9: Firm Connectedness and Nearby Wage Work After a Major Plausibly Exogenous Shock: Directly Elicited Network

	(1)	(2)	(3)	(4)
	Degree	Betweenness	Supported degree	Community size
Network measure	0.0436**	0.0376	0.0238	-0.00492
	(0.0160)	(0.0258)	(0.0167)	(0.0180)
Observations	282	282	282	282
Subsector FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Firm size control	Yes	Yes	Yes	Yes

Dependent variable is an indicator for taking nearby wage work in response to the plausibly exogenous shock that most affected the firm.
The main independent variable is the standardized measure from the directly elicited firm network indicated in each column.
Sample is restricted to firms whose shock that most affected them was plausibly exogenous.
Standard errors are clustered at the subsector level.
*** p<0.01; ** p<0.05; * p<0.10

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