Endogenous Transfer Networks Under Spatial Risk[*†]

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Abstract

This paper studies how digital payment technologies affect the amount of insurance households can attain under spatially-correlated shocks when risk-sharing links are *endogenously formed*. I develop a quantitative model in which households form transfer networks over space, treating their own partnerships as substitutable and others' linking decisions as strategic complements to their own. Households jointly agree to strengthen their partnerships but can unilaterally weaken them, leading to multiple stable network configurations. I use the model to quantify welfare gains from informal transfer networks in Tanzania after the 2008 introduction of mobile money, which lowered the costs of transporting money across space. By 2028, the diffusion of mobile money generates average welfare gains of 0.9%, about two-thirds of which arise from network reorganization in response to the technology. Welfare gains are progressive, driven by an enhanced redistributive role of transfers but diminished insurance benefits.

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1 Introduction

Households in developing countries face very volatile incomes but limited access to formal insurance mechanisms, like bank loans and government programs. As a result, households typically rely on informal transfers to smooth consumption. Transfers take the form of cash gifts granted to the household by others in their social network and are the subject of a vast literature in development economics (Rosenzweig and Stark 1989; Townsend 1994; Udry 1994; Kocherlakota 1996; Ligon, Thomas, and Worrall 2000; Attanasio and Rıos-Rull 2000; Munshi and Rosenzweig 2016; Ambrus, Gao, and Milán 2022). Nearly all of this work assumes households share risks among fixed members of a group (e.g., a village), treating households' ex-ante sets of potential partners—or the *transfer network* itself—as fixed. Consequently, this work is unable to evaluate key policy considerations when initially stable transfer arrangements are disrupted by large changes in the value of network links.

One source of these changes is the emergence of digital payment technologies. Pioneered by Safaricom's M-Pesa in 2008 across sub-Saharan Africa, mobile money enables cashless transfers for households without access to bank accounts (Jack and Suri 2014; Economides and Jeziorski 2017). By lowering money transport costs, the technology facilitates payments over long distances, which interacts with the transfer network in two ways. First, such reductions in distance-dependent transfer frictions have implications for risk-sharing due to the prominence of *spatially-correlated* shocks in developing economies (Rosenzweig and Stark 1989; Morten 2019; Allen and Atkin 2022; Meghir et al. 2022; Balboni, Boehm, and Waseem 2023). For instance, droughts and floods can depress the agricultural yields of many nearby households at once, and these spatial patterns may be predictable. Second, large changes in costs alter the value of risk-sharing ties, which creates incentives for households to restructure their transfer partnerships (Riley 2018). The impact of this restructuring depends in part on who is included and excluded from new arrangements.

These observations raise broader questions about how technology interacts with informal institutions of risk-sharing. How do lower transfer frictions systematically reshape transfer networks, and thus, alter their capacity to manage spatial risk across heterogeneous households? How are the gains from such technologies distributed when households differ by productivity and location? What levels of insurance can be sustained when risk-sharing arrangements themselves are elastic to technological change?

To begin, I study the empirical setting of Tanzania from 2008 to 2015. I use household-level panel data to establish three motivating facts about the transfer network. First, the introduction and diffusion of mobile money in the economy coincided with a substantial spatial expansion of transfer networks. Second, households face spatially-correlated shocks.

Third, households rely disproportionately on sources that are *less-productive* than them for insurance after such shocks, where I proxy for productivity with education level of the household head. This fact suggests that insurance-like transfers arise systematically from sources with on average higher marginal utilities of consumption than the household. By contrast, traditional models with fixed network composition would predict that households rely on well-resourced connections with *lower* marginal utilities of consumption, even when shocked (Townsend 1994; Ligon, Thomas, and Worrall 2000). The re-optimization of transfer partnerships after shocks can account for this fact: when expected income falls, a household's anticipated transfer needs rise, reducing the net returns that more-productive partners receive from the arrangement. In response, these partners scale back their engagement, leaving the household dependent on less-productive sources. The previous observations motivate an alternative class of risk-sharing models in which the composition of transfer partnerships is endogenously determined rather than fixed feature of the environment.

Next, I develop a quantitative model in which households, differentiated by productivity and location, form transfer partnerships over space. Pairs choose partnership levels that specify income shares to be transferred if requested. Each household experiences idiosyncratic and spatially-correlated income shocks. After the realization of shocks, households choose one partner from whom to demand payments, prescribing recipient transfers (i.e., inflow). An aggregation of the converse process yields sender transfers (i.e., outflow). Payments are subject to distance-dependent transport costs, which mobile money reduces. I study the pairwise-stable equilibria of this network formation game: all partnerships must be mutually beneficial and no pair of agents can gain from increasing their partnership levels (Jackson and Wolinsky 1996).

In this setting, households face three main strategic considerations. First, transfer partners are *substitutable*: households value additional partnerships less when they are better-connected. This substitutability arises because households benefit only from the largest transfer draw they receive. As a result, an extra or deeper partnership increases net transfers only if it yields a draw greater than the current maximum, which becomes less likely the better-connected a household is. Second, partnership choices exhibit s*trategic complementarities*: households prefer partners with strong connections, since these types of partners are otherwise well-insured and demand less transfers. Third, in the presence of correlated geographic shocks, households aim both to spatially diversify their sets of potential transfer sources and to connect with others that are spatially diversified. Taken together, transfer partnership choices are *strategically interdependent*: the value a household places on one partner depends on its other links *and* on the linking decisions of its partners (Hellmann 2013; Jackson and Zenou 2015). I establish that a pairwise-stable equilibrium exists in my

setting using relatively recent results on the existence of weighted, pairwise-stable networks (Bich and Morhaim 2020).

The model generates micro-level predictions for how the introduction of mobile money impacts transfer outcomes within a pairwise-stable equilibrium. First, the effect of mobile money on network density is theoretically ambiguous. By reducing frictions in money transfer, mobile money encourages households to form new links. Yet, by increasing the value of existing partnerships, it also strengthens incentives to maintain fewer, more productive relationships—a force driven by partner substitutability. Second, mobile money raises the average productivity of a household's partners. As existing partnerships become more valuable, households attract more-productive members through strategic complementarities while scaling back engagement with less-productive ones. Third, networks evolve as household circumstances change, leaving households unevenly exposed to risk. Following negative shocks, low-productivity households experience a contraction in the maximum transfer distance sustainable in equilibrium, while high-productivity households see it expand. Mobile money amplifies both effects. I test predictions using a shift-share identification strategy that utilizes variation in village-level "tech-savviness" to instrument for mobile money adoption. Mobile money increases a source's education levels by 2.8 years. After negative shocks, less-educated households reduce transfer span by 9.7 km, while more-educated households double their transfer amounts.

I quantify the model to assess the impact of mobile money on welfare across heterogeneous household types. Equipped with household consumption and price data from the survey, I estimate the dispersion of households' agricultural production using a log-linear, model-implied relationship that maps asymmetries in the aggregated, cross-region transfer share matrix to differences in regional price levels. I separate households into four discrete education levels, corresponding to a household's productivity type in the model. I exploit a log-linear, model-implied relationship between a household's real income and concurrent local shock realization to estimate moments of the joint local shock distribution across household types.

The model generates aggregate transfer inflow shares. I calibrate remaining structural parameters to match empirical moments of these shares from the survey. First, I use the average spatial (across-region) transfer source Herfindahl to calibrate households' money transport frictions. The convexity of this friction with respect to distance dictates the likelihood a household calls upon geographically far partners for transfers, keeping income constant. Second, I use the local (within-region) transfer source Herfindahl to calibrate costs of intensifying transfer partnerships.[1] If partnership levels are costly to raise between pairs,

[1]These costs may represent liquidity constraints, information verification, or relationship maintenance

households have "diversified" local portfolios of multiple, shallow relationships—decreasing the local concentration of transfer sources. Importantly, local shares do not depend on geographic considerations (e.g., distance, local shock correlation). Third, I use the share of households that do not receive transfers to calibrate an exogenous self-weight. In the model, a household may choose not to receive transfers from partners if it generates its own highest recipient transfer draw, the probability of which is greater under a larger self-weight. Fourth, I calibrate the minimum level of partnerships a household is required to sustain through the transfer-to-income share, as households receive more transfers under higher partnership levels, which weakly increases in the required minimum.

The model features multiple equilibria (Jackson and Zenou 2015). Under the baseline calibration, I examine the *distribution* of equilibrium real consumption after isolated, region-specific shocks to local productivities under fixed and endogenous networks. In the model, households may form mutually-beneficial partnerships across productivity types for insurance purposes; however, one member may send more to the other in expectation, acting as a net giver. I consider two types of shocks: those to regions composed on average of net receivers, and to regions composed on average of net givers.

For *net receiver* regions, the distribution of real consumption under fixed networks stochastically dominates that under endogenous networks. Net receivers fare better when networks remain fixed because they retain access to high-productivity partners who might otherwise sever unprofitable links. When networks adjust, these partners exit, reducing post-shock recipient transfers. For *net giver* regions, the opposite pattern emerges. Net givers fare better when they can readjust their network after shocks—they intensify partnership levels that were previously marginal, increasing post-shock receiver transfers; furthermore, they reduce sender transfers to others through partner substitution.

Next, I trace the distribution of household welfare as average money transport costs decline, occurring when more households have adopted mobile money. I pin down the rate of mobile money diffusion through changes in the average spatial Herfindahl of transfer sources. Assuming the same five-year rate of decline from 2008 to 2013, I project households' outcomes into the future. By 2028, average welfare—measured by households' expected real consumption—improved by 0.9% relative to its 2013 level. Welfare gains follows a progressive pattern: non-educated households see an average welfare gain of 1.4% relative to their 2013 baseline, while university-educated households see a 0.7% welfare *loss*. I decompose gains into two effects: (i) a *direct* mechanical effect, as households more easily access payments from geographically distant partners under existing partnership levels, and (ii) an *indirect* network effect, as households changed the intensity of transfer partnerships. Quantitatively, the

costs that intensify when expected payouts increase

indirect network effect accounts for over two-thirds of the gains. This exercise suggests that the fixed network perspective substantially *underestimates* aggregate welfare gains associated with mobile money.

I additionally consider the welfare gains households receive from the network relative to autarky. By construction, these are positive, as household pairs only intensify partnerships if they are mutually beneficial. I decompose these gains into two components: (i) *redistribution*, or real consumption gains that occur when local shocks realize their expectation, and (ii) *insurance*, or additional welfare gains that arise due to uncertainty around local shock realizations. In 2008, welfare gains from the transfer network stem nearly entirely from insurance. They display no clear progressive pattern and hover around 2.8% across education groups. By 2028, redistribution accounts for nearly nine-tenths of gains for non-educated households on average and one-quarter for university-educated types. Gains also follow a progressive pattern, as non-educated types see an average welfare improvement of 4.1% relative to autarky, and university types see improvements of only 1.3%. By reducing transfer frictions, mobile money makes the redistributive motive more salient in the linking decisions of households. As a result, university types weaken partnerships whose increased redistributive costs no longer outweigh insurance benefits. Instead of finding partners with negatively-correlated income draws, less-educated types exploit partnerships that are now profitable in expectation.

Related Literature The paper relates to many strands of literature, spanning the fields primarily of trade and development. The first involves household risk-sharing in developing countries. This literature considers risk-sharing arrangements under a large range of contracting frictions, including limited commitment, information asymmetry, and autarkic spatial hedging (Rosenzweig and Stark 1989; Coate and Ravallion 1993; Townsend 1994; Udry 1994; Kocherlakota 1996; Ligon 1998; Attanasio and Rıos-Rull 2000; Munshi and Rosenzweig 2016; Ambrus, Gao, and Milán 2022). In contrast to these papers, I consider the transfer network itself as an endogenous equilibrium outcome, which both empirically matches micro-level patterns and alters the amount of insurance sustainable in equilibrium. I allow for crucial dimensions of heterogeneity in risk-sharing arrangements: in particular, households decide not only who to partner with, but also how deeply entwined the partnership should be.

Relative to Morten (2019)—who considers the interaction of village risk-sharing networks with households' binary choices of temporary migration—my framework grants households as many choice variables as household types. The added flexibility permits households to have different and overlapping sets of transfer partners (De Weerdt and Dercon 2006). Con-

trary to fixed-network mutual insurance models like Ligon, Thomas, and Worrall (2000), my framework allows households to be in "partial" risk-sharing arrangements with some but not all other households in a village. More closely related to this paper, Banerjee et al. (2024) include a model of network formation where access to micro-finance reduces informal insurance connections through the presence of global network externalities via strategic complementarities in socialization effort. Although I examine only local network externalities in my paper, I introduce a new strategic consideration: households smooth consumption in part by partnering with others who are themselves well-diversified.

The paper is also situated in a growing literature about mobile money and digital payment systems (Yang 2008; Jack and Suri 2014; Batista and Vicente 2020a; Batista and Vicente 2020b; Alvarez and Argente 2022; Alvarez et al. 2023; Blumenstock et al. 2023; Houeix 2025). Closely related to this paper, Riley (2018) finds that mobile money users in Tanzania have lower pass-throughs of village-level shocks to household consumption than their non-user counterparts. Building on this literature, I find new empirical relationships between mobile money and transfer source characteristics that are closely linked to my theory. I demonstrate that the ways in which transfer amounts from sources respond *empirically* to changing household circumstances are consistent with my model of network re-organization after shocks.

Second, the paper contributes to a growing literature on endogenous network formation in quantitative spatial models (Lim 2017; Kopytov et al. 2021; Bernard et al. 2022; Eaton et al. 2022; Arkolakis, Huneeus, and Miyauchi 2023; Fontaine, Martin, Mejean, et al. 2023; Dhyne et al. 2023; Demir et al. 2024). To this class of models, I add *strategic* linking decisions. By "strategic", I refer to scenarios where agents find the linking decisions of others payoff-relevant, internalizing others' linking decisions when forming their own. As a result, my paper is—to the best of my knowledge—the first to implement a pairwise-stable equilibrium in a quantitative spatial model (Jackson and Wolinsky 1996). Relatedly, the quantitative model in my paper adds a strategic dimension to a rapidly growing series of papers in trade on quantifying interdependent choices (Alfaro-Urena et al. 2023; Arkolakis, Eckert, and Shi 2023; Head et al. 2024; Sabal 2025).[2]

The paper further speaks to a literature on volatility and uncertainty in space (Van Wincoop 1999; Clark and Van Wincoop 2001; Burgess and Donaldson 2012; Di Giovanni and Levchenko 2012; Gârleanu, Panageas, and Yu 2015; Brooks and Donovan 2020; Donovan 2021; Allen and Atkin 2022; Castro-Vincenzi 2022; Castro-Vincenzi et al. 2024; Fan and Luo

[2]The term "interdependence" in these papers refers to the dependence of an agent's valuation of an additional inclusion in its choice set on its other choices. In my setting, this valuation also depends on the choices of others, and this strategic interaction is internalized by agents when making decisions.

2025). In this paper, I permit agents to care directly about the impact of trade (in cash) on consumption volatility, resulting in agents who manage risk directly by spatially diversifying their location choices. While Caselli et al. (2020) include a spatial diversification motive in their model of trade, households in my framework additionally consider the spatial diversification of their partners when forming links over space—constituting a *strategic* spatial risk consideration.

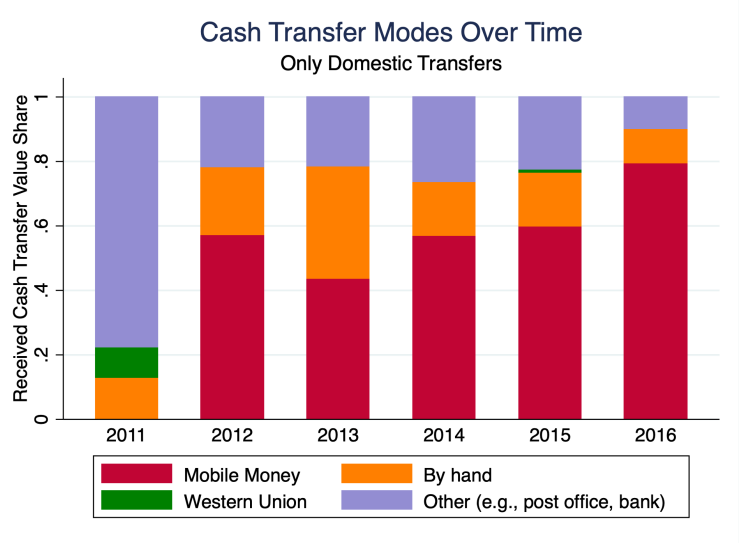
Lastly, the paper draws from a mostly theoretical literature on pairwise-stable networks (Ambrus and Elliott 2021; Bich and Morhaim 2020; Hellmann 2013; Jackson and Wolinsky 1996; Jackson and Watts 2001; Jackson and Zenou 2015; Miyauchi 2016). Relative to these papers, my framework is quantitative and allows me to conduct counterfactuals that explore changes in welfare across heterogeneous households. Additionally, the strategic considerations that characterize the network in my paper—*strategic complementarity* and *partner substitutability*, in tandem, among arbitrarily many players—is theoretically distinct from those conventional in the literature. For example, Hellmann (2013) and Miyauchi (2016) establish the existence of an unweighted pairwise stable equilibrium *only* under both partner and strategic complementarity. Most related to my paper, Celebi (2021) examines unweighted networks with the same strategic considerations. Under this set of considerations, he derives an upper bound of relationships players can sustain and finds that networks where players reach this upper bound are equilibria. An equilibrium does not always exist in his setting, which makes the model difficult to adapt for quantitative analysis. In my setting, I establish the existence of a pairwise-stable equilibrium by allowing for a realistic *intensive* margin of network formation. This moves the problem to a class of weighted networks, where conditions for existence are weaker (Bich and Morhaim 2020).

The paper proceeds as follows. In Section 2, I introduce the empirical context and motivating facts. In Section 3, I present the model. In Section 4, I discuss the model's calibration and quantitative results. Section 5 concludes.

2 Data & Motivating Facts

In this section, I introduce the Tanzania National Panel Survey (NPS), the main data source for this project. I use the NPS to establish three facts about households' use of transfer networks in response to negative spatial shocks. These facts motivate a model of risk-sharing in geography with endogenous network formation.

Figure 1: Modes of Cash Transfer Over Time



Note: The graph displays answers to the following survey question over NPS rounds 2 to 4: "Which of the following remittance channels did [source] use in the last 12 months?" Responses are labeled "Other" if respondents record "Post Office", "Bank Account", and "Other (Specify)". Responses are labeled "By Hand" if respondents record "Friends/Relatives."

2.1 Empirical Context

The NPS is a nationally-representative household-level panel survey implemented by the Tanzania National Bureau of Statistics. Following 14,985 households, this dataset covers a large number of topics, including consumption, self-reported shocks, and sources of income. In April 2008, Vodacom's M-Pesa introduced mobile money to Tanzania. From 2010 onwards, the NPS included a question on mobile money use and adoption. Data for this project spans three survey rounds (i.e., NPS rounds 2 to 4), starting in October 2010 and ending in January 2016. Pooling across rounds, 54.8% of household heads report a primary job in agriculture or livestock in the previous year. The average household contains 5.7 members. The median household head is a primary school graduate (i.e., nine years of education) who earns 1,092,917 TZS (around $445) per year.[3]

The NPS tracks household outcomes before and after widespread mobile money use in the economy. Figure 1 shows that mobile money became the dominant mode of cash transfers during the time period of the survey. I record a household as using mobile money if the respondent reports receiving transfers through M-Pesa, ezyPesa, Airtel Money, Tigo Pesa, Z-Pesa, or Zap. In 2011, no household reported receiving domestic transfers through mobile money. By 2016, 79.4% of the transfer value reported in the survey was remitted via mobile

[3]I calculate annual income as the sum of wage income, business profits, and the fifty times the sales values of weekly self-produced consumption.

money. Mobile money seemed to replace banks, post offices, Western Union, and other financial institutions as popular methods of cash transfer.

A particularly informative NPS survey module asks households about transfers, including the demographic characteristics of transfer sources. I record a household as having received a transfer if a respondent answers "yes" to whether "[the respondent] or anyone in [the respondent's] household received...remittances or financial assistance in the form of cash during the last 12 months". Pooling across rounds, 98.9% of households report two or less transfer sources in a year, suggesting that the network of realized transfers is sparse.[4] Conditional on receipt, the median value of received annual transfers is 120,000 TZS (around $49 USD) and constitutes 12.2% of a household's yearly income. The median source has lived in his current location of residence for 15 years and has nine years of education. Of the 4,517 transfers reported across rounds, 82.3% were used for "household consumption."[5]

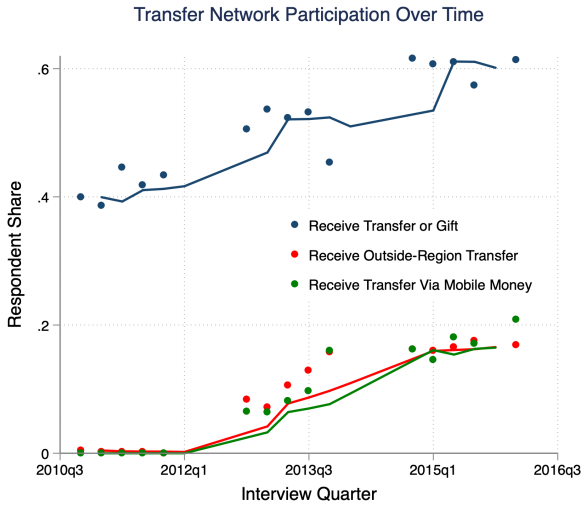
The NPS also asks households how they respond to shocks. In this module, the enumerator lists eighteen types of negative shocks a household may encounter and asks if the household was "severely affected negatively [over the past two years]" by such shocks. The enumerator additionally asks what respondents "[did] in response...to try to regain [their] former welfare level."[6] The three most common ways households cope with shocks include: (i) doing nothing, constituting 54.2% of responses, (ii) relying on own-savings, constituting 21.0% of respondents, and (iii) receiving unconditional help from relatives and friends, constituting 9.6% of respondents. Responses are striking for two reasons. First, the large proportion of respondents who do not identify methods of smoothing consumption suggests that consumption may be very sensitive to negative shocks. Second, households rely on social networks for risk management. The dominance of this risk management mechanism justifies my paper's focus on transfer networks over other forms of insurance, such as temporary migration (0.2% of responses), labor supply adjustments (0.8%), or government programs (0.9%).

[4]The maximum number of sources a household can report is four. The share of respondents reporting two or less sources does not change substantially when considering a household's mobile money adoption status (i.e., 97.7% of adopter households) or round (i.e., 100% in NPS round 2, 98.0% in NPS round 3, and 96.1% in NPS round 4).

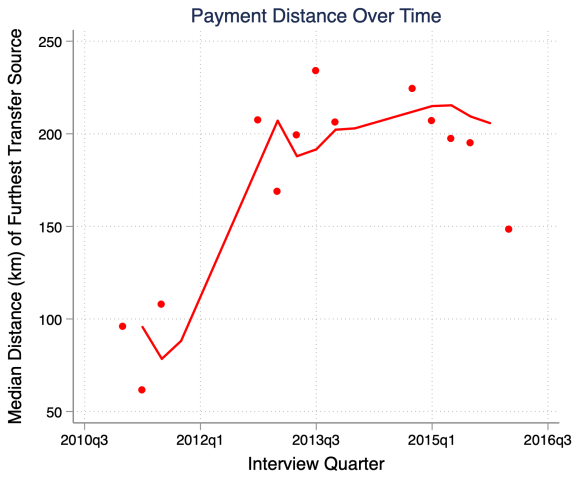
[5]The survey asks: "For what did you or anyone in your household use the cash sent from [source] in the last 12 months?" The second and third most popular answers were "health", constituting 6.0% of answers, and "education", constituting 5.5%.

[6]78.9% of respondents report being affected by a shock. The five most commonly-cited shocks include: (i) a large rise in the price of food, composing 20.2% of recorded shocks; (ii) death of a non-household family member, composing 3.8%; (iii) a severe water shortage, composing 10.9%; (iv) droughts or floods, composing 9.1%; and (v) a large fall in the sales price of crops, composing 7.8%.

Figure 2: Spatial Expansion of Transfer Network in the NPS



(a) Respondent Share in Transfer Network



(b) Median Payment Distance Among Recipients

Note: Quarters with less than ten respondents are dropped. Smoothed time series have a window of five. A household is recorded as receiving a transfer if it reports more than zero transfer sources or reports receiving a gift. The payment distance is the maximum centroid-to-centroid kilometer between source and respondent regions reported by the source in the interview quarter.

2.2 Motivating Facts

In the previous section, I introduced the NPS and described the empirical setting of Tanzania following the 2008 advent of mobile money. In this section, I present three motivating facts about the transfer network.

Fact 1. Mobile money coincided with a substantial spatial expansion of the transfer network.

I document substantial changes in the transfer network after the 2008 advent of mobile money. These changes point to the presence of transfer frictions that scale with distance, which mobile money may alleviate. Figure 2 displays these trends over time.

In Figure 2a, I document extensive margin participation in the transfer network over time. I record a household as receiving a transfer or a gift if the households either (i) responds "yes" to receiving financial support or assistance in the form of cash or in-kind domestic remittances, or (ii) reports a positive consumption value associated with receiving a gift. In 2011, 38.6% of respondents report receiving either a transfer or a gift. By 2016, the share increased to 61.4%. I further examine the share of respondents that report receiving a transfer from outside the region. In 2011, this share was only 0.4% of respondents. By 2016, 16.6% of respondents report receiving outside-region transfers. The level of increase in

overall receipt of transfers or gifts during the survey period corresponds with the new receipt of outside-region transfers. Furthermore, the increase in receipt of outside-region transfers exactly corresponds with an increase in the respondent share receiving transfers via mobile money.

The diffusion of mobile money also appears to change the spatial configuration of transfer networks. In Figure 2b, I show that households obtain cash from geographically further origins conditional on receiving transfers. I define transfer distance as the centroid-to-centroid kilometer span between a household and source's region. At the beginning of 2011, the maximum transfer distance a household reported was a median 95.6 km away. By 2016, the measure increased to 195.1 km. The spread of mobile money coincided with rapid changes in the spatial structure of transfer networks.

In Appendix C.2, I show that transfers follow a gravity-like pattern, where households receive transfers from geographically proximate social contacts. Among mobile money users, this geographic pattern in transfer flows remains but is substantially attenuated.

Fact 2. Households face spatially-correlated shocks.

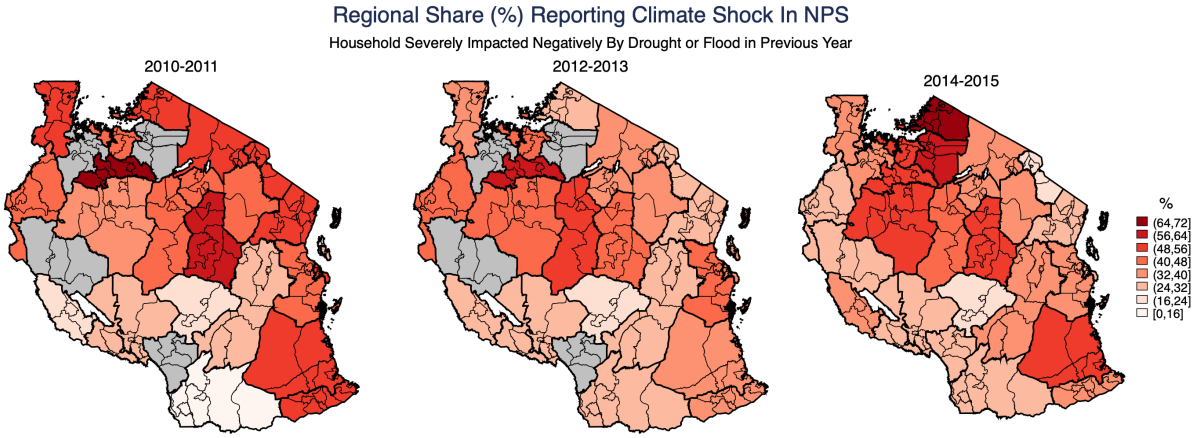
If distant locations experience different shock patterns, the relaxation of distance-dependent transfer frictions documented in Fact 1 can help households stabilize consumption. Here, I show that households face spatially-correlated shocks. In Figure 3, I map the proportion of a region's respondents that report being "severely affected negatively" by droughts or floods in each round.

There are a few observations to note about the map. First, climate shocks are a common occurrence: pooling across rounds and regions, approximately 38.1% of households report experiencing droughts or floods. Second, substantial *spatial heterogeneity* exists in the reported salience of climate shocks. For example, in 2010 to 2011 (i.e., round 2 of the NPS), 53.9% of 1292 respondents living in Dar Es Salaam reported being impacted by a climate shock.[7] By contrast, only 12.3% of 316 respondents in Ruvuma reported begin impacted by a climate shock in the same time period. Third, responses also display *temporal variation*. By round 4 (i.e., year 2014 to 2015), only 24.7% of 799 respondents living in Dar Es Salaam reported a climate shock. However, regions surrounding Lake Victoria such as Mara and Simiyu saw increases in the respondent share reporting climate shocks—65.0% and 59.6%, respectively—reflecting heavy flooding in the area during this time.

In Figure 4, I plot a binned scatterplot of pairwise correlations of respondent shares

[7]This share reflects a substantial flooding episode of the Mkondoa river that occurred in December 2009, reported in the EM-DAT database. Similarly, 62.6% of 219 respondents living in Dodoma reported being impacted by a flood during this time.

Figure 3: Respondent Share Reporting Climate Shocks in NPS by Region



Note: This graph reports the proportion of respondents in the NPS that report being "severely affected" by "droughts or floods" in the past year across rounds. Redder regions correpond to greater respondent proportions. I exclude regions with less than ten respondents in a round.

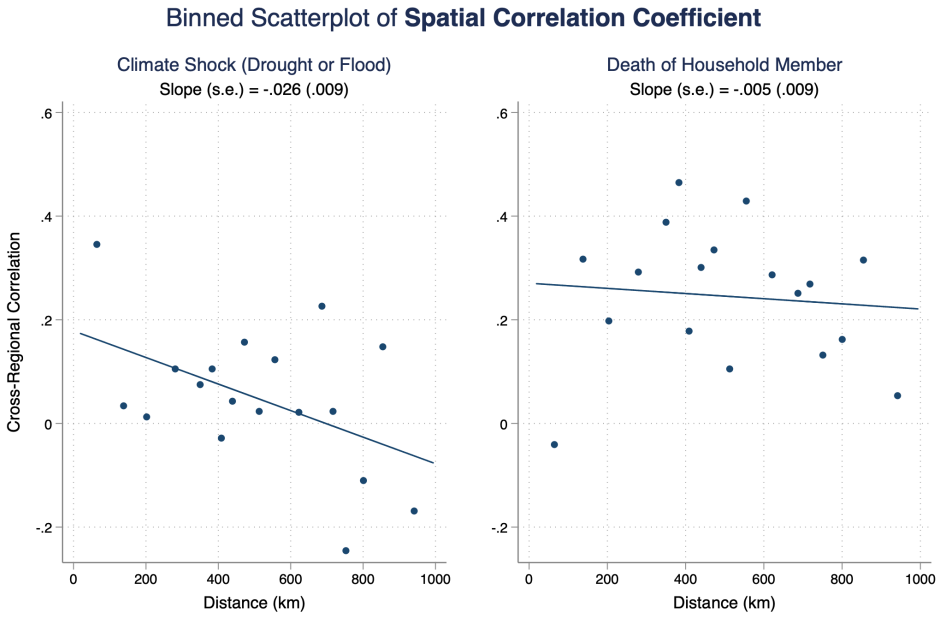
reporting climate shocks in a region against the centroid-to-centroid kilometer distance of region pairs.[8] A 100 kilometer increase in the distance between regions is associated with an average 0.03 decline in the correlation of respondent shares, indicating spatial correlation in climate shocks. This association is statistically significant at the 1% level. I compare this relationship to one generated by the idiosyncratic shock of experiencing the death of a household member, which impacts 8.3% of respondents, and should not be spatially clustered. Distance between regions is not statistically significantly associated with the pairwise correlation of regional respondent shares reporting a death shock. In summary, households face some types of shocks that are spatially-correlated and others that are not. The presence of spatially-correlated shocks suggests gains from spatially diversifying one's transfer sources.

In Appendix C.2, I show that a household's geographic transfer span acts as insurance against climate (i.e., spatial) shocks. In particular, households that can access more distant sources receive more transfers after droughts or floods, which have a spatial component, but not after a family member's death, which does not. These results are consistent with Riley (2018), who uses the NPS to document that mobile money users in Tanzania see lower pass-throughs of village-level shocks to consumption.

Facts 1 and 2 point to space and geography as key features of the transfer network. In Fact 3, I motivate network re-organization as another potential feature of this network. To do so, I document a robust empirical pattern on *who* insures households when they experience

[8] I exclude self-pairs in this regression. Correlations are taken for observations at the region and interview year level, corresponding to six observations per region.

Figure 4: Binned Scatterplot of Respondent Share Shock Correlations and Distance



Note: This graph shows a binned scatterplot of the regression $\rho_t(\Pi_{\ell t}, \Pi_{\ell' t}) = \alpha + \beta \cdot d(\ell, \ell') + \epsilon_{\ell\ell'}$, where $\rho_t(\Pi_{\ell t}, \Pi_{\ell' t})$ is the across-time, pairwise correlation of repondent shares that report being impacted by a shock in location ℓ at time t, $d(\ell, \ell')$ is the 100 kilometer distance between locations ℓ and ℓ', and $\epsilon_{\ell\ell'}$ is a structural error term. The *spatial correlation coefficient* β and associated standard error is in the subtitle of each graph. The responses of "drought and flood" reports display a clear and statistically significant spatial pattern, while the "death of a household member" reports do not.

negative shocks.

Fact 3. Most insurance-like transfers arise from sources that are less-productive than the household head.

Households connect with sources of varying productivity levels. In this setting, I proxy for a household's productivity level with its head's years of education, as years of education closely relate to annual income, and is a characteristic that is already fixed at the time the shock occurs. I separate out household heads into four productivity types, corresponding to discrete education levels. These groups are non-educated or pre-primary, primary school graduates, secondary school graduates, and university or more.[9] Pooling across rounds and households, 51.3% of the value of total transfers arise from sources that are more-educated than the household head. 9.2% of the value of total transfers arise from sources that are less-educated than the household head. Unsurprisingly, across Tanzania, transfers redistribute funds from higher-productivity to lower-productivity households.

In this section, I document a salient empirical pattern: in response to negative shocks, Tanzanian households receive most *insurance-like transfers*—i.e., additional transfers because they experience difficult circumstances—from sources that are *less productive than them*. This finding is puzzling in light of standard risk-sharing models with fixed network composition. In canonical environments of informal insurance—such as Townsend (1994)—households insure income risk by allocating resources to equalize marginal utilities of consumption.[10] Under this arrangement, even as households experience negative shocks, net transfers flow from agents with lower marginal utilities of consumption (i.e., higher income, better-resourced) to those with higher marginal utilities of consumption (i.e., lower income, poorer). In contrast, I find that shocked households systematically receive more transfers from partners who, on average, appear to have *higher* marginal utilities of consumption. Models with limited commitment, like Ligon, Thomas, and Worrall (2000), can rationalize such flows only in knife-edge cases—specifically, when a shocked household moves from being participation-constrained in normal times to unconstrained when shocked.

To show this pattern, I run the following PPML regression for a household h of type s

[9] In the groups: (i) *pre-primary* corresponds to two or less years of education and constituting 25.6% of respondents, (ii) *primary school* graduate corresponds to more than two but less than nine years of education and constituting 56.2% of respondents, (iii) *secondary school* graduate corresponds to more than nine but less than fifteen years of education and constituting 15.4% of respondents, and (iv) *university* or more corresponds to more than fifteen years of education and constituting only 2.8% of respondents.

[10] This is true when households have equal Pareto weights and identical preferences.

at interview time t given source type s':

$$Y_{hss't} = \exp\Bigg[\alpha + \beta \cdot Shock_{hst} + \delta^M \cdot \mathbf{1}(s' > s) + \xi^M \cdot (Shock_{hst} \times \mathbf{1}(s' > s)) \tag{1}$$

$$+\delta^S \cdot \mathbf{1}(s' = s) + \xi^S \cdot (Shock_{hst} \times \mathbf{1}(s' = s)) + \gamma_h + \gamma_{s'} + \gamma_t\Bigg] + \epsilon_{hss't},$$

where $Y_{hss't}$ is the total transfers a household h of type s receives from sources of type s' at time t, $Shock_{hst}$ is an indicator that equals one when a household h of type s experiences a shock at time t, $\mathbf{1}(s' > s)$ is an indicator that equals one when a source type s' is more-educated than the household's type s, $\mathbf{1}(s' = s)$ is an indicator that equals one when a source type s' is equally-educated to the household's type s, γ_h are household fixed effects, $\gamma_{s'}$ are source type fixed effects, γ_t are interview time fixed effects, and $\epsilon_{hss't}$ is an error term. Sources that are less-educated than the household head compose the omitted group. I focus on shock indicators generated by self-reported climate shocks in Table 1a.

The coefficient β is positive when households receive more transfers from less-educated households after shocks. The interaction terms ξ^M and ξ^S are positive when households receive relatively more transfers from, respectively, more- or similarly-educated sources than from less-educated sources *after shocks*. Therefore, the insurance-like transfers households receive from more- or similarly-educated sources is given by the linear combinations of $\beta+\xi^M$ and $\beta + \xi^S$, respectively.

Table 1a displays results of specification (1) across different specifications of the outcome variable. In column (1), I consider total transfer amounts irrespective of a household's relationship to its source; in columns (2) and (3), I fix source relationships to consider only transfers arising from friends and children as outcomes, respectively. Across specifications, households increase transfers from less-educated sources after reporting climate shocks. Additionally, coefficient estimates are consistent with redistribution in the absence of shocks, as $\delta^M > \delta^S > 0$ across specifications, suggesting that transfers flow from more-educated sources on average. Interaction coefficients, however, are negative across all specifications, suggesting that transfers from less-educated sources display the largest increases after households report shocks. The estimates imply that households rely disproportionately on *less*-educated sources for insurance, and not relatively well-resourced, more-educated sources.

In Figure 1b, I plot 95% confidence intervals around the total transfer amounts households receive when both not shocked and shocked by source types, relative to the amount they receive from less-educated sources when not shocked. In the absence of shocks, households receive transfers in a redistributive manner, obtaining more transfers from more- and similarly-

Table 1: Estimated Shock Response of Transfer Amount (TZS) By Source Type

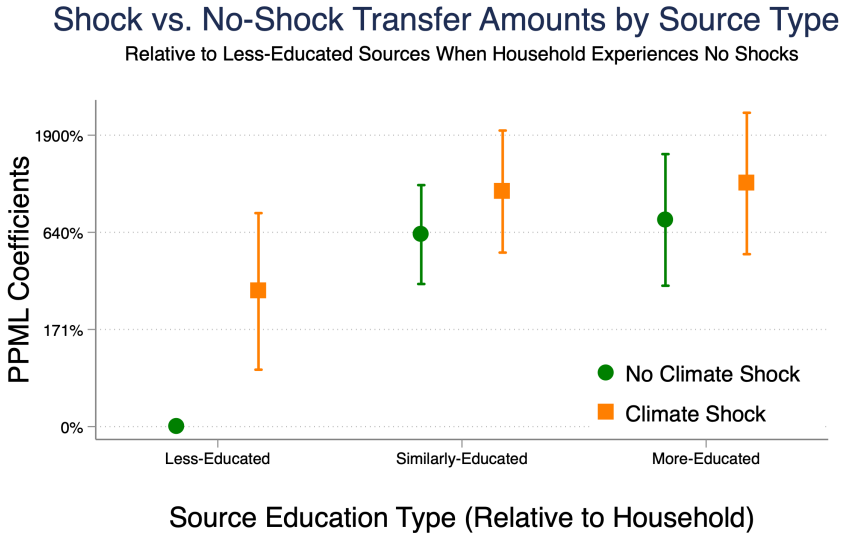
(a) Response of Transfer Amount (TZS) To Climate Shocks By Source Type

	Transfer Amount (1) PPML	From Friend (2) PPML	From Child (3) PPML
Climate Shock=1	1.392***	1.232**	0.809
	(0.411)	(0.601)	(0.504)
More-Educ. Source=1	2.128***	3.704***	2.531***
	(0.346)	(0.562)	(0.533)
More-Educ. Source=1 × Climate Shock=1	-1.017***	-1.473***	-0.904*
	(0.347)	(0.561)	(0.468)
Same Educ. Source=1	1.977***	3.216***	2.494***
	(0.260)	(0.434)	(0.389)
Same Educ. Source=1 × Climate Shock=1	-0.950***	-1.111**	-1.737***
	(0.338)	(0.541)	(0.441)
N	20040	6700	7796
Household FE	✓	✓	✓
Quarter FE	✓	✓	✓
Source Type FE	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table displays the regression results of specification (1). Indicator variables equal one if (i) a household is similarly-educated to its source, or (ii) a household is less-educated than its source. A household who experienced a shock reports being "severely impacted" by a "drought or flood" in the past year. We include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard errors clustered at the household level are shown in parentheses. Outcomes include transfers from all sources, transfers from only friends, and transfer from only children.

(b) Coefficient Plot of Total Transfer Amounts by Source Type After Shocks



Note: Consider the regression of Equation (1) This plot shows total transfers from similarly-educated sources (δ^S) and more-educated sources (δ^M) relative to less-educated sources when households do not report shocks. The plot also shows post-shock transfer amounts from less-educated sources (β), similarly-educated sources ($\beta + \delta^S + \xi^S$), and more-educated sources ($\beta + \delta^M + \xi^M$). 95% confidence intervals constructed with Huber-White standard errors clustered at the household level are shown. Controls include household fixed effects, interview quarter fixed effects, and source education group fixed effects. Outcomes include transfers (in TZS) from all sources.

educated sources than less-educated sources. However, the only source type from which households receive statistically significantly *more* transfers when shocked are less-educated sources. These empirical patterns remain true when holding fixed source relationships—considering, for example, only transfers arising from children or only transfers arising from friends—as well as in response to the idiosyncratic shock of household member death. These results are displayed in Appendix C.1.

How can a framework in which households re-optimize partnership levels after changes in income processes explain this fact? In Section 3, I present a model that proposes the following mechanism. A negative income shock increases a household's demand for transfers from more-productive partners, raising the expected costs of these relationships. In response, more-productive partners scale back the intensity of their transfer ties, prompting the household to rely more heavily on less-productive partners.

3 Model

In this section, I devise a quantitative framework to assess the endogenous formation of transfer networks under spatial risk. The presentation of the model proceeds as follows. Section 3.1 describes production technologies and formalizes a notion of spatial risk. Section 3.2 describes stages of the network payment game. Section 3.3 provides the solution to the game through backwards induction. Section 3.4 discusses micro-implications of the model in equilibrium.

3.1 Technology and Spatial Risk

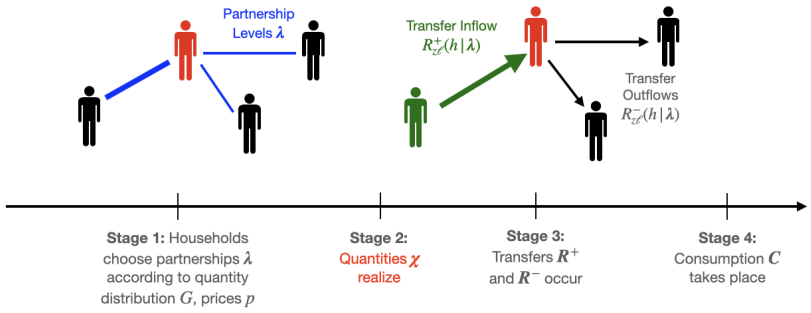
Consider a continuum of households of Z productivities that reside in L locations. A household's type is its location-productivity (ℓ, z) pair. Each type possesses an exogenous measure $\Omega_{z\ell}$, such that the sum of measures equals one. I consider an endowment economy in which households produce a stochastic quantity of agricultural goods.

The output quantity $\chi_{z\ell}(h)$ of a household h of productivity z living in location ℓ is distributed Fréchet with c.d.f.

$$G_{z\ell}(\chi) = \exp\left(-\chi^{-\theta} z \Phi_\ell\right), \tag{2}$$

where the shape parameter θ dictates the dispersion of draws and Φ_ℓ indicates a stochastic local productivity. On average, agricultural yields are larger when households are of higher productivity z and when locations realize high productivity Φ_ℓ draws. Conditional on local shocks $\mathbf{\Phi}$, a non-zero variance of quantity draws $\text{Var}\left(\chi_{z\ell}(h) \,|\mathbf{\Phi}\right)$ maps conceptually

Figure 5: Timeline Illustration



to idiosyncratic uncertainty. The dependence of Equation (2) on stochastic $\mathbf{\Phi}$ induces further variation in the distribution of agricultural yields. Households obtain income $I_{z\ell}(h)$ by selling agricultural goods $\chi_{z\ell}(h)$ for local prices p_ℓ, such that $I_{z\ell}(h) = p_\ell \chi_{z\ell}(h)$.

The framework permits spatial correlation in the vector of local productivities $\mathbf{\Phi}$. The first moments of $\mathbf{\Phi}$ are given by the $L \times 1$ vector $\boldsymbol{A}$, where the ℓth entry A_ℓ represents the average local productivity draw of location ℓ. The second moments of $\mathbf{\Phi}$ can be summarized by an $L \times L$ variance-covariance matrix $\mathbf{\Sigma}$, where the (ℓ, ℓ')th entry $\sigma_{\ell\ell'}$ represents the covariance of shocks $\text{Cov}(\Phi_\ell, \Phi_{\ell'})$ between locations ℓ and ℓ'. Each household in a location ℓ observes the same realization of the local shock Φ_ℓ. Of other papers that have modeled spatial risk, this formulation most closely resembles that in Caselli et al. (2020).

An economy displays *spatial risk* if there is no constant $c \geq 0$ such that $\sigma_{\ell\ell'} = c$ for all location pairs (ℓ, ℓ'). This definition excludes cases with no local uncertainty, where $c = 0$, as well as cases with only aggregate uncertainty, where $c > 0$. Furthermore, an economy displays *spatial correlation* under non-zero off-diagonal terms of the variance-covariance matrix $\mathbf{\Sigma}$. Relative to standard spatial models, the presence of $\mathbf{\Sigma}$ permits a location shock's covariance with other locations' shocks to constitute an additional dimension of geographic heterogeneity.

3.2 The Network Payment Game

Inter-household transfers are allocated according to a network payment game. Figure 5 provides a timeline of the game. The game proceeds in four stages. In Stage 1, prior to shock realizations, households are randomly matched to a representative of each other household type as partners. Notationally, I assign productivity-location type (z, ℓ) to household h and

type (z', ℓ') to household h'. Household pairs assign partnership levels $\lambda_{z\ell z'\ell'}$ (and $\lambda_{z'\ell' z\ell}$) to their link, which specifies the income share a partner h' transfers to household h (and a household h transfers to household h') if requested. At Stage 2, local productivities $\mathbf{\Phi}$ realize. At Stage 3, households observe the income draws of their partners and demand payments from one partner in their network. They receive transfers from partners they approach and give transfers to partners who approach them. At Stage 4, households consume income net of transfers and regional prices clear. In this section, I discuss the stages of the game in further detail.

Stage 1: Partnership Formation

Household pairs decide on partnership levels $\boldsymbol{\lambda}$, which are the key choice variables of the model. At this stage, households know the distribution—but not the realization—of income distributions $\boldsymbol{G}$ and local productivities $\mathbf{\Phi}$. The partnership level $\lambda_{z'\ell' z\ell}$ denotes household h's claim on a share of the realized income $I_{z'\ell'}(h')$ of partner h'. Concretely: if approached by household type h at Stage 3, a household h' must pay its partner a portion $\lambda_{z'\ell' z\ell}$ of its realized income $I_{z'\ell'}(h')$.[11] Note that, within types, households at this stage are ex-ante identical, so partnership levels $\boldsymbol{\lambda}$ are the same across all households of the same type. Additionally, note that households make *extensive margin* decisions, as household pairs may decide to set their partnership levels to zero.

The sum of partnerships are subject to a feasibility constraint that ensures always-positive consumption for each household in the economy, regardless of income realizations. Let the sender-borne transfer friction $\kappa_{z\ell z'\ell'}$ denote a wedge between sender h's payment and the received transfer of h'.[12] For each household h, the feasibility constraint is

$$\underline{\lambda} \leq \sum_{h' \neq h} \kappa_{z\ell z'\ell'} \lambda_{z\ell z'\ell'} \leq 1 - \bar{\lambda}. \tag{3}$$

The right inequality of constraint (3) states that the sum of others' claims on a household's realized income, inclusive of transfer frictions borne by the sender, may not exceed $1 - \bar{\lambda}$. The "capacity" parameter $\bar{\lambda}$ enters into the feasibility constraint as an exogenous self-weight

[11] Equivalently, one may interpret the partnership level $\lambda_{z'\ell' z\ell}$ as the proportion of time a household h' spends aiding h if called upon for help. The household has foregone income to help its partner, so the opportunity cost of aid is $\lambda_{z'\ell' z\ell} I_{z'\ell'}(h')$.

[12] From the time use interpretation of partnerships, friction $\kappa_{z\ell z'\ell'}$ is a wedge between the effort of sender h and perceived benefit of receiver h'. One can take the transfer friction $\kappa_{z\ell z'\ell'}$ literally: all mobile money platforms, including Vodacom's M-PESA and PayPal, impose merchant fees that scale with the transaction amount on the platform. However, as with geographic money transport costs $\tau_{\ell\ell'}$, the friction needs not be pecuniary. Larger transfers may require greater time verifying the claim, coordinating the payment, or consolidating sources of liquidity at the expense of the sender.

of sender h. When $\bar{\lambda}$ is close to 1, households are unable to form many partnerships with others without violating the feasibility constraint, suggesting limited partnership capacity. I set the self-weight $\lambda_{z\ell z\ell} = \bar{\lambda}$ for all $(z, \ell) \in \mathcal{H}$. This allows a household to generate its own highest transfer draw and forego receiving a transfer under particularly high income realizations.

The left inequality of constraint (3) states that the sum of others' claims on a household's realized income must exceed an exogenous "altruism" parameter $\underline{\lambda} > 0$. This constraint may be viewed as a social norm: households must engage marginally in these networks to avoid social sanction. Importantly, this restriction bounds expected transfers away from zero, which provides a motive for even the highest-productivity households to allocate partnerships strategically. Both the "capacity" and "altruism" parameters, respectively $\overline{\lambda}$ and $\underline{\lambda}$, may be interpreted as social conventions that are informed by a community's history, kinship ties, or levels of trust. For tractability, I abstract away from forces that may determine these parameters and take them to be exogenous.

I assume that the wedge follows the functional form $\kappa_{z\ell z'\ell'} = 1 + \bar{c}\lambda^{\gamma}_{z\ell z'\ell'}$, where the parameter $\bar{c}$ dictates the extent to which transfer frictions scale with payouts and the parameter γ describes the curvature of this scaling. Importantly, transfer frictions $\kappa_{z\ell z'\ell'}$ are increasing in partnership levels $\lambda_{z\ell z'\ell'}$, implying that deeper partnerships are more costly. This property induces convexity in the cost of partnerships, which acts as a necessary condition for equilibrium existence. Let $\kappa_{z\ell z\ell} = 1$ for all $(z, \ell) \in \mathcal{H}$, where $\mathcal{H}$ denotes the set of household types.

At this stage, households determine how intensely they wish to partner with other types, given existing network connections. To fix ideas, in Definition 1, I consider a household's most profitable, unilateral deviation in a partnership, keeping the rest of the network fixed. To do so, I denote $\boldsymbol{\lambda}_{-z\ell z'\ell'}$ as the set of transfer partnerships in the network excluding the link $\lambda_{z\ell z'\ell'}$.

Definition 1. A household h's *desired partnership level* $\lambda^{*}_{z\ell z'\ell'}$ in its partnership with h' given other partnerships $\boldsymbol{\lambda}_{-z\ell z'\ell'}$ is

$$\lambda^{*}_{z\ell z'\ell'}\left(\boldsymbol{\lambda}_{-z\ell z'\ell'}\right) = \arg\max_{\lambda} \quad \mathbb{E}\left[U\left(C_{z\ell}\left(h|\lambda \cup \boldsymbol{\lambda}_{-z\ell z'\ell'}\right)\right)\right] \quad \text{s.t.} \quad \text{Equation (3)}, \tag{4}$$

where $U(.)$ denotes a household's payoffs.

The desired partnership level $\lambda^{*}_{z\ell z'\ell'}$ can be interpreted as a household h's best-response in its relationship with h' given other network connections $\boldsymbol{\lambda}_{-z\ell z'\ell'}$, subject to the feasibility constraint. Importantly, the desired partnership level $\lambda^{*}_{z\ell z'\ell'}$ maximizes household h's expected payoffs and does not take into consideration the effect of the partnership level $\lambda^{*}_{z\ell z'\ell'}$

on the expected payoffs of household h'.

Stage 2: Shock Realizations

Between Stages 1 and 2, spatial shocks $\boldsymbol{\Phi}$ realize. At Stage 2, agricultural quantities $\boldsymbol{\chi}$, and thus households' incomes $\boldsymbol{I}$, realize. Households observe the income draws of their partners and derive their *recipient transfer draws*, or the transfers they would receive if approaching partners for payments. In transiting money from location ℓ to ℓ', a receiver household retains only a portion $\tau_{\ell\ell'} < 1$ of the remitted amount, where $\tau_{\ell\ell'}$ declines in the geographic distance $d_{\ell\ell'}$ between locations ℓ and ℓ'. I refer to the inverse of $\tau_{\ell\ell'}$ as the money transport cost, which multiplicatively discounts payments received from far places and equates to an iceberg cost in the trade literature. I assume the functional form $\tau_{\ell\ell'} = d_{\ell\ell'}^{-\delta}$, where δ denotes the convexity of money transport costs with respect to distance. Mobile money reduces δ and lowers the scaling of money transport costs with distance.[13] A recipient transfer draw of a household h with respect to its partner h' is $\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}I_{z'\ell'}(h')$.

In the counterfactuals of Section 4, I map economic outcomes along the diffusion path of mobile money by examining equilibrium-to-equilibrium changes as the distance discount δ declines. As I have abstracted away from a micro-founded technology adoption decision, one can interpret the decline as occurring when more households adopt mobile money,which reduces the *average* household's costs of transporting money over space.

Stage 3: Transfers

A household chooses to receive payments from the partner associated with the highest recipient transfer draw.[14] Conditional on incomes $\boldsymbol{I}$ and partnership levels $\boldsymbol{\lambda}$, the *recipient (positive) transfer* of a household h in location ℓ is

$$R_{z\ell}^{+}(h|\boldsymbol{\lambda}, \boldsymbol{\Phi}, \boldsymbol{I}) = \max_{(z',\ell')\in\mathcal{H}} \tau_{\ell'\ell}\lambda_{z'\ell'z\ell}I_{z'\ell'}(h'). \tag{5}$$

Households are more likely to demand payments from those with whom they engage in strong partnerships (high $\lambda_{z'\ell'z\ell}$) and share geographic proximity (low $\tau_{\ell'\ell}$), or who observe high income realizations. Note that a household may generate its own highest payment draw, the likelihood of which is dictated by capacity parameter $\bar{\lambda}$. If a household generates its own

[13] The micro-foundations for the money transport cost of payments may embed non-pecuniary aspects of transacting with others at larger distances. These costs include cultural differences, relationship maintenance, and the easing of information asymmetry between partners.

[14] The restriction that households receive payments from only one other household type is largely consistent with the data: 98.9% of NPS respondents report two or less transfer sources annually. The NPS permits respondents to report at most four sources.

highest recipient transfer draws, or $\bar{\lambda} I_{z\ell}(h) \geq \max_{h' \neq h} \tau_{\ell'\ell} \lambda_{z'\ell' z\ell} I_{z'\ell'}(h')$ for a realization of incomes $\boldsymbol{I}$ and partnership levels $\boldsymbol{\lambda}$, a household does not receive a transfer from its partners.

The converse process dictates a household's payment outflow. Multiple other households may request payments from household h, who transfers the specified amount $\lambda_{hh'} I_{z\ell}(\boldsymbol{\lambda})$ to a claimant household h', exclusive of sender-borne transfer frictions $\kappa_{hh'}$. The *sender (negative) transfers* of household h in location ℓ is

$$R^{-}_{z\ell}(h|\boldsymbol{\lambda}, \boldsymbol{\Phi}, \boldsymbol{I}) = \sum_{h' \in \mathcal{H}} \kappa_{z\ell z'\ell'} \lambda_{z\ell z'\ell'} I_{z\ell}(h) \cdot \mathbf{1}\left(h = \arg\max_{h'' \in \mathcal{H}} \tau_{\ell''\ell} \lambda_{z''\ell'' z'\ell'} I_{z''\ell''}(h'')\right). \quad (6)$$

Crucially, a household's sender transfer depends on its partner's partnership levels among pairs that do not directly involve the household, or $\lambda_{z''\ell'' z'\ell'}$ for $h', h'' \neq h$. The presence of sender transfers generates high-order dependence of a household's consumption on the broader network structure $\boldsymbol{\lambda}$ and not just its own partnership levels.

A household's valuation of its network depends on how closely it is situated, relationally or geographically, to high-productivity partners. Households with stronger partnerships λ or closer proximity τ with high-productivity individuals can more easily access payments from others. In Definition 2, I represent a network's value as the distance $\tau_{\ell'\ell}$ and relationship $\lambda_{z'\ell' z\ell}$ weighted sum of partners' income determinants, where income determinants include not only partners' idiosyncratic z' and location-specific productivities $\Phi_{\ell'}$, but also their nominal levels $p_{\ell'}$.

Definition 2. The *network access* of a household in location ℓ with productivity z to be

$$S_{z\ell}(\boldsymbol{\lambda}, \boldsymbol{\Phi}) = \sum_{z', \ell'} \left(\lambda_{z'\ell' z\ell} \tau_{\ell'\ell} p_{\ell'}\right)^{\theta} z' \Phi_{\ell'}. \quad (7)$$

Resembling the deterministic "market access", the unconditional network access term $S_h(\boldsymbol{\lambda})$ of Equation (7) depends on location-specific productivities $\boldsymbol{\Phi}$ and is stochastic (Anderson and Van Wincoop 2003; Donaldson and Hornbeck 2016; Redding and Sturm 2008).

Absent distributional assumptions on $\boldsymbol{\Phi}$, the first and second moments of network access $S_{z\ell}(\boldsymbol{\lambda})$ are

$$S^{(1)}_{z\ell}(\boldsymbol{\lambda}) = \sum_{z', \ell'} \left(\lambda_{z'\ell' z\ell} \tau_{\ell'\ell} p_{\ell'}\right)^{\theta} z' A_{\ell'} \quad (8)$$

and

$$S^{(2)}_{z\ell}(\boldsymbol{\lambda}) = \sum_{z', \ell'} \left(\lambda_{z'\ell' z\ell} \tau_{\ell'\ell} p_{\ell'}\right)^{2\theta} z'^2 \sigma_{\ell'\ell'} + \sum_{z', \ell' \neq z'', \ell''} \left(\lambda_{z'\ell' z\ell} \lambda_{z''\ell'' z\ell} \tau_{\ell'\ell} \tau_{\ell''\ell} p_{\ell'} p_{\ell''}\right)^{\theta} z' z'' \sigma_{\ell''\ell'}. \quad (9)$$

The variance of network access $S^{(2)}_{z\ell}(\boldsymbol{\lambda})$ decreases only when households diversify their links. Households diversify links by strengthening partnerships with others experiencing negatively-correlated shocks, as dictated through the off-diagonal terms of variance-covariance matrix $\boldsymbol{\Sigma}$. Without the spatial correlation of geographic shocks, strengthening partnership can only make network access noisier.

Stage 4: Consumption

At Stage 4, households consume income net of transfers:

$$C_{z\ell}(h|\boldsymbol{\lambda}, \boldsymbol{\Phi}, \boldsymbol{I}) = I_{z\ell}(h) + R^{+}_{z\ell}(h|\boldsymbol{\lambda}, \boldsymbol{\Phi}, \boldsymbol{I}) - R^{-}_{z\ell}(h|\boldsymbol{\lambda}, \boldsymbol{\Phi}, \boldsymbol{I}). \tag{10}$$

Prices $\boldsymbol{p}$ may be set so local markets clear upon the fulfillment of transfers, moving this partial equilibrium game to a general equilibrium environment. I include a discussion of a goods market clearing condition and show quantitative general equilibrium results in the Appendix.

In my baseline setting, I restrict payoffs to be linear such that households maximize expected transfers. In Section 3.3, I show that a spatial diversification motive still exists under such payoffs, as households aim to decrease the variance of their own network access in Equation (9).

3.2.1 Equilibrium Definition

Introduced by Jackson and Wolinsky (1996), the concept of pairwise stability characterizes networks likely to persist when links require mutual consent. Bich and Morhaim (2020) extend this concept to weighted networks, such as the partnership levels brought about in our payment game. I adapt their definition to the context of the network payment game below.

Definition 3. A network $\bar{\boldsymbol{\lambda}}$ is *pairwise stable* with respect to expected payoffs $\mathbb{E}[C_{z\ell}(h|\boldsymbol{\lambda})]$ if

(a) for each (h, h') and for $\lambda_{z\ell z'\ell'} \in [0, \bar{\lambda}_{z\ell z'\ell'})$, $\mathbb{E}\left[C_{z\ell}\left(h|\bar{\boldsymbol{\lambda}}_{-z\ell z'\ell'} \cup \lambda_{z\ell z'\ell'}\right)\right] \leq \mathbb{E}\left[C_{z\ell}\left(h|\bar{\boldsymbol{\lambda}}\right)\right]$ and $\mathbb{E}\left[C_{z'\ell'}\left(h'|\bar{\boldsymbol{\lambda}}_{-z\ell z'\ell'} \cup \lambda_{z\ell z'\ell'}\right)\right] \leq \mathbb{E}\left[C_{z'\ell'}\left(h'|\bar{\boldsymbol{\lambda}}\right)\right]$.

(b) for each (h, h') and for $\lambda_{z\ell z'\ell'} \in (\bar{\lambda}_{z\ell z'\ell'}, 1]$, at least one of the following two conditions are true: $\mathbb{E}\left[C_{z\ell}\left(h|\bar{\boldsymbol{\lambda}}_{-z\ell z'\ell'} \cup \lambda_{z\ell z'\ell'}\right)\right] \leq \mathbb{E}\left[C_{z\ell}\left(h|\bar{\boldsymbol{\lambda}}\right)\right]$ or $\mathbb{E}\left[C_{z'\ell'}\left(h'|\bar{\boldsymbol{\lambda}}_{-z\ell z'\ell''} \cup \lambda_{z\ell z'\ell'}\right)\right] \leq \mathbb{E}\left[C_{z'\ell'}\left(h'|\bar{\boldsymbol{\lambda}}\right)\right]$.

The first condition requires that single households have no incentives to weaken their partnerships: in equilibrium, partnership levels do not admit downward deviations that are

profitable to any member of any pair. The second condition requires that two households must agree to strengthen their partnership: in equilibrium, partnership levels do not admit upward deviations that are profitable for both members of any pair. The concept of pairwise stability captures the *informality* of transfer partnerships: no external agency can require two households to send or receive transfers, so the realized network must be privately beneficial to players.

Comparison With Other Models My framework differs in important ways from canonical models of risk sharing. Existing approaches typically consider how ex-post dynamics shape consumption allocations within risk-sharing groups, including limited commitment settings in which households can deviate into autarky (Coate and Ravallion 1993; Townsend 1994; Ligon 1998; Attanasio and Rıos-Rull 2000; Ligon, Thomas, and Worrall 2000; Genicot and Ray 2003; Bloch, Genicot, and Ray 2007; Bloch, Genicot, and Ray 2008; Bold 2009; Ambrus, Mobius, and Szeidl 2014; Morten 2019; Kinnan 2022; Meghir et al. 2022). In contrast, my framework abstracts from ex-post bargaining and enforcement, allowing transfers to follow tractable, statistical distributions.[15] This simplification prevents a direct mapping to these models but permits a richer analysis of ex-ante network formation. In particular, exploring network re-organization allows for the examination of new economic considerations in risk-sharing arrangements—such as the strategic selection of partners based on observed traits, households' ex-ante risk exposure via social connections, and motives of spatial diversification.

I quantitatively implement a limited commitment extension of this model in Appendix Chapter D. While limited commitment is typically viewed as an obstacle to informal insurance when the transfer network is exogenous, when network participation is endogenous, the additional ability of high-productivity households to renege on payments reduces their redistributive costs of joining transfer partnerships—which, counterintuitively, encourages their participation and *sustains the insurance role of transfer networks.*

Additionally, I focus on a perfect information setting, though some distance-dependent verification costs may be captured in the distance discount parameter δ.

[15]The standard approach to this problem is to apply a large "punishment" under deviations from the contract such that households always deem cooperation optimal. My setting complicates this approach, as the income distribution has infinite support. Put simply, there is always a positive probability that households draw a high enough income that they deviate. I suggest, instead, a sufficiently costly "punishment" that income draws for which deviation is optimal are rare and the game approximates transfer flows on aggregate reasonably well.

3.3 Solving the Model

In this section, I solve the game described in Section 3.2 through backwards induction. In Section 3.3.1, I calculate expected transfer flows at Stage 3 of the game under particular realizations of the spatial shock $\mathbf{\Phi}$ and network $\boldsymbol{\lambda}$. These flows determine households consumption at Stage 4 of the game. In Section 3.3.2, I derive the privately-optimal partnership levels of households that are calculated at Stage 1 of the game. In Section 3.3.3, I show that a pairwise-stable equilibrium in households' partnership levels exists.

3.3.1 Expected Transfers Under Fixed $\boldsymbol{\lambda}$

In Lemma 1, I consider the distribution of transfers conditional on the network $\boldsymbol{\lambda}$ of partnerships. The information structure of Lemma 1 places calculations temporally between Stages 1 and 2 of the payment game.

Lemma 1. *Consider a spatial shock realization $\mathbf{\Phi}$ and fixed partnership levels $\boldsymbol{\lambda}$. For a household in location ℓ of productivity z:*

(a) Recipient transfers $R^{+}_{z\ell}(h|\boldsymbol{\lambda},\mathbf{\Phi})$ is distributed Fréchet with a shape parameter θ and shifter $S^{1/\theta}_{z\ell}(\boldsymbol{\lambda},\mathbf{\Phi})$.

(b) Let $\tilde{R}^{-}_{z\ell}(h|\boldsymbol{\lambda},\mathbf{\Phi})$ denote a normalized sender transfer $R^{-}_{z\ell}(h|\boldsymbol{\lambda},\mathbf{\Phi})$ scaled by the inverse of income $I_{z\ell}(h)$. This variable is distributed as a Poisson binomial distribution with probabilities $\pi_{z\ell z'\ell'}(\boldsymbol{\lambda},\mathbf{\Phi})$ that a household h' receives a payment from h

$$\pi_{z\ell z'\ell'}(\boldsymbol{\lambda},\mathbf{\Phi}) = \left(\lambda_{z\ell z'\ell'}\tau_{\ell\ell'}p_{\ell}\right)^{\theta} z\Phi_{\ell}S^{-1}_{z'\ell'}(\boldsymbol{\lambda},\mathbf{\Phi}). \tag{11}$$

Proof. The proof is found in Appendix A.1. □

The network access term of Equation (7) arises endogenously as a shifter in the distribution of transfer inflows $R^{+}_{h\ell}(h|\boldsymbol{\lambda},\mathbf{\Phi})$ and in the denominator of of sender probabilities in Equation (11).

From an inflow perspective, a household faces decreasing returns to enhanced network access. From Lemma 1, a household h's expected recipient transfer is given by the expression

$$\mathbb{E}\left[R^{+}_{z\ell}(h|\boldsymbol{\lambda},\mathbf{\Phi})\right] = \Gamma(1-1/\theta)\,S^{1/\theta}_{z\ell}(\boldsymbol{\lambda},\mathbf{\Phi}). \tag{12}$$

Note that the expression in Equation (12) is an increasing and concave function in own network access conditional on location-specific shocks $S_{z\ell}(\boldsymbol{\lambda},\mathbf{\Phi})$.[16] Equivalent increases in network access are valued less when the base level is large rather than small. An economic

[16] The concavity arises from a restriction on the Fréchet distribution that $\theta > 1$.

interpretation of this concavity goes as follows: by the time transfers take place after income realizations, households view their partners as perfectly substitutable. Suppose a household h increases its network access by raising its partnership level $\lambda_{z\ell z'\ell'}$ with h'.[17] At the margin, the more valuable partnership with h' is helpful to household h *only if* its h' recipient transfer draw overtakes the maximum draw under the prior network. The possibility of this marginal benefit declines when network access is large. This economic force is described as *partner substitutability*.

From an outflow perspective, households benefit when their partners have greater network access $S_{z'\ell'}(\boldsymbol{\lambda}, \boldsymbol{\Phi})$, inducing a *strategic complementarity* in partnership levels. From Lemma 1, a household h's expected sender transfer is given by the expression

$$\mathbb{E}\left[R^{-}_{z\ell}(h|\boldsymbol{\lambda}, \boldsymbol{\Phi})\right] = \Gamma(1-1/\theta) \sum_{z',\ell'} \kappa_{z\ell z'\ell'} \tau^{-1}_{\ell\ell'} \mathbb{E}\left[S^{1/\theta}_{z'\ell'}(\boldsymbol{\lambda}, \boldsymbol{\Phi}) \pi_{z\ell z'\ell'}(\boldsymbol{\lambda}, \boldsymbol{\Phi})\right]. \tag{13}$$

A household's expected sender transfer in Equation (13) is a decreasing and convex function of others' network access $S_{z'\ell'}(\boldsymbol{\lambda}, \boldsymbol{\Phi})$. This benefit arises because the probability a household's partners demand a payment $\pi_{z\ell z'\ell'}(\boldsymbol{\lambda}, \boldsymbol{\Phi})$ declines when the partner is better-connected. Well-connected households rely less on any one of their partners than poorly-connected households.

In a corollary to Lemma 1, I consider a household's expected consumption *unconditional* on the realization of location-specific productivities $\boldsymbol{\Phi}$. The relaxed information structure temporally places the implications of Corollary 1 at Stage 1 of the game. The corollary describes the manner in which spatial risk considerations enter into households' calculations of expected consumption prior to the realization of location-specific productivities $\boldsymbol{\Phi}$.

Corollary 1. *Consider fixed partnership levels $\boldsymbol{\lambda}$. Approximating with a second-order Taylor expansion around the vector of local productivity expectations $\boldsymbol{A} = \mathbb{E}(\boldsymbol{\Phi})$:*

(a) A household h's expected recipient transfer $\mathbb{E}\left[R^{+}_{z\ell}(h|\boldsymbol{\lambda})\right]$: (i) increases in the expectation of own network access $S^{(1)}_{z\ell}(\boldsymbol{\lambda})$, or $\frac{\partial \mathbb{E}\left[R^{+}_{z\ell}(h|\boldsymbol{\lambda})\right]}{\partial S^{(1)}_{z\ell}(\boldsymbol{\lambda})} > 0$, and (ii) decreases in own network access volatility $S^{(2)}_{z\ell}(\boldsymbol{\lambda})$, or $\frac{\partial \mathbb{E}\left[R^{+}_{z\ell}(h|\boldsymbol{\lambda})\right]}{\partial S^{(2)}_{z\ell}(\boldsymbol{\lambda})} < 0$.

(b) A household h's expected sender transfer $\mathbb{E}\left[R^{-}_{z\ell}(h|\boldsymbol{\lambda})\right]$: (i) decreases in the expectation of partners' network access $S^{(1)}_{z'\ell'}(\boldsymbol{\lambda})$, or $\frac{\partial \mathbb{E}\left[R^{-}_{z\ell}(h|\boldsymbol{\lambda})\right]}{\partial S^{(1)}_{z'\ell'}(\boldsymbol{\lambda})} < 0$, (ii) increases in the network access volatility of its partners $S^{(2)}_{z'\ell'}(\boldsymbol{\lambda})$, or $\frac{\partial \mathbb{E}\left[R^{-}_{z\ell}(h|\boldsymbol{\lambda})\right]}{\partial S^{(2)}_{z'\ell'}(\boldsymbol{\lambda})} > 0$, and (iii) increases in the partners' diversification with respect to its own local productivities, or $\frac{\partial \mathbb{E}\left[R^{-}_{h\ell}(\boldsymbol{\lambda})\right]}{\partial Cov(S_{z'\ell'}(\boldsymbol{\lambda}), \Phi_{\ell})} < 0$.

[17] Equivalently, by reducing geographic money transport costs and raising $\boldsymbol{\tau}$, or finding its partner has received a positive, permanent productivity $z_{h'}$ or $A_{\ell'}$ shock.

Proof. The proof is found in the Appendix A.2. □

I provide intuition about Corollary 1 below. First, expected consumption is higher under smoother network access, or low $S^{(2)}_{z\ell}(\boldsymbol{\lambda})$. By Jensen's inequality, expected recipient transfers skew away from high network access draws via partner substitutability. Low network access realizations are less likely when a household is well-diversified, as a low draw of one partner necessarily implies a high draw of another in expectation. Network access volatility acts as a quality measure of a households' transfer partnerships conditional on partners' productivities.

Second, expected consumption is higher when partners' network access is smooth, or when $S^{(2)}_{z'\ell'}(\boldsymbol{\lambda})$ is low. Also by Jensen's inequality, expected sender transfers skew away from the high network access draws of partners. The low network access realizations of others are less likely when they are well-diversified. A well-diversified household does not lean disproportionately on any one of its links for payments.

An additional spatial risk consideration arises when considering the outflow perspective of expected consumption: a household's expected consumption is greater when its income co-moves with the network access of its partner, or when $\text{Cov}\left(S_{z'\ell'}(\boldsymbol{\lambda}), \Phi_\ell\right)$ is high. A partner leans disproportionally on its diversification agent. A partner's portfolio of partners, which determines both statistical objects $S^{(2)}_{z'\ell'}(\boldsymbol{\lambda})$ and $\text{Cov}\left(S_{z'\ell'}(\boldsymbol{\lambda}), \Phi_\ell\right)$, influences a household's expected consumption.

Without the distribution of yields $\boldsymbol{\chi}$ in Equation (2), one may be tempted to claim that a household requires knowledge of the entire $|\mathcal{H}| \times |\mathcal{H}|$ network $\boldsymbol{\lambda}$ to accurately compute its expected consumption, even in a fixed network context. However, the assumption of Fréchet-distributed yields substantially reduces the dimensionality of a household's information requirements. Instead, to accurately compute expected consumption to a second-order Taylor approximation, a household needs only know: (i) the $|\mathcal{H}| \times 1$ vector of network access expectations $S^{(1)}_{z'\ell'}(\boldsymbol{\lambda})$ across $(z', \ell') \in \mathcal{H}$, (ii) the $|\mathcal{H}| \times 1$ vector of network access volatilities $S^{(2)}_{z'\ell'}(\boldsymbol{\lambda})$ across $(z', \ell') \in \mathcal{H}$, and (iv) its $|\mathcal{H}| \times 1$ diversification vector $\text{Cov}\left(S_{z'\ell'}(\boldsymbol{\lambda}), \Phi_\ell\right)$ across $(z', \ell') \in \mathcal{H}$.

The discussion above makes explicit that—in the presence of spatial correlation in local shocks—expected net transfers increase when households are spatially diversified (have low $S^{(2)}_{z\ell}(\boldsymbol{\lambda}, \boldsymbol{\Phi})$) and connected to others that are themselves spatially diversified (have low $S^{(2)}_{z'\ell'}(\boldsymbol{\lambda}, \boldsymbol{\Phi})$). Fact 2 in Section 2.2 shows that spatially-correlated shocks have widespread impact in the empirical setting of this paper, indicating that the welfare gains arising from a spatially diversified transfer network may be substantial.

3.3.2 Household Optimization

In this section, I use the results about the transfer distribution in Section 3.3.1 to solve for households' preferred partnership levels in Equation (4). I derive and interpret the comparative statics of this partnership level in Proposition 1. The preferred partnership levels refer to a household's privately optimal partnership level in its relationship with another, keeping the rest of the network $\boldsymbol{\lambda}_{-z\ell z'\ell'}$ fixed.

Proposition 1. *Denote the solution to Equation (4) as the preferred partnership level $\lambda^*_{z\ell z'\ell'}$. The preferred partnership level $\lambda^*_{z\ell z'\ell'}$:*

(a) increases in the network productivity ratio $\frac{S^{(1)}_{z'\ell'}(\boldsymbol{\lambda})}{S^{(1)}_{z\ell}(\boldsymbol{\lambda})}$ of the partner to the household,

(b) increases in the idiosyncratic productivity ratio $\frac{p^{\theta}_{\ell'} z' A_{\ell'}}{p^{\theta}_{\ell} z A_{\ell}}$ of the partner to the household,

(c) decreases in transfer frictions, or $\frac{\partial \lambda^*_{z\ell z'\ell'}}{\partial \delta}\Big|_{\boldsymbol{S}} > 0$, $\frac{\partial \lambda^*_{z\ell z'\ell'}}{\partial \gamma} < 0$, and $\frac{\partial \lambda^*_{z\ell z'\ell'}}{\partial \bar{c}} < 0$,

(d) increases when own network access is noisy, or $\frac{\partial \lambda^*_{z\ell z'\ell'}}{\partial S^{(2)}_{z\ell}} > 0$,

(e) decreases when others' network access is noisy, or $\frac{\partial \lambda^*_{z\ell z'\ell'}}{\partial S^{(2)}_{z'\ell'}} < 0$,

(f) increases when local shocks co-move with others' partners, or $\frac{\partial \lambda^*_{z\ell z'\ell'}}{\partial Cov(S_{z'\ell'}, \Phi_{\ell})} > 0$.

Proof. The proof is found in the Appendix A.3. □

I discuss the comparative statics of households' preferred partnership levels to pair-specific characteristics.

Consider a household of type z in location ℓ who wishes to optimize its partnership level with a household of type z' in location ℓ'. Consider the ratio of mean network access between one's partner and oneself $\frac{S^{(1)}_{z'\ell'}(\boldsymbol{\lambda})}{S^{(1)}_{z\ell}(\boldsymbol{\lambda})}$. I term this object the *network productivity ratio*. The ratio answers the following: on average, how much more productive are my partner's partners than my own? The preferred partnership levels of Proposition 1 increases in the ratio: simply, a household prefers to strengthen partnerships with those who are relatively better-connected than them. This comparative static embeds the strategic considerations of households in the model. A partner's average network access $S^{(1)}_{z'\ell'}(\boldsymbol{\lambda})$ decreases a household's expected sender transfers via strategic complementarities, which reduces the household's costs of intensifying the partnership. One's own average network access $S^{(1)}_{z\ell}(\boldsymbol{\lambda})$ lowers a household's marginal benefit of intensifying partnerships, causing preferred partnership levels to abate.

Spatial risk considerations similarly reflect households' strategic instincts. On one hand, a partner's noisy network, or large $S^{(2)}_{z'\ell'}(\boldsymbol{\lambda})$, decreases preferred partnership levels. This relationship reflects strategic complementarities: households prefer partners with higher quality networks, conditional on network productivity $S^{(1)}_{z'\ell'}(\boldsymbol{\lambda})$. On the other hand, one's own noisy

network, or large $S_{z\ell}^{(2)}(\boldsymbol{\lambda})$, increases preferred partnership levels. Indicating partner substitutability, households seek to intensify relationships when their existing network quality is low. Additionally, households dislike acting as the diversification agent of their partners: a high co-movement $\text{Cov}\left(S_{z'\ell'}(\boldsymbol{\lambda}), \Phi_\ell\right)$ of a household's location productivity with its partner's network access lowers preferred partnership levels.

Furthermore, the preferred partnership level increases in the ratio of a partner's and own non-network income determinants $\frac{p_{\ell'}^{\theta} z' A_{\ell'}}{p_{\ell}^{\theta} z A_{\ell}}$. Income determinants are both real and nominal. I term this object the *idiosyncratic productivity ratio*. The ratio answers the following: on average, how much greater is my partner's income relative to my own? The idiosyncratic and network productivity ratios both increase preferred partnership levels. This relationship suggests that households view the two types of productivities as substitutable: a partner can compensate for a low idiosyncratic productivity by enhancing its network.

Finally, preferred partnership levels depend directly on transfer frictions. Keeping other terms fixed, the preferred partnership levels of equation increases the scaling of transfer frictions with payouts $\bar{c}$ and γ are high. Irrespective of partner characteristics, low transfer frictions $\bar{c}$ and γ decrease expected sender transfers. The same is true for the geographic money transport costs: when more money is retained in transit from sender to receiver, or $\tau_{\ell\ell'}$ is high, the preferred partnership level increases.

Mobile Money and Preferred Partnership Levels Do households prefer to increase partnership levels under mobile money? In a model with strategic network formation, the answer is nuanced, as mobile money not only reduces transfer frictions but, in doing so, positively shocks a household's network access $S_{z\ell}(\boldsymbol{\lambda})$.

Suppose money transport costs for a location ℓ has declined, while costs in other locations ℓ' have remained constant. From the chain rule, I consider the following derivative of a household h's preferred partnership level $\lambda^*_{z\ell z'\ell'}$ in its relationship to h' with respect to the retained transfer share $\tau_{\ell'\ell}$ when remitting from location ℓ' to ℓ:

$$\left.\frac{\partial \lambda^*_{z\ell z'\ell'}}{\partial \tau_{\ell'\ell}}\right|_{\boldsymbol{\lambda}} = \underbrace{\left.\frac{\partial \lambda^*_{z\ell z'\ell'}}{\partial \tau_{\ell'\ell}}\right|_{S^{(1)}_{z\ell},\boldsymbol{\lambda}}}_{>0,\text{ Direct Effect}} + \underbrace{\frac{\partial \lambda^*_{z\ell' z\ell'}}{\partial S^{(1)}_{z\ell}} \frac{\partial S^{(1)}_{z\ell}}{\partial \tau_{\ell'\ell}}}_{\leq 0,\text{ Indirect Effect}}\Bigg|_{\boldsymbol{\lambda}}. \tag{14}$$

From Equation (14), one can see that the derivative can be decomposed into two additive terms: (i) a *direct* effect, which keeps network access $S^{(1)}_{z\ell}$ constant, and (ii) an *indirect* effect, which incorporates the impact of changes to network access $S^{(1)}_{z\ell}$. Through the direct effect, lower transport costs reduce distance-dependent transfer frictions and increase households' desires to connect with others $\lambda^*_{z\ell z'\ell'}$ irrespective of sender characteristics. The indirect effect,

however, places downward pressure on $\lambda^*_{z\ell z'\ell'}$: from partner substitutability, preferred levels decline when own-network access is high, or $\frac{\partial \lambda^*_{hh'}}{\partial S^{(1)}_{z\ell}} \leq 0$, and own-network access decreases in transport costs, or $\frac{\partial S^{(1)}_{z\ell}}{\partial \tau_{\ell'\ell}} > 0$.

The indirect effect dominates when

$$\sum_{h'' \in \mathcal{H}} \pi_{z''\ell''z\ell}(\boldsymbol{\lambda}) \frac{\log d_{\ell''\ell}}{\log d_{\ell'\ell}} > \frac{1}{\theta - 1}. \tag{15}$$

This condition corresponds to a case where θ is sufficiently large, or where the substantial partnerships on which household h depends occur with others residing in relatively far locations.

Mobile money's positive impact on network density is the main theoretical and empirical point of Jack and Suri's (2014) seminal paper. In this paper, Fact 1 of Section 2.2 shows that, empirically, mobile money adoption coincided with increased participation in the network. My model justifies these results by noting that the direct effect of Equation (14) dominates under adoption waves: when multiple households adopt simultaneously, changes in network productivity ratios $\frac{S^{(1)}_{z'\ell'}(\boldsymbol{\lambda})}{S^{(1)}_{z\ell}(\boldsymbol{\lambda})}$—which drive the indirect effect—are ambiguous. The same is not necessarily true when a household adopts mobile money among non-adopters, which *reduces* the network productivity ratio of partners with respect to itself.

3.3.3 Equilibrium Existence

The previous section considers only the household's preferred partnership levels, but not the partnership levels that are ultimately implemented in equilibrium, as partners cannot force a household into relationships that are not privately profitable. Proposition 2 establishes that a pairwise stable equilibrium exists under the payment game. However, since payoffs display strategic complementarities, multiple pairwise stable equilibria may exist (Jackson and Zenou 2015).

Proposition 2. *Assume partnership levels are symmetric, where $\lambda_{\ell z\ell' z'} = \lambda_{\ell' z'\ell z}$ for all pairs (ℓ, z) and (ℓ', z'). The following is true:*

(a) Under the game described in Section 3.2, expected consumption is continuous and concave in partnership levels $\boldsymbol{\lambda}$.

(b) A pairwise stable equilibrium exists.

(c) The unconstrained partnership levels that get implemented in equilibrium are symmetric and follow $\lambda_{\ell z\ell' z} = \lambda_{\ell' z'\ell z} = \min\left\{\lambda^*_{\ell z\ell' z'}, \lambda^*_{\ell' z'\ell z}\right\}$.

Proof. The proof is found in the Appendix A.4. □

In addition to equilibrium existence, Proposition 2 establishes that the equilibrium level is the minimum of each household's desired partnership level with another.[18] Furthermore, a household can separate their equilibrium partnership levels into two qualitative types: (i) *own-constrained* partnerships whose levels are set to their own preferred intensity, for whom $\lambda_{\ell z \ell' z'} = \lambda_{\ell' z' \ell z} = \lambda^*_{\ell z \ell' z'}$, and (ii) *others-constrained* partnerships whose levels are set to others' preferred intensity, for whom $\lambda_{\ell z \ell' z'} = \lambda_{\ell' z' \ell z} = \lambda^*_{\ell' z' \ell z}$. This characterization of partnerships aids in the interpretation of within-equilibrium model predictions at the micro-level, which are discussed in Section 3.4.

How are the partnerships implemented in equilibrium consistent with Fact 3 of Section 2.2? Suppose the climate shock in location ℓ results in changes in beliefs about the distribution of $\mathbf{\Phi}$: in particular, the expectation of local productivity A_ℓ declines. The nominal income determinants $p^\theta_\ell z A_\ell$ of a household in location ℓ decrease relative to that of its partners $p^\theta_{\ell'} z' A_{\ell'}$. From Proposition 1, the preferred levels $\lambda^*_{z\ell z'\ell'}$ of the household broadly increase, while the preferred levels of its partners $\lambda^*_{z'\ell' z\ell}$ *decline* with respect to the household. Since the household's relationship with more-productive sources are on average others-constrained, Proposition 2 implies that the equilibrium partnerships with more-productive sources *decline* after the shock. By contrast, Proposition 2 suggests that equilibrium partnership levels with less-productive sources *increase* after the shock, as the household's relationship with these partners are on average own-constrained.

3.4 Testing Model Implications

In this section, I describe and test the model's within-equilibrium predictions of how transfer outcomes change after mobile money or changes in household circumstances. To examine the causal impact of mobile money on transfer outcomes, I introduce a shift-share instrument for mobile money adoption that utilizes variation in neighbors' "tech-savviness" in a base period prior to widespread mobile money use.

3.4.1 Mobile Money and Cross-Productivity Group Links

As in Section 3.3.2, suppose money transport costs for a location ℓ has declined, while costs in other locations ℓ' have remained constant. This represents a case where a household adopts mobile money among non-adopters. Once again, mobile money reduces the transfer friction $\tau_{\ell'\ell}$ directly, but also positively shocks network access $S_{z\ell}(\boldsymbol{\lambda})$, as households can more easily access payments from an existing network.

[18] The concavity of expected consumption with respect to $\boldsymbol{\lambda}$ arises from the assumption that partnership levels are symmetric. If payoffs were concave absent this assumption, partnership levels would be *endogenously symmetric*.

In this case, the model suggests that mobile money *increases* the average productivity $p^{\theta}_{\ell'} z' A_{\ell'}$ of sources. The proof of this result can be found in Appendix A.5. The intuition for the result proceeds as follows. When a household adopts among non-adopters, mobile money reduces the household's network productivity ratio $\frac{S^{(1)}_{z'\ell'}(\boldsymbol{\lambda})}{S^{(1)}_{z\ell}(\boldsymbol{\lambda})}$, which lowers its own preferred partnership levels with respect to others $\lambda^{*}_{z\ell z'\ell'}$, but raises others' preferred partnership levels with respect to the household $\lambda^{*}_{z'\ell' z\ell}$. In equilibrium, the household strengthens its relationship with others-constrained partners (corresponding to high-productivity sources) and lowers its relationship with own-constrained partners (corresponding to low productivity sources). In other words, the household becomes a more attractive partner through strategic complementarities, and can reduce its dependence on less-productive sources through partner substitutability.

Empirical Test I can test this implication with the following regression for a source s of household h at interview time t:

$$Y_{hst} = \alpha + \beta \cdot MM_{ht} + \Gamma' \boldsymbol{\omega_{hst}} + \epsilon_{hst}, \tag{16}$$

where Y_{hst} is a source s's education years, MM_{ht} is an indicator variable for whether a household h reports using mobile money at time t, $\boldsymbol{\omega_{ht}}$ is vector of source- and time-level controls, and ϵ_{ht} is a normally-distributed structural error term. The coefficient β captures the causal impact of mobile money on outcome Y_{hst} if $\mathbb{E}\left(\epsilon_{ht} | MM_{ht}, \boldsymbol{\omega_{ht}}\right) = 0$. However, households adopt mobile money only when it is profitable for them to do so, resulting in a variety of endogeneity concerns—including reverse causality and selection into adoption. Note that empirical results match model predictions if $\beta > 0$.

Shift-Share Instrument To counter these concerns, I propose a shift-share instrument that uses variation in adoption *costs*. Such variation should shift adoption decisions without changing adoption gains. I use two insights about mobile money adoption found in the literature to construct my instrument: (i) households are more likely to adoption when co-locating neighbors adopt, due to reductions in information costs or local complementarities of use (Björkegren 2019; Alvarez et al. 2023); and (ii) early mobile money adopters tend to vary by demographic characteristics (Hamdan, Lehmann-Uschner, and Menkhoff 2022; Jack and Suri 2014; Aker and Mbiti 2010). Differential adoption patterns by demographic factors—such as age of head, education of head, household size, and gender of head—reflect fundamental complementarities of mobile money technologies with potential adopters (e.g.,

tech savviness).[19]

Consider the instrument Z_{ht} for a household h in village v at interview time t for the mobile money use indicator MM_{ht} :

$$Z_{ht} = \sum_{k=1}^{K} \Omega_{vk0,-h} \Delta \overline{MM_{kt}}, \tag{17}$$

where $\Omega_{vk0,-h}$ is the leave-one-out, size-weighted share of demographic group k in village v of in a base period 0, and $\Delta \overline{MM_{kt}} = \overline{MM_{kt}} - \overline{MM_{k0}}$, where $\overline{MM_{kt}}$ is the national adoption rate at time t of a demographic group k, where the base period corresponds to round 1 of the NPS, occurring from 2008 to 2009.[20]Intuition for the instrument's relevance goes as follows: "I am more likely to adopt when my neighbors are more likely to adopt."

From Goldsmith-Pinkham, Sorkin, and Swift (2020), the instrument's exclusion restriction can be written as conditional independence of base demographic shares from structural error terms (i.e., unobserved determinants of transfer outcomes) given controls. Formally, the condition under the regression specification in Equation (16) is $\mathbb{E}\left[\Omega_{vk0,-h}\epsilon_{ht}|\boldsymbol{\omega_{ht}}\right] = 0$. I argue that the exclusion restriction is likely to hold due to low rates of permanent moves in the NPS.

However, one may still be concerned that village-level mechanisms—such as long-term spatial sorting on social network characteristics or the impact of mobile money's local spillovers on transfer activity—may violate the exclusion restriction. To account for these concerns, I add a vector of time-varying village characteristics as controls, which include the leave-one-out averages of village income, transfer distance, and number of transfer sources. To account for other issues around selection into adoption, I incorporate household fixed effects for as many IV specifications as I can without sacrificing the first-stage relevance of the instrument. To keep constant simultaneous changes in the transfer network, I incorporate time fixed effects for all IV specifications.

First-stage results are shown in Table C3 of the Appendix. The IV displays a strong first-stage F-statistic of 65.14. Keeping household characteristics and other time trends constant, a 10.0% increase in the imputed village-level adoption rate from Equation (17) increases the

[19]In my instrument's shares, I cut demographic groups into bins that differ by (i) household head age quartiles (16 to 33 years, 34 to 43 years, 44 to 56 years, and over 57 years old), (ii) household education groups (none, primary, secondary, university or more), (iii) household size terciles (1 to 4 members, 5 to 6 members, 6 or more members), and (iv) household head gender (male or female). This exercise results in 180 demographic groups that feed into the "shares". There are 246 different villages in the dataset.

[20]Mobile money adoption is not explored in round 1 of the NPS. Since the first mobile money deployment in Tanzania occurred only in April 2008 by Vodacom's M-Pesa, I assume that there is limited adoption in round 1, so that "shifts" at time t reflect the national adoption rate of a demographic group k at time t. I measure time by interview quarters, resulting in 16 temporal "shifts".

Table 2: The Impact of Mobile Money on Partner Productivity

	Panel A. Source Education Years					
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Mobile Money	3.006***	6.937***	2.672***	3.780***	1.807***	2.787*
	(0.202)	(0.859)	(0.196)	(1.169)	(0.211)	(1.636)
N	2673	2673	2673	2673	2566	2566
Wald F		117.8		50.80		25.79
Quarter & Region FE			✓	✓	✓	✓
Additional Controls					✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The outcome variable is the number of years of education of the source. Huber-White standard errors clustered at the household level are in parentheses. Additional controls include source region fixed effects; fixed effects for the source relationship with household head; length of time the source has lived in its current residence; age, gender, and years of education of the household head; and household size.

average probability a households uses mobile money by 7.3%.

Empirical Results Table 2 displays OLS and IV estimates. The instrument remains strong as I add more controls in the different specifications. Without controls and without the instrument, mobile money is associated with a 3.0 year increase in the source's education level. In the IV specification without controls, mobile money increases the education years of the source by 6.9 years. Both estimates are statistically significant at the 1% level. The magnitude of this estimate erodes as I add additional controls. With the full vector of controls in the IV specification, mobile money increases the source's education level by 2.8 years. The estimate is statistically significant at the 10% level. Empirical results support model implications: the productivities of a household's partners respond to money transport costs.

3.4.2 Transfer Span and Idiosyncratic Shocks

In the model, the maximum transfer distance a household can sustain in equilibrium depends on a household's nominal income determinants $p_\ell^\theta z A_\ell$. Therefore, shocks—even those of non-spatial, household-specific productivity z—to a household's *expected* income may trigger network readjustments that alter the household's equilibrium transfer span, i.e., the maximum distance between a household and one of its sources. The theoretical results in Appendix A.6 explore the impacts of such shocks and are summarized below.

The model incorporates two kinds of shocks. First, a *temporary* shock is a low income re-

alization $I_{z\ell}(h)$ conditional on a household's nominal productivity $p_\ell^\theta z A_\ell$. This type of shock does not change a household's expected income, and consequently, does not alter equilibrium transfer span. Second, a *persistent* shock changes a household's nominal productivity $p_\ell^\theta z A_\ell$, which modifies the equilibrium network and associated transfer span.

Consider a persistent shock to the non-spatial, household-specific productivity z. A household's idiosyncratic productivity ratio $\frac{p_{\ell'}^\theta z' A_{\ell'}}{p_\ell^\theta z A_\ell}$ *increases* with respect to others, which, from Propositions 1 and 2, decreases equilibrium partnership levels in others-constrained relationships and increases them in own-constrained relationships. Reflecting these dynamics, the model predicts that a less-productive household (who is, on average, others-constrained in their partnerships) experiences a post-shock *contraction* in transfer span, while a more-productive household (who is, on average, own-constrained) experiences a post-shock *expansion*. The heterogeneous response reflects mirror-image matching frictions. A less-productive household faces more difficulties attracting partners under the shock; they see their networks become endogenously thin and lose geographically distant sources. Meanwhile, a more-productive household finds others to be more attractive partners, and endogenously expand their networks after shocks.

Empirical Test Notably, one cannot observe whether a household's partnership levels are constrained by their own or others' preferences.[21] To test the implication, I proxy for *own-preference constrained* households as those with an above-median education level head and for *others-preference constrained* households as those with a below-median education level heads.[22] The median years of education of a household head is nine.[23]

The NPS includes a module on household shocks, asking questions on shock severity, type, and dispersion. I characterize idiosyncratic shocks as events that both severely impact a household and impact "only this household" in a community. Pooling across rounds, 41.8% of households report experiencing a negative idiosyncratic shock. I further characterize idiosyncratic shocks as *persistent* if households report capital loss. Shocks are *temporary* if only associated with income loss. Pooling across rounds, only 18.4% of households experience persistent, idiosyncratic shocks.

Before examining the impact of mobile money on transfer distance, I test whether the predicted responses of transfer distance to shocks hold in the data. I run the following

[21] Another caveat in the mapping of theory to data is that the theoretical transfer span includes both net senders and recipients in a household's transfer network. The NPS, however, only permits observation of the transfer distance between households and transfer *senders*.

[22] This proxy is theoretically grounded, as a household's preferred partnership levels in Proposition 1 increase in their idiosyncratic productivity ratios, which are on average decreasing in a household's productivity level.

[23] In this setting, nine years of education corresponds to finishing primary school.

Table 3: The Impact of Shocks on Transfer Distance

	Panel A. Transfer Distance (km)		*Panel B.* Transfer Amount	
	(1)	(2)	(3)	(4)
	OLS	OLS	PPML	PPML
High Prod.=1	-8.264*	-6.661	-0.873*	-0.104
	(4.583)	(4.501)	(0.464)	(0.608)
Pers. Shock=1	-9.694**		-0.527	
	(4.857)		(0.436)	
High Prod.=1 × Pers. Shock=1	6.477		2.323***	
	(6.519)		(0.623)	
Temp. Shock=1		3.139		0.947***
		(4.958)		(0.348)
High Prod.=1 × Temp. Shock=1		-0.635		-1.540***
		(6.408)		(0.536)
N	15158	15158	2423	2423
Household FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
Village Chars.	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Huber-White standard errors clustered at the household level are in parentheses. Village characteristics include leave-one-out averages of log income, number of transfer sources, and transfer distance. The outcome is total transfer amounts a household receives.

regression specification for a household h at interview time t:

$$Y_{ht} = \alpha + \beta \cdot Shock_{ht} + \zeta \cdot HighProd_{ht} + \delta \cdot (Shock_{ht} \times HighProd_{ht}) + \Gamma' \boldsymbol{\omega_{ht}} + \gamma_h + \gamma_t + \epsilon_{ht}, \tag{18}$$

where the outcome Y_{ht} is a household h's maximum transfer distance at time t, $Shock_{ht}$ is an indicator variable that equals one if a household h experiences a persistent, idiosyncratic shock at time t, and $HighProd_{ht}$ is an indicator variable that equals one if a household h identifies an individual with an above-median education level as the head. As a "placebo" shock, I replace $Shock_{ht}$ with an indicator variable that equals one if a household h experiences only a temporary shock at time t.

The model predicts that $\beta < 0$. Less-educated households, who are on average constrained by others' preferences in their partnerships, experience spatial contractions in their networks after persistent shocks. The model also predicts that $\beta + \delta > 0$. More-educated households, who are on average constrained by their own preferences in their partnerships, experience spatial expansions. Under "placebo" temporary shocks, households should not experience a change in their transfer distance.

Empirical Results Results are found in Panel A of Table 3. Including the entire vector of controls, low-productivity households see an average 9.7 km decline in their transfer distances after a persistent, idiosyncratic shock. This decline is statistically significant at the 5% level. The coefficient in front of the interaction term is positive but not statistically significant. In the "placebo" results, a temporary, idiosyncratic shock does not statistically significantly change transfer distance for either household type.

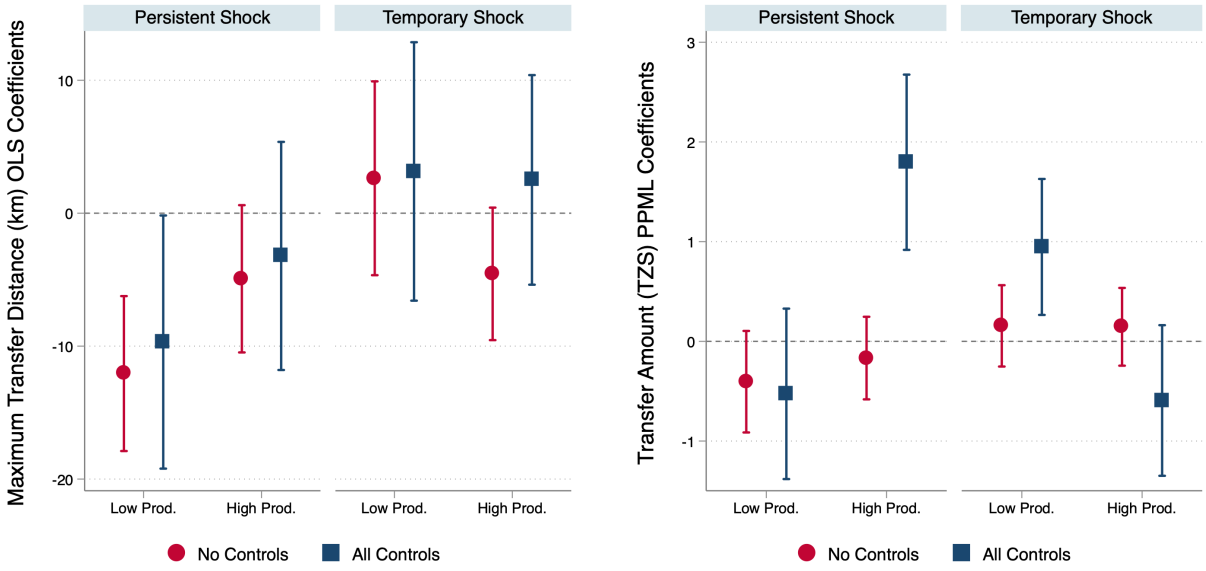
To examine the welfare relevance of post-shock changes in span, I include PPML results using transfer amount as an outcome variable in Panel B of Table 3. After a persistent, idiosyncratic shock, high-productivity households experience a near two-fold increase in transfer amount. Low-productivity households see their transfer incomes halve, though this change is not statistically significant. The coefficient signs flip when considering the "placebo" shock. Taken together, the empirical results provide suggestive evidence for the mechanisms discussed in the model. They also suggest that the impact of persistent shocks on household welfare is qualitatively different than the impact of temporary shocks: the two different shock types induce opposite responses of transfer amounts for both household types.

In Figure 6, I plot 95% confidence intervals around the post-shock response of low and high-productivity households.[24] In these plots, it is easy to see that low productivity households contract transfer distance after persistent, but not temporary, shocks. Furthermore, low productivity households increase recipient transfer amounts after temporary, but not persistent, shocks. By contrast, high productivity households do not alter their transfer distance, but see a substantial increase in recipient transfer amounts after persistent, but not temporary, shocks. In the eyes of the model, this pattern is generated if high productivity households strengthen partnership levels after shocks. In Appendix Table C5, I examine the impact of mobile money on fluctuations in transfer span.

4 Quantitative Results

In this section, I quantify the model presented in Section 3. In Section 4.1, I discuss how the model is calibrated using aggregated transfer flows in the NPS. I present a series of quantitative results in Section 4.2. The results point to the capacity of transfer networks to absorb shocks under fixed vs. endogenous networks and welfare gains from mobile money.

Figure 6: Coefficient Plots of Household Response of Transfer Outcomes After Shocks



Note: The figure displays coefficient plots for regression results of Equation (24). The response for low-productivity households correspond with estimates for β and associated standard errors. The response for high-productivity households corresponds to a linear combination of estimates $\beta + \delta$ and associated standard errors.

Table 4: Parameter List

Parameter		Value	Source	Moment	Target	Model
Estimation						
Fréchet Shape	θ	2.760				
Calibration						
Capacity	$\overline{\lambda}$	0.026	NPS	Own-Type Transfer Share	87.7%	87.9%
Distance Discount	δ	0.283	NPS	Mean Between-Region Transfer Source HHI	0.86	0.86
Transfer Friction Convexity	γ	10.40	NPS	Mean Within-Region Transfer Source HHI	0.92	0.92
Altruism	$\underline{\lambda}$	0.148	NPS	Median Inflow-to-Income Share	3.21%	2.95%
From Literature						
Transfer Friction Level	$\bar{c}$	0.083	2023 IPA TCI			

4.1 Structural Parameters

I calibrate the model in four steps. First, I derive aggregated, across-type transfer shares and regional price indices from the NPS. I use these empirical objects to estimate the Fréchet shape parameter θ. Second, equipped with an estimate for θ, I use model-implied relationships between real income and household characteristics over time to obtain estimates of local productivities $\boldsymbol{A}$, variance-covariance matrix $\boldsymbol{\Sigma}$, and household-type productivities $\boldsymbol{z}$. Third, I internally calibrate the distance discount δ, relationship cost convexity γ, capacity parameter $\bar{\lambda}$, and altruism parameter $\underline{\lambda}$ to match relevant moments in the aggregated transfer shares.

Fourth, I obtain transfer friction level $\bar{c}$ from the literature. In 2022, the Innovations for Poverty Action lab created a Transaction Cost Index to record fees associated with using mobile money. Of the countries examined, Tanzania had the largest mobile money cash-out fee, constituting an average of 8.6% the transaction value. Reflecting this estimate, I set $\bar{c} = 0.086$.

Parameter values are listed in Table 4.

4.1.1 Estimation of θ

I separate out households into the four productivity types of Section 2.2, corresponding to discrete education levels.

As in Eaton and Kortum (2002), when aggregating across the continuum of households, the probabilities of receiving transfers in Equation (11) map to regional transfer inflow shares by source type. Taking logs, the model generates the following gravity equation for the share of transfers that a household type z' in location ℓ' receives from a household type z in location ℓ at time t:

$$\log \hat{\pi}_{z\ell z'\ell' t} = \theta \log \lambda_{z\ell z'\ell' t} - \theta\delta \log d(\ell, \ell') + \underbrace{\theta p_{\ell t} + z + \Phi_{\ell t}}_{\text{Absorbed by } z,\ell,t \text{ f.e.}} - \underbrace{S_{z'\ell' t}}_{\text{Absorbed by } z',\ell',t \text{ f.e.}} + \epsilon_{z\ell z'\ell' t}, \quad (19)$$

where $\epsilon_{z\ell z'\ell'}$ is a structural error term. The outcome $\hat{\pi}_{z\ell z'\ell' t}$ is the aggregated transfer shares of recipient type z in location ℓ arising from source type z' in location ℓ' recorded in the NPS at round t. If a household does not report a transfer, I classify the household's transfer source type as its own.

The key innovation of the model is the inclusion of endogenous and context-specific partnership levels $\boldsymbol{\lambda}$. These unobservable levels impact realized transfer shares across time periods in a pairwise manner. If ignored, the partnership level acts as an omitted variable and

[24] These are estimates of β and $\beta + \delta$ in regression specification (18), respectively

induces a positive correlation between the structural error term $\epsilon_{z\ell z'\ell' t}$ and realized transfer shares $\log \hat{\pi}_{z\ell z'\ell' t}$. Therefore, one cannot use Equation (19) to uncover unbiased estimates of parameters θ or δ.

To address this concern, I note that—from Proposition 2—partnership levels $\boldsymbol{\lambda}$ are endogenously symmetric, and adjust specification (19) by taking the ratio of $\pi_{z\ell z'\ell'}$ to $\pi_{z'\ell' z\ell}$. This adjustment removes partnership levels $\boldsymbol{\lambda}$ from the expression. The adjusted gravity regression specification is:

$$\log\left(\frac{\hat{\pi}_{z\ell z'\ell' t}}{\hat{\pi}_{z'\ell' z\ell t}}\right) = \theta \log\left(\frac{p_{\ell t}}{p_{\ell' t}}\right) - \theta\delta \log \frac{d\left(\ell,\ell'\right)}{d\left(\ell',\ell\right)} + \underbrace{\log\left(\Phi_{\ell t}\, z\, S_{z\ell t}\right)}_{\text{Absorbed by } z,\ell,t \text{ f.e.}} - \underbrace{\log\left(\Phi_{\ell' t}\, z'\, S_{z'\ell' t}\right)}_{\text{Absorbed by } z',\ell',t \text{ f.e.}} + \epsilon_{z\ell z'\ell' t}. \tag{20}$$

Given credible measures of time-varying, regional prices $\boldsymbol{p}$, one can uncover an unbiased estimate of the Frechét shape parameter θ. Note that if money transport costs $\boldsymbol{\tau}$ are systematically asymmetric—due to traffic patterns, route-specific tolls, or elevation changes—one can also use this specification to uncover an unbiased estimate of the distance discount δ. I include observations for which both shares $\hat{\pi}_{z\ell z'\ell' t}$ and $\hat{\pi}_{z'\ell' z\ell t}$ are non-zero. As the matrix of aggregate transfer flows is sparse due to data limitations, this exercise results in around 100 pairs.

In the NPS, I directly observe prices that households pay for quantities of various food consumption items, such as rice, maize, and sugar. I construct a "standard consumption bundle" by taking the median purchase quantity of each consumption category across time.[25] I remove categories from which less than 10% of households report purchasing items. Next, I construct round-specific regional prices by calculating the average unit price households pay in distinct consumption categories. The regional price level is the average amount households pay to purchase the "standard consumption bundle".

Results are shown in Table 5. Without fixed effects, regional price differences account for 57.5% of the observed variation in transfer inflow matrix asymmetries. With fixed effects, the specification (20) yields an estimate of $\theta = 2.78$ that is statistically significant at the 5% level.

4.1.2 Estimation of $\boldsymbol{A}$, $\boldsymbol{\Sigma}$, and $\boldsymbol{z}$

I use the model-implied relationship between real income and household characteristics in Lemma 1 to estimate local productivities $\boldsymbol{A}$, the variance-covariance matrix $\boldsymbol{\Sigma}$ of spatial shocks, and average household productivities $\boldsymbol{z}$.

[25] Examples of items in the weekly consumption bundle include 1.5 kilograms of wheat flour, 1 kilogram of sugar, and 3.5 kilograms of husked rice.

Table 5: Estimate θ

	Log Transfer Inflow Share Difference	
	(1)	(2)
	OLS	OLS
Regional Price Difference	4.411***	2.780**
	(0.379)	(1.153)
N	100	96
R-squared	0.580	0.881
Region Time FE		✓
Source Region Time FE		✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows results of Equation (20). The outcome variable is the logged differences between the aggregate share of transfers received by a household type z in location ℓ from a source of type z' in location ℓ' and that received by a household type z' in location ℓ' from a source of type z in location ℓ. The independent variable is the difference in local prices as measured by a regional "price index", where details of the construction of this index are included in the main text.

From Lemma 1, the conditional expectation of real income is

$$\mathbb{E}\left(\frac{I_{h\ell}}{p_\ell}|\mathbf{\Phi}\right) = \Gamma\left(1 - 1/\theta\right)\left(z_h \Phi_\ell\right)^{\frac{1}{\theta}}. \tag{21}$$

Taking logs, I obtain the following regression specification for a household h of education group z in location ℓ at year t,

$$\log \mathcal{I}_{hz\ell t} = \alpha + \gamma_z + \gamma_{\ell t} + \Gamma' \boldsymbol{\omega}_h + \epsilon_{hz\ell t}, \tag{22}$$

where $\log \mathcal{I}$ is the real income of a household h, γ_z are fixed effects for education group z, $\gamma_{\ell t}$ are region-year fixed effects, $\boldsymbol{\omega}_h$ is a vector of household income determinants that should not impact productivity estimates, and $\epsilon_{hz\ell t}$ is a normally-distributed structural error term. The estimated fixed effects $\hat{\gamma}_z$ and $\hat{\gamma}_{\ell t}$ respectively map onto $\frac{1}{\theta}\log z_h$ and realizations of stochastic $\frac{1}{\theta}\log \Phi_\ell$. I include a household's marital status, mobile money use, and occupation fixed effects in the control vector $\boldsymbol{\omega}_h$. I define real income as the sum of wages, business profits, and self-produced consumption value, divided by the regional prices computed in Section 4.1.1.

I interpret the region-year fixed effects estimates $\hat{\gamma}_{\ell t}$ as realizations of the spatial shock $\frac{1}{\theta}\log \mathbf{\Phi}$. With this understanding, I estimate entries of the local productivity vector $\boldsymbol{A}$ as

$$\hat{A}_\ell = \frac{1}{|t|}\sum_t \exp\left(\theta \hat{\gamma}_{\ell t}\right), \tag{23}$$

where $|t|$ is the number of interview years represented in the NPS. I estimate entries of the

variance-covariance matrix $\boldsymbol{\Sigma}$ as

$$\hat{\sigma}_{\ell\ell'} = \frac{1}{|t|} \sum_{t} \left(\exp\left(\theta \hat{\gamma}_{\ell t}\right) - \bar{A}_{\ell} \right) \left(\exp\left(\theta \hat{\gamma}_{\ell' t}\right) - \bar{A}_{\ell'} \right). \tag{24}$$

Similarly, entries of household type productivities $\boldsymbol{z}$ can be estimated through fixed effects γ_z as

$$\hat{z} = \frac{1}{|t|} \sum_{t} \exp\left(\theta \hat{\gamma}_{z}\right).$$

The largest variation in estimated productivities remains across education groups vs. across locations. Kusini Unguja—located in Zanzibar island, a popular global tourist destination—is estimated to be the highest-productivity region of Tanzania. The capital Dar Es Salaam closely follows Kusini Unguja in productivity estimates. Pwani—a largely agricultural region neighboring Dar Es Salaam—is estimated to be the lowest-productivity region in Tanzania.

4.1.3 Calibration of δ, γ, $\bar{\lambda}$,and $\underline{\lambda}$

I calibrate the distance discount δ, transfer friction convexity γ, capacity parameter $\bar{\lambda}$, and altruism parameter $\underline{\lambda}$ using relevant moments of empirical, across-type transfer shares. The parameters are pinned down by the following moments, respectively: the across-type unweighted average of (i) across-region (i.e., spatial) transfer source type concentration, (ii) within-region (i.e., local) transfer source type concentration, (iii) own-type transfer shares, and (iv) transfer-to-income ratio.

First, I use the spatial concentration of transfer sources to calibrate the distance discount δ. I measure concentration in across-region transfer source types by constructing a Herfindahl index of cross-regional transfer shares. For households type z in location ℓ, the across-region (spatial) transfer source Herfindahl index is

$$\text{HHI}_{z\ell} = \sum_{\ell'} \left(\sum_{z'} \hat{\pi}_{z'\ell' z\ell} \right)^2, \tag{25}$$

where values closer to one denote greater spatial concentration in transfer sources and values closer to zero denote greater diversification. From Equation (11), when $\ell \neq \ell'$, transfer shares hinge on the distance discount δ, where smaller discounts result in greater cross-regional shares.

Similarly, I measure concentration in within-region transfer source types by constructing a Herfindahl index of across-type transfer shares. For a household of type z in location ℓ,

the within-region (local) transfer source Herfindahl index is

$$\text{HHI}_{z\ell}|_{\ell'=\ell} = \sum_{z'} \hat{\pi}^2_{z'\ell z\ell}. \tag{26}$$

Values closer to one denote greater local concentration and values closer to zero denote greater local diversification. Unlike the spatial transfer source Herfindahl index, the distance discount δ does not impact the local transfer source Herfindahl index when the network $\boldsymbol{\lambda}$ is fixed. From Proposition 1, deeper partnerships are facilitated by lower transfer friction convexity γ, which raises preferred partnership levels for both parties. When convexity γ is high, households rely on more sources with shallower (i.e., low λ) partnerships.

Third, I calibrate the capacity parameter $\bar{\lambda}$ with the average of own-type transfer shares. For households of type z in location ℓ, the own-type transfer share is

$$\pi_{z\ell z\ell} = \left(\overline{\lambda} p_\ell\right)^\theta z \Phi_\ell S_{z\ell}^{-1}, \tag{27}$$

which is obtained from adapting Equation (11). This value increases in the capacity parameter $\overline{\lambda}$ relative to other partnership levels that push own-network access $S_{z\ell}$ upwards.

Fourth, I use average transfer amounts from other types as a proportion of average income to calibrate the altruism parameter $\underline{\lambda}$. For households of type z in location ℓ, this amount is

$$\frac{\mathbb{E}\left(R^+_{z\ell}\right) - \pi_{z\ell z\ell}\bar{\lambda}\mathbb{E}\left(I_{z\ell}\right)}{\mathbb{E}\left(I_{z\ell}\right)} = \frac{\sum_{z',\ell'\neq z,\ell} \pi_{z'\ell' z\ell}\lambda_{z\ell z'\ell'}\mathbb{E}\left(I_{z\ell}\right)}{\mathbb{E}\left(I_{z\ell}\right)}. \tag{28}$$

I exclude transfers from own-type households, as the model makes no distinction between receiving no transfers and receiving a transfer from a household of one's own type. The altruism parameter $\underline{\lambda}$ weakly increases the partnership levels $\boldsymbol{\lambda}$ realized in equilibrium, which raises the value of the numerator of Equation (28).

4.1.4 Multiple Equilibria

The existence of pairwise-stable equilibria hinges on well-behaved characteristics of *improving paths*, which are sequences of profitable, link-by-link network adjustments (Jackson and Watts 2001; Bich and Morhaim 2020). An equilibrium is a network with no improving path. The model yields multiple pairwise-stable equilibria, a fundamental characteristic of network formation models with strategic complementarities (Jackson and Zenou 2015). In this context, the determinants for which equilibrium one ultimately arrives at depends on: (i) the initial network, and (ii) the sequence over which pairs best-respond to the existing network, where an individual's best-response is given by Proposition 1 and—from Proposition

2—a pair's best-response is the minimum of the individuals' best-responses.

To generate quantitative results, I fix the initial network to be complete: households have self-weights of $\overline{\lambda}$ and set equal partnerships with other types such that the feasibility constraint of Equation (3) binds. I take 1000 randomly generated sequences of pairs and calculate their respective equilibria. One can interpret each equilibrium as the network realization for one set of households, of which there are infinitely many. When possible, I display the distribution of outcomes generated through this procedure. Outcomes are often normally-distributed. In other instances, I focus on the average outcome. More information about the algorithm is discussed in Appendix B.

4.2 Results

I use the calibration to consider changes in economic outcomes as the geographic costs of money transport δ become less convex. Figure 7 shows the path that the spatial Herfindahl of Equation (25) takes as δ declines.[26] The post-mobile money period in Tanzania coincided with a substantial spatial diversification in transfer sources. The model quantitatively matches this trend.

I refer to the year 2008 as the "base" period, where δ_0 associated with the "base" period facilitates only slight spatial diversification and generates an average spatial Herfindahl index close to one. The difference between the "base" δ_0 and calibrated δ pins down the five-year rate of decline in transfer frictions. I use this rate of decline in δ to project economic outcomes over the next few decades as mobile money diffuses in the economy.

4.2.1 Real Consumption Under Shocks

I use the calibrated model to examine how transfers flow and real consumption changes in response to shocks at the calibrated baseline. Suppose local productivities $\mathbf{\Phi}$ realize.

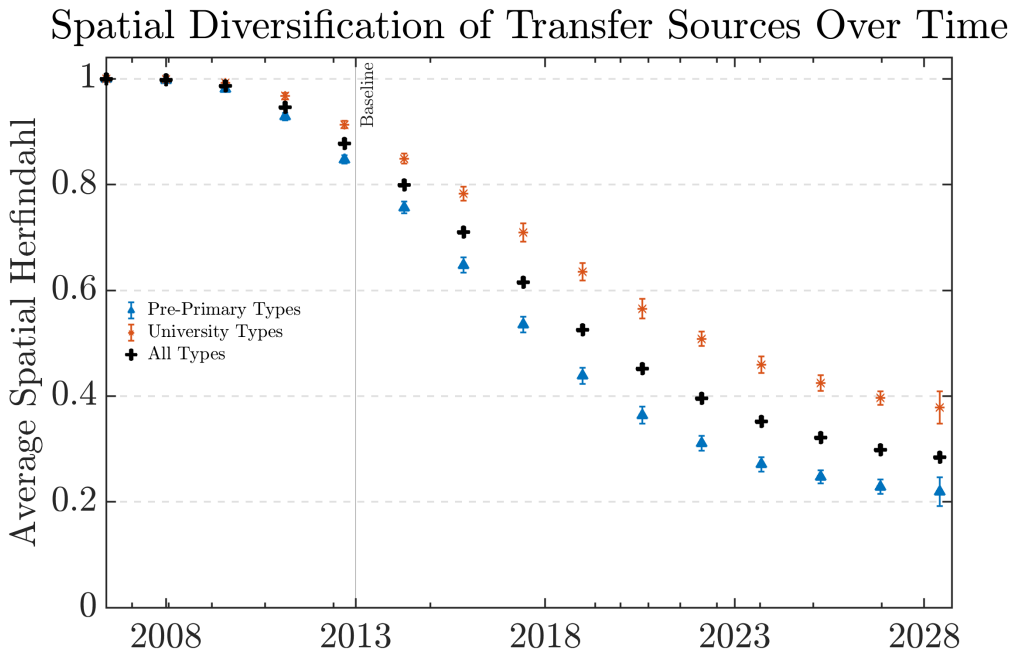
I consider the real consumption allocation of type z, location ℓ households under shock $\mathbf{\Phi}$. Let $\boldsymbol{\lambda}(\boldsymbol{A}, \mathbf{\Sigma})$ be the equilibrium network of partnerships formed under the local productivity expectations vector $\boldsymbol{A}$ and variance-covariance matrix $\mathbf{\Sigma}$. Under *fixed networks*, the consumption of households of type z in location ℓ given shock realizations $\mathbf{\Phi}$ is

$$\bar{C}_{z\ell}\left(\boldsymbol{\lambda}\left(\boldsymbol{A}, \mathbf{\Sigma}\right), \mathbf{\Phi}\right).$$

This expression incorporates transfers determined by partnership levels formed under the

[26] One may view this parameter as the average transfer friction households face in the year. Mobile money adoption and the enhanced supply of mobile money agents may be viewed as the source of transfer friction decline over time.

Figure 7: The Diffusion Path of Mobile Money



Note: Each point in the scatterplot corresponds to averages taken over the equilibria associated with 100 randomly-generated sequence draws for a value of δ.

belief that local shocks, on average, realize their expectation $\boldsymbol{A}$.

Under *endogenous networks*, the consumption allocation is given by

$$\bar{C}_{z\ell}\left(\boldsymbol{\lambda}\left(\boldsymbol{\Phi},\boldsymbol{\Sigma}\right),\boldsymbol{\Phi}\right).$$

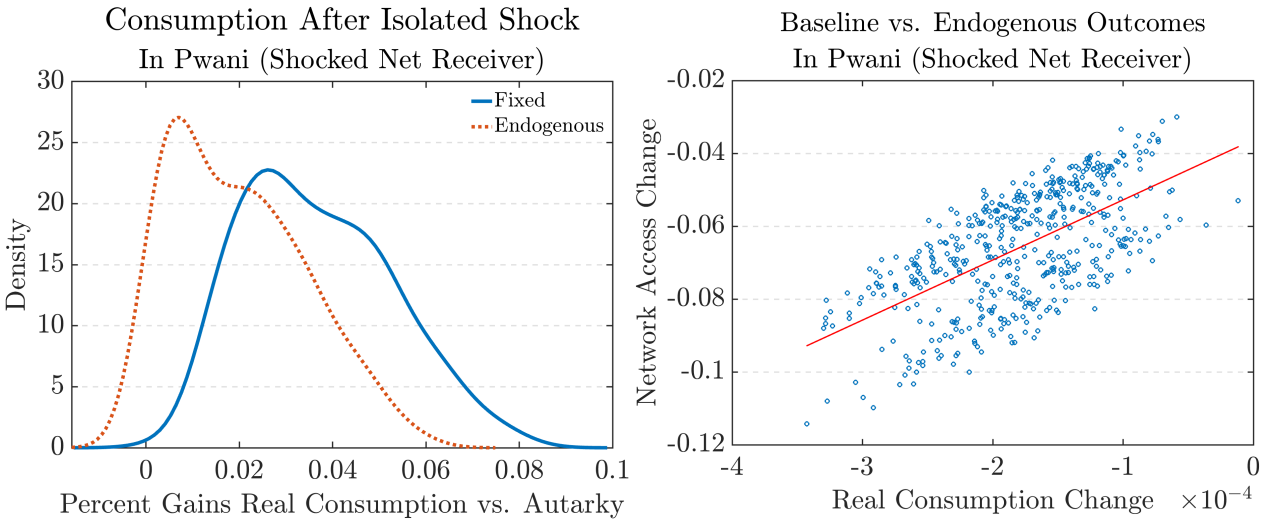
This expression captures equilibrium transfers arising when households adjust their expectations of local productivities to the realized value $\boldsymbol{\Phi}$. This allocation can be viewed as more realistic in environments with persistent shocks that change households' beliefs about underlying local productivity distributions, which trigger network reorganization.

First, I consider isolated, regional shocks. Suppose that the region of Pwani experiences a local productivity Φ_ℓ that is 40% lower than its expectation A_ℓ. In Table 4, we estimate Pwani to have the lowest average regional productivity in Tanzania. In the left panel of Figure 8, I consider the kernel density of post-shock real consumption gains relative to autarky under the network in Pwani.[27] On the right panel, I compare the wedge in real consumption under endogenous vs. fixed networks against changes in network access.

There are three items of note about this figure. First, the transfer network improves consumption levels for households in Pwani relative to autarky, indicating that they receive

[27] I aggregate from household-type to region level using demographic weights $\Omega_{z\ell}$.

Figure 8: Outcomes in Pwani After Isolated Shock

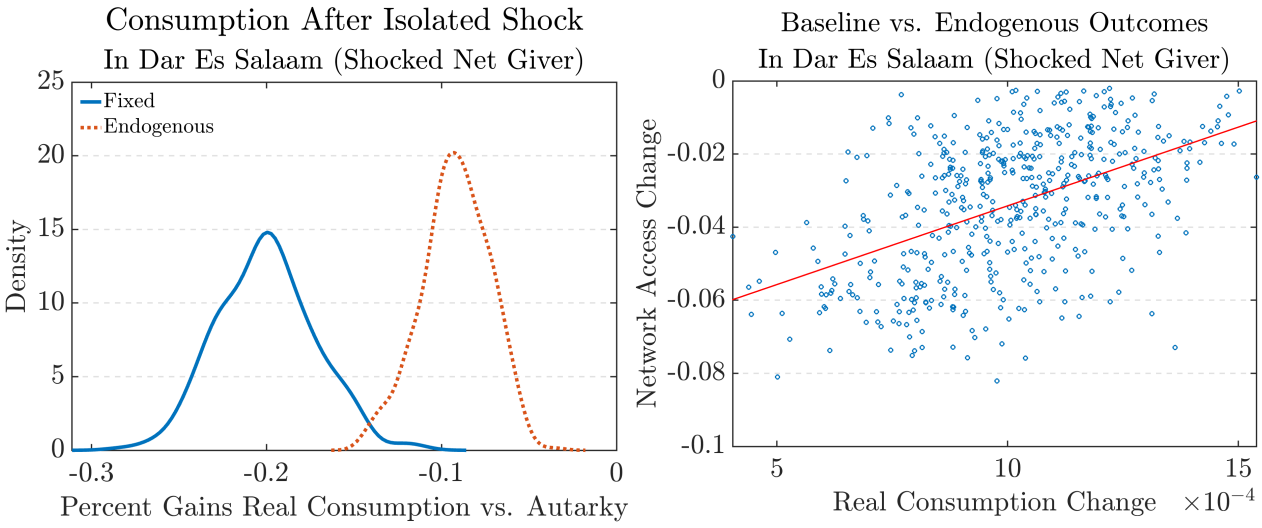


Note: The left panel is a kernel density plot of average real consumption gains relative to autarky of households living in Pwani after a small shock. Under the small shock, productivity in Pwani Φ_ℓ realizes a value 40% less than its average A_ℓ. The right panel compares the wedge between fixed and endogenous real post-shock consumption and losses in average network access $\bar{S}_\ell = \sum z\Omega_{z\ell}\bar{S}_{z\ell}$ for Pwani households.

more transfers than they pay out. Second, the distribution of consumption gains under the fixed network stochastically dominates that under the endogenous network. This pattern suggests that the re-organization of the network after shocks may mitigate network benefits for net-receiving households. Third, the difference between consumption under endogenous vs. fixed networks can be mostly attributed to changes in network access. For households in Pwani, changes in consumption and network access are strongly positively correlated: losses in network access result in real consumption losses. The correlation between the two quantitative objects is $\rho = 0.62$. This correlation suggests that—after networks re-organize in response to the shock—households lose access to high-productivity partners, which lowers the transfer amounts they receive after shocks.

Next, I consider a similar shock to households in Dar Es Salaam, the economic capital of Tanzania. Similar visualizations for this shock are displayed in Figure 9. Unlike in Pwani, households in Dar Es Salaam consume less under the network than in autarky, suggesting they give out more transfers than they receive. In this case, the distribution of real consumption under endogenous networks stochastically dominates the distribution under fixed networks, suggesting the network re-organizes to increase net transfers for households in Dar Es Salaam after the shock. When plotting changes in consumption against changes in network access, the correlation is still positive but weaker at $\rho = 0.49$. The weakened correlation reflects that households in Dar Es Salaam across household types additionally improve their real consumption in equilibrium by severing network ties, which lowers expected sender

Figure 9: Outcomes in Dar Es Salaam After Isolated Shock



Note: The left panel is a kernel density plot of average real consumption gains relative to autarky of households living in Pwani after a small shock. Under the small shock, productivity in Pwani Φ_ℓ realizes a value 40% less than its average A_ℓ. The right panel compares the wedge between fixed and endogenous real post-shock consumption and losses in average network access $\bar{S}_\ell = \sum z\Omega_{z\ell}\bar{S}_{z\ell}$ for Pwani households.

transfers.

The shocks I have examined so far are geographically isolated—in particular, local productivities deviate from expectations for only one region. Next, I consider a "disaster" scenario of large, correlated shocks. To do so, I suppose that local productivities realize their minimum empirical values, or $\Phi_\ell = \min_t \hat{\gamma}_{\ell t}$. I consider the fixed and endogenous network responses of real consumption to the "disaster", which are displayed in maps on Figure 10.

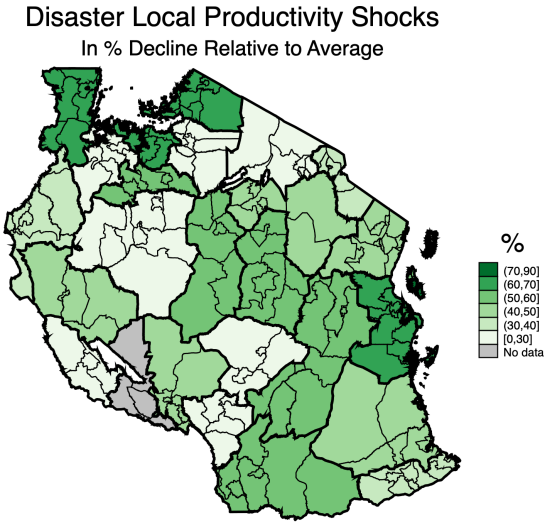
The map of Figure 10a shows the severity of shocks by region as measured by percentage decline from the local productivity average A_ℓ. Coastal regions—such as Dar Es Salaam, Pwani, and the Lake Victoria Region—are most impacted by the "disaster", which reflects flood risk and coincides with the self-reported climate experiences of Figure 3 (Mikova, Makupa, and Changa 2016).

The left-most map of Figure 10b shows average real consumption changes by region under fixed networks relative to autarky. Darker blue regions indicate consumption gains associated with the network, while darker red regions indicate consumption losses. The network varies in how well it accommodates the "disaster." Lower-productivity regions surrounding Lake Victoria fare better than they would in autarky—they receive transfers from neighboring Tabora, which—though less productive than other regions—is relatively un-impacted by the "disaster". Though vulnerable to the "disaster", higher-productivity regions like Dar Es Salaam and Morogoro still act as net givers in the transfer network.

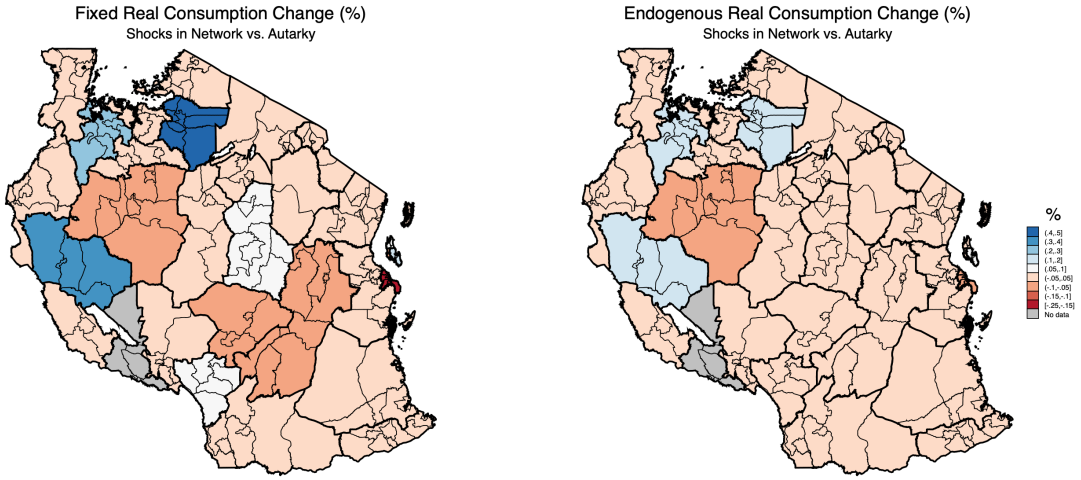
The right-most map of Figure 10b displays average changes in real-consumption under

Figure 10: Fixed vs. Endogenous Network Real Consumption Changes Under "Disaster"

(a) Disaster Intensity as Percentage Decline from Average Productivity

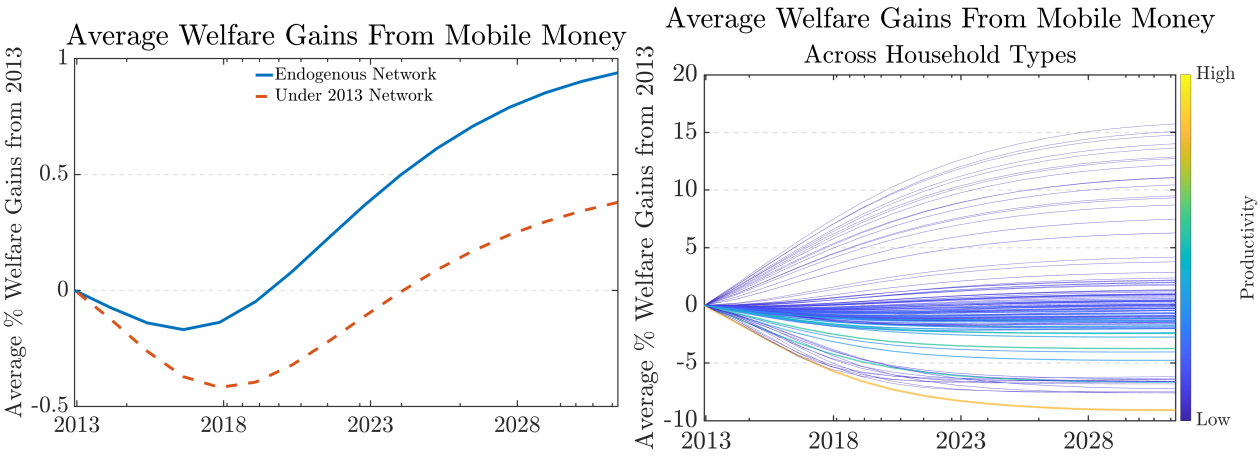


(b) Regional Real Consumption After Disaster Under Fixed vs. Endogenous Networks



Note: This figure maps real consumption gains under the network relative to autarky under the "disaster" scenario, where each local productivity realizes its lowest value, or $\Phi_\ell = \min_t \hat{\gamma}_{\ell t}$. The map in panel (a) corresponds to percent changes in Φ_ℓ relative to average productivity A_ℓ, where darker colors correspond to more severe shocks. The left-most map in panel (b) corresponds to fixed network consumption changes as percentages relative to autarky, where blue regions experience gains and red regions experience losses. The right-most map in panel (b) corresponds to endogenous network consumption gains as percentages relative to autarky, where blue regions experience gains and red regions experience losses.

Figure 11: Welfare Gains From Mobile Money Relative to 2013 Baseline



Note: The left figure considers average welfare gains, weighted by demographic shares, as the distance discount δ declines. We compare welfare for each households type relative to that calculated in the 2013 baseline. The right figure shows the evolution of welfare over the diffusion path for each household type, where the paths of households with higher nominal "productivities", or $p_\ell^\theta z A_\ell$ are represented by thicker, more yellow lines, and households with lower nominal "productivities" have thinner, blue lines. This graph shows that, on average, more productive households experience welfare losses after mobile money, and on average, less productive households experience welfare gains. Furthermore, welfare gains are monotonic in the distance discount within types.

endogenous networks relative to autarky. Consistent with the isolated shock example in Figure 9, net-giver regions like Dar Es Salaam reduce their partnership levels and send fewer transfers, leading to higher consumption relative to their fixed network allocation. Though net-receiving regions still benefit from the network, they increasingly rely on proximate, less-productive partners in Tabora rather than on distant, more-productive ones. They experience consumption losses relative to their fixed network allocation.

Net-giver regions fare better after negative, local shocks when networks are allowed to adjust. Though on average, net-receiver regions consume more under the network than in autarky, their partnerships display fragility: when networks adjust after shocks, they lose access to high-productivity partners, which decreases consumption levels in equilibrium.

4.2.2 Welfare Under Mobile Money

The previous quantitative exercise considers real consumption changes in response to specific local productivity $\mathbf{\Phi}$ realizations. However, the vector $\mathbf{\Phi}$ may realize infinite possibilities, as the Fréchet distribution takes infinite support. The next exercise considers the ex-ante welfare of household types prior to the realization of shocks. The welfare of a household h in location ℓ is its expected real consumption $\mathbb{E}\left[C_{z\ell}\left(\boldsymbol{\lambda}, \mathbf{\Phi}\right)\right]$. I calculate this object for each network realization at baseline, then aggregate according to demographic shares $\mathbf{\Omega}$.

In the left panel of Figure 11, I plot the evolution of average welfare from 2008 to 2028.

I decompose welfare gains at a time period t relative to the calibrated 2013 "base" period t_0 as:

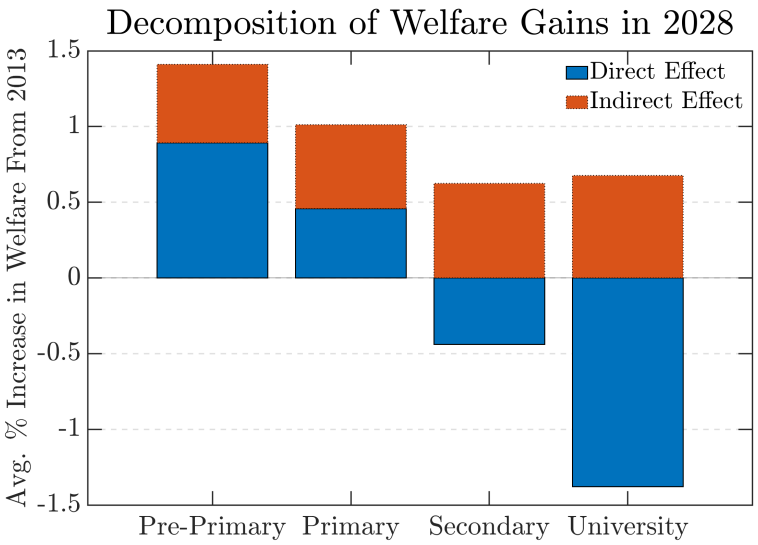
$$\mathbb{E}\left(C_{z\ell}\left(\delta_t\right)\right) - \mathbb{E}\left(C_{z\ell}\left(\delta_0\right)\right) = \underbrace{\mathbb{E}\left(C_{z\ell}\left(\boldsymbol{\lambda}\left(\delta_t\right), \delta_t\right)\right) - \mathbb{E}\left(C_{z\ell}\left(\boldsymbol{\lambda}\left(\delta_0\right), \delta_t\right)\right)}_{\text{Indirect (Network) Effect}} + \underbrace{\mathbb{E}\left(C_{z\ell}\left(\boldsymbol{\lambda}\left(\delta_0\right), \delta_t\right)\right) - \mathbb{E}\left(C_{z\ell}\left(\boldsymbol{\lambda}\left(\delta_0\right), \delta_0\right)\right)}_{\text{Direct Effect}}. \tag{29}$$

The direct effect considers changes in average welfare when the network is "fixed" at its 2013 level, but the transfer friction declines from δ_0 to δ_t. The indirect effect considers the impact of endogenous network changes from $\boldsymbol{\lambda}\left(\delta_0\right)$ to $\boldsymbol{\lambda}\left(\delta_t\right)$ that occurs as a result of the transfer friction reduction. On average, mobile money diffusion initially results in short-term losses to household welfare relative to 2013. By 2028, average welfare has improved by 0.9% relative to its 2013 level. The indirect effect accounts for nearly two-thirds of this improvement: without considering welfare gains from endogenous readjustments of the network, one quantitatively undershoots the gains of mobile money.

The right panel of Figure 11 maps welfare gains for each household type along the diffusion path of mobile money. The figure offers two insights for interpreting the average welfare gains shown in the left panel. First, the average value conceals substantial heterogeneity across households: university-educated households in Dar es Salaam experience average welfare *losses* of 9.3% by 2028 relative to their baseline, while non-educated households in Kilimanjaro gain 15.6%. Second, the non-monotonic pattern in average welfare gains is purely compositional—it arises because, early on, the expected transfers sent by net-senders increase faster than the expected transfers received by net-receivers. The decline in average welfare, however, is only temporary.

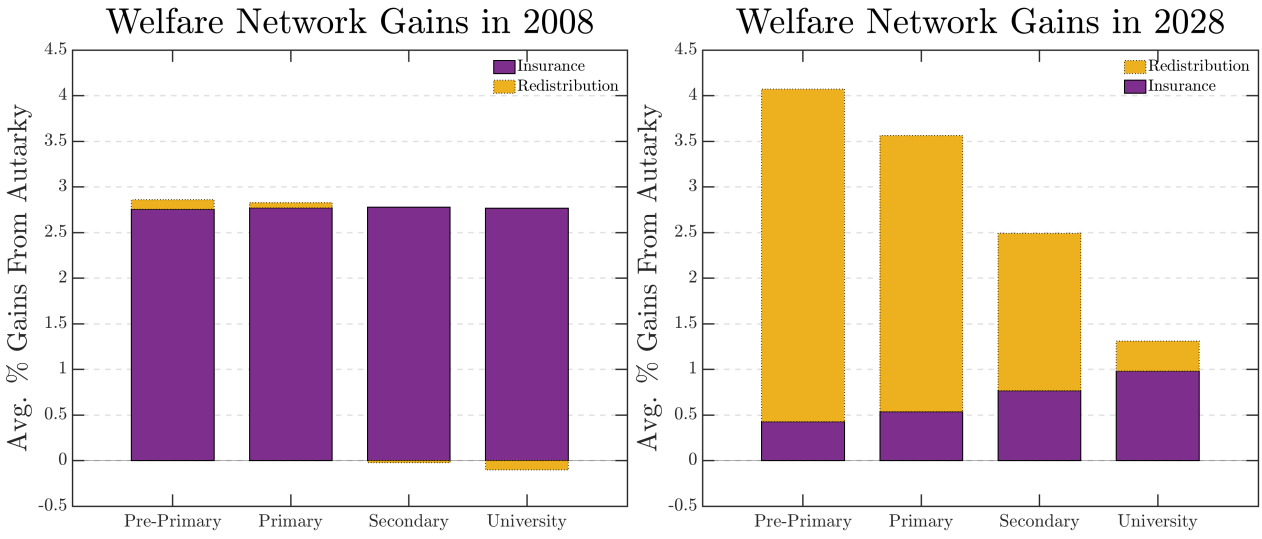
In Figure 12, I show the decomposition of Equation (29) across education groups. Welfare gains from mobile money are progressive, as pre-primary households see an average gain of 1.4% relative to their 2013 baseline, but university-educated households see an average loss of 0.7%. The direct effect of mobile money is on average *negative* for more-educated households, but positive for less-educated households. As transfer frictions decline, less-educated households can more easily access transfers from high-educated partners, which raises both their recipient transfers and the sender transfers of their more-educated partners. On average, the indirect effect accounts for more than one-third of the gains for non-educated households and over one-half of the gains for primary school educated households. Endogenous network reorganization more than offsets the direct losses that secondary school educated households face under mobile money and reduces the direct losses that university educated households face by a half.

Figure 12: Decomposition of 2028 Mobile Money Welfare Gains Into Direct vs. Indirect Effect



Note: This graph shows the unweighted averages of welfare gains in 2028 relative to the calibrated 2013 baseline by education group. The direct effect keeps the network $\boldsymbol{\lambda}$ fixed at its 2013 level, while the indirect effect considers additional welfare gains arising from the adjustment of $\boldsymbol{\lambda}$.

Figure 13: Insurance vs. Redistribution Decomposition of Welfare Gains in the Network Relative to Autarky



Note: This graph shows the unweighted average of welfare gains of the transfer network relative to autarky by education group for 2008 (the left panel) and 2028 (the right panel).

I additionally decompose households' welfare gains into those attributable to redistribution or insurance. In this exercise, I consider household welfare under the transfer network relative to autarky. By construction, if households' feasibility constraints do not bind, these gains are positive: household pairs do not enter partnerships unless it is mutually beneficial for both parties. The decomposition is shown in the following equation:

$$\frac{\mathbb{E}\left(C_{z\ell}\left(\mathbf{\Phi}\right)\right)-\mathbb{E}\left(I_{z\ell}\left(\mathbf{\Phi}_{\ell}\right)\right)}{\mathbb{E}\left(I_{z\ell}\left(\mathbf{\Phi}_{\ell}\right)\right)}=\underbrace{\frac{C_{z\ell}\left(\mathbb{E}\left(\mathbf{\Phi}\right)\right)-\mathbb{E}\left(I_{z\ell}\left(\mathbf{\Phi}\right)\right)}{\mathbb{E}\left(I_{z\ell}\left(\mathbf{\Phi}\right)\right)}}_{\text{Redistribution}}+\underbrace{\frac{\mathbb{E}\left(C_{z\ell}\left(\mathbf{\Phi}\right)\right)-C_{z\ell}\left(\mathbb{E}\left(\mathbf{\Phi}\right)\right)}{\mathbb{E}\left(I_{z\ell}\left(\mathbf{\Phi}\right)\right)}}_{\text{Insurance}}. \tag{30}$$

The redistribution component examines real consumption gains that would occur if spatial shocks realized their expectation. Note that—despite the risk-neutrality of my baseline setup—expected consumption is non-linear in the spatial shock realization $\mathbf{\Phi}$ from the results of Lemma 1.[28] The insurance component measures the welfare gains that are attributable to this non-linearity, which shapes the relationships of households' expected consumption to noise in network access.

I examine welfare gains in 2008 and 2028. In 2008, the average household's network gains stem almost entirely from insurance, and there is no clear progressive pattern across education groups. Average gains differ by only 0.2 percentage points across groups, hovering around 2.8%. By 2028, a progressive pattern emerges: pre-primary types see average welfare network gains of 4.1%, while university types see gains of 1.3%. However, insurance plays a much smaller role than in 2008, both in levels and as a share of total gains. Redistribution, instead, accounts for roughly nine-tenths of the gains for pre-primary types and one-quarter for university types.

The loss of insurance is—perhaps counterintuitively—a direct result of the friction reduction introduced by mobile money. Lowered frictions make the costs and benefits of transfer partnerships more salient. University-types (especially in high-productivity regions) enter partnerships primarily for insurance; they sever connections whose redistributive costs now outweigh the insurance benefit. Meanwhile, less-educated types form profitable partnerships with these insurance-seekers, foregoing opportunities for insurance themselves. In Appendix B, I show that partnership levels decrease along the path of mobile money diffusion.

[28] The non-linearity occurs because expected consumption is concave in both own-network access $S_{z\ell}$ and others' network access $S_{z'\ell'}$, which are linear in $\mathbf{\Phi}$.

5 Conclusion

In this paper, I examine household welfare under informal insurance arrangements when the network of social contacts is endogenously formed. I consider the empirical context of Tanzania after the 2008 introduction of mobile money technologies, which reduced distance-dependent costs of money transport. I document that households rely disproportionately on less-educated sources after shocks, which motivates my model of transfers under endogenous risk-sharing groups. In the model, households aim to spatially diversify their transfer sources and view transfer partners as substitutable. Partnership decisions also display strategic complementarities: households aim to connect with others that are better-connected, as these households demand less transfers in expectation. I establish that a pairwise-stable equilibrium exists in this context.

I quantify the model to assess the welfare gains of mobile money across heterogeneous households. Mobile money is a progressive technology: by 2028, non-educated households see average gains of 1.4% relative to their 2013 baseline; university-educated households see average losses of 0.7%. Across types, endogenous re-organization of transfer partnerships accounts for roughly two-thirds of mobile money's welfare gains. Most of the welfare changes stem from the strengthened redistributive role of networks following the introduction of mobile money. In contrast, network gains directly attributable to insurance *decline*: relative to autarky, average insurance benefits from the network fall by 2.3 percentage points for non-educated households and by 1.3 percentage points for university-educated households.

Even before Townsend (1994), a long literature on informal transfer networks in developing countries has centered around one question: is informal insurance enough to shield the most vulnerable households from income risk? This paper provides two new reasons for why the answer is "no". First, the transfer partnerships of less-educated households display particular fragility with respect to negative shocks to expected income. In my model of endogenous network formation, the shocked household's expected demands for recipient transfers increase and raise the expected costs of partnerships: as a result, more-productive partners disinvest in their relationships with shocked households. These changes in network partnerships reduce a shocked household's net transfers in equilibrium. Empirically, less-educated households reduce their transfer distance by 9.7 km on average after an unexpected, negative shock involving the loss of capital—an effect that is statistically significant at the 5% level. Second, despite the progressivity of welfare gains arising from mobile money, the technology may actually reduce network gains arising from insurance. As mobile money makes the redistributive role of transfer partnerships more pronounced, net-giver households may disinvest from partnerships whose insurance benefits no longer exceed redistributive

costs.

Pairwise-stability is a key concept in models of network formation with strategic considerations. Methodologically, this paper handles its quantitative challenges—including multiple equilibria, the estimation of structural parameters, and equilibrium existence under mixed sources of substitutability and complementarity. These methodological insights can be applied to generate "realistic" supply chains, firm, and social networks in a variety of quantitative models.

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A Proofs and Derivations

A.1 Proof of Lemma 1

(a) The probability an income draw $I_{h\ell}$ is less than a value $\mathcal{I}$ is

$$\begin{aligned} I_{h\ell}\left(\mathcal{I}\right) = \Pr\left(I_{h\ell} \leq \mathcal{I}\right) &= \Pr\left(\chi_{h\ell} \leq \frac{\mathcal{I}}{p_\ell}\right) \\ &= \exp\left(-\left(\mathcal{I}/p_\ell\right)^{-\theta} z_h \Phi_\ell\right), \end{aligned}$$

where the second equality arises from the distribution $G_{h\ell}$. The c.d.f. of $I_{h\ell}$ corresponds to a Fréchet distribution with shape parameter θ and scale parameter $p_\ell \left(z_h \Phi_\ell\right)^{\frac{1}{\theta}}$.

The probability that a remittance inflow draw $R^+_{h\ell}\left(\boldsymbol{\lambda}|\boldsymbol{\Phi}\right)$ is less than a value $\mathcal{R}$ is

$$\begin{aligned} R^+_{h\ell}\left(\mathcal{R}|\boldsymbol{\lambda},\boldsymbol{\Phi}\right) = \Pr\left(R^+_{h\ell}\left(\boldsymbol{\lambda},\boldsymbol{\Phi}\right) \leq \mathcal{R}\right) &= \prod_{h' \in \mathcal{H}} \Pr\left(\lambda_{h'h}\tau_{\ell'\ell} I_{h'\ell'} \leq \mathcal{R}\right) \\ &= \prod_{h' \in \mathcal{H}} \Pr\left(I_{h'\ell'} \leq \frac{\mathcal{R}}{\lambda_{h'h}\tau_{\ell'\ell}}\right) \\ &= \prod_{h' \in \mathcal{H}} \exp\left(-\left(\frac{\mathcal{R}}{\lambda_{h'h}\tau_{\ell'\ell}p_{\ell'}}\right)^{-\theta} z_{h'}\Phi_{\ell'}\right) \\ &= \exp\left(-\mathcal{R}^{-\theta}\sum_{h' \in \mathcal{H}} \left(\lambda_{h'h}\tau_{\ell'\ell}p_{\ell'}\right)^{\theta} z_{h'}\Phi_{\ell'}\right), \end{aligned}$$

where the third equality arises from the distribution of $I_{h\ell}$ derived in part (a).

(c) The choice probability arises from

$$\begin{aligned} \Pr\left(h' = \arg\max_{h'' \in \mathcal{H}} \lambda_{h''h}\tau_{\ell''\ell} I_{h''\ell''}\right) &= \int_0^\infty \prod_{h'' \neq h' \in \mathcal{H}} \Pr\left(\lambda_{h''h}\tau_{\ell''\ell} I_{h''\ell''} < \mathcal{I}\right) dI_{h'\ell'}\left(\lambda_{h'h}\tau_{\ell'\ell} I_{h'\ell'}\right) \\ &= \int_0^\infty \exp\left(-\mathcal{I}^\theta S_{h|\boldsymbol{\lambda}}\right)\theta\mathcal{I}^{\theta-1}\left(\lambda_{h'h}\tau_{\ell'\ell}p_{\ell'}\right)^{\theta} z_h\Phi_\ell d\mathcal{I} \\ &= \frac{\left(\lambda_{h'h}\tau_{\ell'\ell}p_{\ell'}\right)^{\theta} z_h\Phi_\ell}{\sum_{h'' \in \mathcal{H}}\left(\lambda_{h''h}\tau_{\ell''\ell}p_{\ell''}\right)^{\theta} z_{h''}\Phi_{\ell''}}. \end{aligned}$$

I calculate the expected recipient $\mathbb{E}\left(R^+_{h\ell}\left(\boldsymbol{\lambda}|\boldsymbol{\Phi}\right)\right)$ and sender transfers $\mathbb{E}\left(R^-_{h\ell}\left(\boldsymbol{\lambda}|\boldsymbol{\Phi}\right)\right)$ in the proof of Corollary 1 found in Section A.2.

A.2 Proof of Corollary 1

(a) From Section A.1, a household's recipient transfers $R_{h\ell}^{+}(\boldsymbol{\lambda}|\boldsymbol{\Phi})$, conditional on local shock $\boldsymbol{\Phi}$ realization, is distributed Fréchet with shape parameter θ and scale parameter $\bar{S}_h^{1/\theta}(\boldsymbol{\lambda})$. The expectation is

$$\begin{aligned}\mathbb{E}\left(R_{h\ell}^{+}(\boldsymbol{\lambda})\right) &= \mathbb{E}\left[\mathbb{E}\left(R_{h\ell}^{+}(\boldsymbol{\lambda}|\boldsymbol{\Phi})\right)\right] \\ &= \Gamma(1-1/\theta)\,\mathbb{E}\left(S_h^{1/\theta}(\boldsymbol{\lambda}|\boldsymbol{\Phi})\right) \\ &\approx \Gamma(1-1/\theta)\,\bar{S}_h^{1/\theta}(\boldsymbol{\lambda})\left(1-\frac{\theta-1}{2\theta}\frac{\sigma_{S_h}^2(\boldsymbol{\lambda})}{\bar{S}_h^2(\boldsymbol{\lambda})}\right).\end{aligned}$$

where the first equality arises from the law of iterated expectations, the second from properties of the Fréchet distribution, and the third from the second-order Taylor expansion. By restrictions on the shape parameter of Fréchet distributions, $\theta > 1$, so $\frac{\partial\mathbb{E}\left(R_{h\ell}^{+}(\boldsymbol{\lambda}|\boldsymbol{\Phi})\right)}{\partial\sigma_{S_h}^2(\boldsymbol{\lambda})} < 0$. Note that the derivative of $\mathbb{E}\left(R_{h\ell}^{+}(\boldsymbol{\lambda})\right)$ with respect to $\bar{S}_h(\boldsymbol{\lambda})$ is

$$\begin{aligned}\frac{\partial\mathbb{E}\left(R_{h\ell}^{+}(\boldsymbol{\lambda}|\boldsymbol{\Phi})\right)}{\partial\bar{S}_h(\boldsymbol{\lambda})} \approx \frac{1}{\theta}\bar{S}_h^{1/\theta-1}(\boldsymbol{\lambda})\underbrace{\left(1-\frac{\theta-1}{2\theta}\frac{\sigma_{S_h}^2(\boldsymbol{\lambda})}{\bar{S}_h^2(\boldsymbol{\lambda})}\right)}_{\text{Inflow risk-adjustment, }\bar{\varphi}_h^{+}(\boldsymbol{\lambda})} \\ -\left(\frac{1}{\theta}-1\right)\bar{S}_h^{1/\theta-3}(\boldsymbol{\lambda})\,\sigma_{S_h}^2(\boldsymbol{\lambda}) > 0\end{aligned}$$

and

$$\begin{aligned}\frac{\partial^2\mathbb{E}\left(R_{h\ell}^{+}(\boldsymbol{\lambda}|\boldsymbol{\Phi})\right)}{\partial\bar{S}_h(\boldsymbol{\lambda})^2} \approx \frac{1}{\theta}\left(\frac{1}{\theta}-1\right)\bar{S}_h^{1/\theta-2}(\boldsymbol{\lambda})\left(1-\frac{\theta-1}{2\theta}\frac{\sigma_{S_h}^2(\boldsymbol{\lambda})}{\bar{S}_h^2(\boldsymbol{\lambda})}\right) \\ -\left(\frac{1}{\theta}-1\right)\left(\frac{1}{\theta}-3\right)\bar{S}_h^{1/\theta-4}(\boldsymbol{\lambda})\,\sigma_{S_h}^2(\boldsymbol{\lambda}) < 0.\end{aligned}$$

If there is no systematic relationship between network access mean $\bar{S}_h(\boldsymbol{\lambda})$ and volatility $\sigma_{S_h}^2(\boldsymbol{\lambda})$, then expected recipient transfers are increasing and concave in the expectation of network access $\bar{S}_h(\boldsymbol{\lambda})$.

(b) To calculate the expectation of the household's sender transfer $\mathbb{E}\left(R_{h\ell}^{-}(\boldsymbol{\lambda})\right)$, we first calculate $\mathbb{E}\left(\tilde{R}_{h\ell}^{-}(\boldsymbol{\lambda})\,I_{h\ell}|\boldsymbol{\Phi}\right)$, where $\tilde{R}_{h\ell}^{-}(\boldsymbol{\lambda})$ is the normalized sender transfer $R_{h\ell}^{-}(\boldsymbol{\lambda}|\boldsymbol{\Phi})$ scaled by the inverse of income $I_{h\ell}$. This object amounts to the expected sender transfer conditional on a local shock Φ realization:

$$
\begin{aligned}
\mathbb{E}\left(\tilde{R}_{h\ell}^{-}\left(\boldsymbol{\lambda}\right)I_{h\ell}|\boldsymbol{\Phi}\right) &= \mathbb{E}\left(\mathbb{E}\left[I_{h\ell}\sum_{h'\in\mathcal{H}}\kappa_{hh'}\lambda_{hh'}\mathbf{1}\left(h=\arg\max_{h''\in\mathcal{H}}\lambda_{h''h'}\tau_{\ell''\ell'}I_{h''\ell''}\right)|\boldsymbol{\Phi},I_{h\ell}\right]\right)\\
&= \mathbb{E}\left(I_{h\ell}\sum_{h'\in\mathcal{H}}\kappa_{hh'}\lambda_{hh'}\Pr\left(h=\arg\max_{h''\in H}\lambda_{h''h'}\tau_{\ell''\ell'}I_{h''\ell''}|\boldsymbol{\Phi},I_{h\ell}\right)\right)\\
&= \sum_{h'\in\mathcal{H}}\mathbb{E}\left(I_{h\ell}\kappa_{hh'}\lambda_{hh'}\prod_{h''\neq h\in\mathcal{H}}\Pr\left(I_{h''\ell''}<I_{h\ell}\frac{\tau_{\ell\ell'}\lambda_{hh'}}{\tau_{\ell''\ell'}\lambda_{h''h'}}\right)\right)\\
&= \sum_{h'\in\mathcal{H}}\mathbb{E}\Bigg(I_{h\ell}\kappa_{hh'}\lambda_{hh'}\exp\left(-I_{h\ell}^{-\theta}\sum_{h''\neq h\in\mathcal{H}}\left(\frac{\tau_{\ell''\ell'}\lambda_{h''h'}}{\tau_{\ell\ell'}\lambda_{hh'}}\right)^{\theta}\cdot\right.\\
&\qquad \left.p_{\ell''}^{\theta}z_{h''}\Phi_{\ell''}\right|\boldsymbol{\Phi}\Bigg)\\
&= \sum_{h'\in\mathcal{H}}\kappa_{hh'}\lambda_{hh'}\int_{0}^{\infty}\mathcal{I}\exp\left(-\mathcal{I}^{-\theta}\sum_{h''\neq h\in\mathcal{H}}\left(\frac{\tau_{\ell''\ell'}\lambda_{h''h'}}{\tau_{\ell\ell'}\lambda_{hh'}}\right)^{\theta}\cdot\right.\\
&\qquad \left.p_{\ell''}^{\theta}z_{h''}\Phi_{\ell''}\right)dI_{h\ell}\left(\mathcal{I}\right)\\
&= \sum_{h'\in\mathcal{H}}\kappa_{hh'}\lambda_{hh'}p_{\ell}^{\theta}z_{h}\Phi_{\ell}\int_{0}^{\infty}\exp\left(-\mathcal{I}^{-\theta}\left[\frac{S_{h'}\left(\boldsymbol{\lambda}|\boldsymbol{\Phi}\right)}{\tau_{\ell\ell'}\lambda_{hh'}}\right]\right)\theta\mathcal{I}^{-\theta}d\mathcal{I}\\
&= \Gamma\left(1-1/\theta\right)\sum_{h'\in\mathcal{H}}\kappa_{hh'}\lambda_{hh'}^{\theta+1}\tau_{\ell\ell'}^{\theta}p_{\ell}^{\theta}z_{h}\Phi_{\ell}S_{h'}^{-1}\left(\boldsymbol{\lambda}|\boldsymbol{\Phi}\right)\cdot\\
&\qquad \left[\left(\tau_{\ell\ell'}\lambda_{hh'}\right)^{-\theta}S_{h'}\left(\boldsymbol{\lambda}|\boldsymbol{\Phi}\right)\right]^{1/\theta}\\
&= \Gamma\left(1-1/\theta\right)\sum_{h'\in\mathcal{H}}\kappa_{hh'}\lambda_{hh'}^{\theta}\tau_{\ell\ell'}^{\theta-1}p_{\ell}^{\theta}z_{h}\Phi_{\ell}S_{h'}^{1/\theta-1}\left(\boldsymbol{\lambda}|\boldsymbol{\Phi}\right).
\end{aligned}
$$

The first equality arises from the law of iterated expectations. The third arises from the linearity of expectations. The fourth arises from the c.d.f.s of $I_{h''\ell''}$ derived in Lemma 1. The fifth arises from the definition of the expectation operator. The sixth arises from the c.d.f. of $I_{h\ell}$ derived in Lemma 1. The seventh from properties of the Fréchet distribution. The eighth collects terms.

Next, I calculate the expectation of the sender transfer term $\mathbb{E}\left(R_{h\ell}^{-}\left(\boldsymbol{\lambda}\right)\right)$:

$$
\begin{aligned}
\mathbb{E}\left(R_{h\ell}^{-}\left(\boldsymbol{\lambda}\right)\right) &= \mathbb{E}\left[\mathbb{E}\left(\tilde{R}_{h\ell}^{-}\left(\boldsymbol{\lambda}\right)I_{h\ell}|\boldsymbol{\Phi}\right)\right]\\
&= \Gamma\left(1-1/\theta\right)\sum_{h'\in\mathcal{H}}\kappa_{hh'}\lambda_{hh'}^{\theta}\tau_{\ell\ell'}^{\theta-1}p_{\ell}^{\theta}z_{h}\mathbb{E}\left(\Phi_{\ell}S_{h'}^{1/\theta-1}\left(\boldsymbol{\lambda}|\boldsymbol{\Phi}\right)\right),
\end{aligned}
$$

where the first equality arises from the law of iterated expectations and the second arises from the linearity of expectations. Approximating with a second-order Taylor expansion

around $\boldsymbol{A} = \mathbb{E}(\boldsymbol{\Phi})$, we have:

$$\frac{\mathbb{E}\left(\Phi_\ell S_{h'}^{1/\theta-1}(\boldsymbol{\lambda}|\boldsymbol{\Phi})\right)}{A_\ell \bar{S}_{h'}^{1/\theta-1}(\boldsymbol{\lambda})} \approx \underbrace{\left[1 + \frac{(1-\theta)(1-2\theta)}{2\theta^2}\frac{\sigma^2_{S_{h'}}(\boldsymbol{\lambda})}{\bar{S}^2_{h'}(\boldsymbol{\lambda})} + \frac{1-\theta}{\theta}\frac{\mathrm{Cov}\left(S_{h'}(\boldsymbol{\lambda}), \Phi_\ell\right)}{\bar{S}_{h'}(\boldsymbol{\lambda}) A_\ell}\right]}_{\text{Outflow risk adjustment, } \bar{\varphi}^-_{hh'}(\boldsymbol{\lambda})}$$

This term is increasing in $\sigma^2_{S_{h'}}(\boldsymbol{\lambda})$ and decreasing in $\mathrm{Cov}\left(S_{h'}(\boldsymbol{\lambda}), \Phi_\ell\right)$. These yield the comparative statics described in Corollary 1, that $\frac{\partial \mathbb{E}\left(R^-_{h\ell}(\boldsymbol{\lambda})\right)}{\partial \sigma^2_{S_{h'}}(\boldsymbol{\lambda})} > 0$ and $\frac{\partial \mathbb{E}\left(R^-_{h\ell}(\boldsymbol{\lambda})\right)}{\partial \mathrm{Cov}(S_{h'}(\boldsymbol{\lambda}), \Phi_\ell)} < 0$. This term is also declining and convex in $\bar{S}_{h'}(\boldsymbol{\lambda})$.

A.3 Proof of Proposition 1

We consider the preferred partnership level $\lambda^*_{hh'}$ of a household h in its relationship with h' as

$$\lambda^*_{hh'}(\boldsymbol{\lambda}_{-hh'}) = \arg\max_{\lambda} \mathbb{E}\left[C_{h\ell}(\lambda \cup \boldsymbol{\lambda}_{-hh'})\right] \text{ s.t. } \sum_{h' \neq h} \kappa_{hh'}\lambda_{hh'} \leq 1 - \bar{\lambda} \text{ and } \lambda_{hh'} \geq \underline{\lambda}$$

Let us assume, for simplicity, that there is no systematic relationship between inflow and outflow risk-adjustment terms, respectively $\bar{\varphi}^+_h$ and $\bar{\varphi}^-_{hh'}$ (defined in Section A.2), and partnership level $\lambda_{hh'}$. Suppose a household can only adjust the link between h and h'. The resulting Lagrangian is

$$\mathcal{L} = \mathbb{E}\left(C_{h\ell}(\lambda \cup \boldsymbol{\lambda}_{-hh'})\right) + \Lambda\left(1 - \bar{\lambda} - \sum_{h''} \kappa_{hh''}\lambda_{hh''}\right) + \Xi\left(\lambda_{hh'} - \underline{\lambda}\right).$$

Under the Paypal Assumption, the first order condition with respect to $\lambda_{hh'}$ is

$$\frac{\partial \mathcal{L}}{\partial \lambda_{hh'}} = \frac{\partial \mathbb{E}\left(R^+_{h\ell}(\boldsymbol{\lambda})\right)}{\partial \lambda_{hh'}} - \frac{\partial \mathbb{E}\left(R^-_{h\ell}(\boldsymbol{\lambda})\right)}{\partial \lambda_{hh'}} - \Lambda\left(1 + \bar{c}(\gamma+1)\lambda^\gamma_{hh'}\right) + \Xi = 0.$$

The complementary slackness conditions are

$$\Lambda\left(1 - \bar{\lambda} - \sum_{h''} \kappa_{hh''}\lambda_{hh''}\right) = 0,$$

where $\Lambda = 0$ if the feasibility constraint does not bind, and

$$\Xi\left(\lambda_{hh'} - \underline{\lambda}\right) = 0,$$

where $\Xi = 0$ if the minimum weight requirement does not bind.

We solve for the weight $\lambda_{hh'}$ for which $\frac{\partial \mathcal{L}}{\partial \lambda_{hh'}} = 0$, which corresponds to a local maximum if $\mathbb{E}\left(C_{h\ell}\left(\lambda \cup \boldsymbol{\lambda}_{-hh'}\right)\right)$is concave in λ (this is a condition for equilibrium existence and is shown in Section A.3). To do so, first, evaluate $\frac{\partial \mathbb{E}\left(R^{+}_{h\ell}(\boldsymbol{\lambda})\right)}{\partial \lambda_{hh'}}$:

$$\begin{aligned}
\frac{\partial \mathbb{E}\left(R^{+}_{h\ell}\left(\boldsymbol{\lambda}\right)\right)}{\partial \lambda_{hh'}} &= \Gamma\left(1-1/\theta\right)\bar{\varphi}^{+}_{h}\left(\boldsymbol{\lambda}\right)\cdot\frac{1}{\theta}\bar{S}^{1/\theta-1}_{h}\left(\boldsymbol{\lambda}\right)\frac{\partial \bar{S}_{h}\left(\boldsymbol{\lambda}\right)}{\partial \lambda_{hh'}} \\
&= \Gamma\left(1-1/\theta\right)\bar{\varphi}^{+}_{h}\left(\boldsymbol{\lambda}\right)\cdot\frac{1}{\theta}\bar{S}^{1/\theta-1}_{h}\left(\boldsymbol{\lambda}\right)\theta\lambda^{\theta-1}_{hh'}\tau^{\theta}_{\ell'\ell}p^{\theta}_{\ell'}z_{h'}A_{\ell'} \\
&= \Gamma\left(1-1/\theta\right)\bar{\varphi}^{+}_{h}\left(\boldsymbol{\lambda}\right)\cdot\bar{S}^{1/\theta-1}_{h}\left(\boldsymbol{\lambda}\right)\lambda^{\theta-1}_{hh'}\tau^{\theta}_{\ell'\ell}p^{\theta}_{\ell'}z_{h'}A_{\ell'}.
\end{aligned}$$

Next, we evaluate $\frac{\partial \mathbb{E}\left(R^{-}_{h\ell}(\boldsymbol{\lambda})\right)}{\partial \lambda_{hh'}}$:

$$\begin{aligned}
\frac{\partial \mathbb{E}\left(R^{+}_{h\ell}\left(\boldsymbol{\lambda}\right)\right)}{\partial \lambda_{hh'}} &= \Gamma\left(1-1/\theta\right)\tau^{\theta-1}_{\ell\ell'}p^{\theta}_{\ell}z_{h}A_{\ell}\lambda^{\theta}_{hh'}\bar{S}^{1/\theta-1}_{h'}\left(\boldsymbol{\lambda}\right)\bar{\varphi}^{-}_{hh'}\left(\boldsymbol{\lambda}\right)\cdot \\
&\qquad\left[\left(\theta\lambda^{-1}_{hh'}+\bar{c}\left(\theta+\gamma\right)\lambda^{\gamma-1}_{hh'}\right)+\left(1/\theta-1\right)\left(1+\bar{c}\lambda^{\gamma}_{hh'}\right)\bar{S}^{-1}_{h'}\left(\boldsymbol{\lambda}\right)\frac{\partial \bar{S}_{h'}\left(\boldsymbol{\lambda}\right)}{\partial \lambda_{hh'}}\right] \\
&= \Gamma\left(1-1/\theta\right)\tau^{\theta-1}_{\ell\ell'}p^{\theta}_{\ell}z_{h}A_{\ell}\lambda^{\theta-1}_{hh'}\bar{S}^{1/\theta-1}_{h'}\left(\boldsymbol{\lambda}\right)\bar{\varphi}^{-}_{hh'}\left(\boldsymbol{\lambda}\right)\cdot \\
&\qquad\left[\left(\theta+\bar{c}\left(\theta+\gamma\right)\lambda^{\gamma}_{hh'}\right)+\left(1-\theta\right)\left(1+\bar{c}\lambda^{\gamma}_{hh'}\right)\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right] \\
&= \Gamma\left(1-1/\theta\right)\tau^{\theta-1}_{\ell\ell'}p^{\theta}_{\ell}z_{h}A_{\ell}\lambda^{\theta-1}_{hh'}\bar{S}^{1/\theta-1}_{h'}\left(\boldsymbol{\lambda}\right)\bar{\varphi}^{-}_{hh'}\left(\boldsymbol{\lambda}\right)\cdot \\
&\qquad\left[\left(\theta-\left(\theta-1\right)\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)+\bar{c}\lambda^{\gamma}_{hh'}\left(\theta+\gamma-\left(\theta-1\right)\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)\right].
\end{aligned}$$

If both $\Lambda = \Xi = 0$, then the expected consumption maximizing value of $\lambda_{hh'}$ is satisfies

$$\frac{p^{\theta}_{\ell'}z_{h'}A_{\ell'}}{p^{\theta}_{\ell}z_{h}A_{\ell}}\tau_{\ell\ell'}\bar{\varphi}^{+}_{h}\left(\boldsymbol{\lambda}\right)=\left(\frac{\bar{S}_{h'}\left(\boldsymbol{\lambda}\right)}{\bar{S}_{h}\left(\boldsymbol{\lambda}\right)}\right)^{1/\theta-1}\bar{\varphi}^{-}_{hh'}\left(\boldsymbol{\lambda}\right)\left[\left(\theta+\bar{c}\left(\theta+\gamma\right)\lambda^{\gamma}_{hh'}\right)+\left(1-\theta\right)\left(1+\bar{c}\lambda^{\gamma}_{hh'}\right)\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right].$$

Rearranging for $\lambda_{hh'}$, we get:

$$\lambda^{*}_{hh'}=\left(\frac{\left(\frac{p^{\theta}_{\ell'}z_{h'}A_{\ell'}}{p^{\theta}_{\ell}z_{h}A_{\ell}}\right)\left(\frac{\bar{S}_{h'}(\boldsymbol{\lambda})}{\bar{S}_{h}(\boldsymbol{\lambda})}\right)^{1-1/\theta}\tau_{\ell\ell'}\frac{\bar{\varphi}^{+}_{h}(\boldsymbol{\lambda})}{\bar{\varphi}^{-}_{hh'}(\boldsymbol{\lambda})}-\theta+\left(\theta-1\right)\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)}{\bar{c}\left(\theta+\gamma-\left(\theta-1\right)\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)}\right)^{\frac{1}{\gamma}}.$$

If $\Xi > 0$ and the minimum weight requirement binds, we have $\lambda^{*}_{hh'} = \underline{\lambda}$. Similarly, if $\Lambda > 0$, we have $\lambda_{hh'} = \frac{1-\sum_{h''\neq h'}\kappa_{hh''}\lambda_{hh''}}{\kappa_{hh'}}$.

Let $\underline{\boldsymbol{\lambda}} = \underline{\lambda} \cup \boldsymbol{\lambda}_{-hh'}$. The preferred partnership level has an interior solution if

$$\frac{1}{\theta}\left(\frac{\bar{S}_{h'}\left(\underline{\boldsymbol{\lambda}}\right)}{\bar{S}_{h}\left(\underline{\boldsymbol{\lambda}}\right)}\right)^{1-1/\theta}\frac{\bar{\varphi}_{h}^{+}\left(\underline{\boldsymbol{\lambda}}\right)}{\bar{\varphi}_{hh'}^{-}\left(\underline{\boldsymbol{\lambda}}\right)}\tau_{\ell\ell'}\left(\frac{p_{\ell'}^{\theta}z_{h'}A_{\ell'}}{p_{\ell}^{\theta}z_{h}A_{\ell}}\right) > \left(1+\bar{c}\frac{\gamma+\theta}{\theta}\left(\underline{\boldsymbol{\lambda}}^{\theta}\right)^{\frac{\gamma}{\theta}}\right)+\left(\frac{1}{\theta}-1\right)\kappa_{hh'}\pi_{h\ell h'\ell'}\left(\underline{\boldsymbol{\lambda}}\right),$$

or if payoffs are initially increasing in $\lambda_{hh'}$ at $\lambda_{hh'} = \underline{\lambda}$. If this condition is not satisfied, we set $\lambda_{hh'}^{*} = \underline{\lambda}$.

A.3.1 Derivation of $\frac{\partial \lambda_{z\ell z'\ell'}^{*}}{\partial \tau_{\ell'\ell}}$

The derivative is

$$\begin{aligned}\frac{\partial \lambda_{hh'}^{*}}{\partial \tau_{\ell'\ell}} &= \frac{1}{\gamma}\left(\lambda_{hh'}^{*}\right)^{1-\gamma}\frac{1}{\bar{c}\left(\theta+\gamma-\left(\theta-1\right)\pi_{h\ell h'\ell'}\right)}\left[1-\left(1-1/\theta\right)\frac{S_{h'}^{(1)}}{\left(S_{h}^{(1)}\right)^{2}}\frac{\partial S_{h}^{(1)}}{\partial \tau_{\ell'\ell}}\right]\\ &= \frac{1}{\gamma}\left(\lambda_{hh'}^{*}\right)^{1-\gamma}\frac{1}{\bar{c}\left(\theta+\gamma-\left(\theta-1\right)\pi_{h\ell h'\ell'}\right)}\left[1-\left(\theta-1\right)\frac{S_{h'}^{(1)}}{S_{h}}\frac{1}{\tau_{\ell'\ell}}\pi_{h'\ell' h\ell}\right].\end{aligned}$$

This derivative is negative if

$$\theta - 1 > \tau_{\ell'\ell}\frac{1}{\pi_{h'\ell' h\ell}}\frac{S_{h}^{(1)}}{S_{h'}^{(1)}}.$$

A.4 Proof of Proposition 2

Consider a weighted network where the weights between households h and h' are given as $\lambda_{hh'}^{\theta}$, a continuous and convex function of the partnership level. From the restrictions in the text, $\lambda_{hh'}^{\theta} \in \left[\underline{\lambda}^{\theta}, 1\right]$,where $\underline{\lambda}^{\theta} > 0$ for $\theta > 1$. From Theorem 3.2 of Bich and Morhaim (2020), the setup admits a pairwise stable network if payoffs $\mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)$ are continuous and quasi-concave with respect to $\lambda_{hh'}^{\theta}$. I demonstrate that $\mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)$ follows these requirements.

First, from the results of Section A.2, expected consumption is

$$\begin{aligned}\frac{\mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)}{\Gamma\left(1-1/\theta\right)} &= p_{\ell}z_{h}\mathbb{E}\left(\Phi_{\ell}^{1/\theta}\right)+\bar{S}_{h}^{1/\theta}\left(\boldsymbol{\lambda}\right)\bar{\varphi}_{h}^{+}\left(\boldsymbol{\lambda}\right)\\ &\quad-\sum_{h'\in\mathcal{H}}\kappa_{hh'}\lambda_{hh'}^{\theta}\tau_{\ell\ell'}^{\theta-1}p_{\ell}^{\theta}z_{h}A_{\ell}\bar{S}_{h'}^{1/\theta-1}\left(\boldsymbol{\lambda}\right)\bar{\varphi}_{hh'}^{-}\left(\boldsymbol{\lambda}\right).\end{aligned}$$

Note that $\bar{S}_{h}\left(\boldsymbol{\lambda}\right)$ and $\mathrm{Cov}\left(S_{h'}\left(\boldsymbol{\lambda}\right),\Phi_{\ell}\right)$ are non-zero, affine functions of $\lambda_{hh'}^{\theta}$ and are thus continuous. As the product of continuous functions are continuous and $\sigma_{S_h}^{2}\left(\boldsymbol{\lambda}\right)$ is an affine function of $\lambda_{hh'}^{\theta}\lambda_{hh''}^{\theta}$ for $h'' \in \mathcal{H}$, $\sigma_{S_h}^{2}\left(\boldsymbol{\lambda}\right)$ is also continuous in $\lambda_{hh'}^{\theta}$. The inflow and outflow risk-adjustment terms, or respectively $\bar{\varphi}_{h}^{+}\left(\boldsymbol{\lambda}\right)$ and $\bar{\varphi}_{hh'}^{-}\left(\boldsymbol{\lambda}\right)$, are affine functions of functions that are continuous in $\lambda_{hh'}^{\theta}$, and are therefore also continuous in $\lambda_{hh'}^{\theta}$. The payoff function

$\mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)$ is also an affine combination of the product of functions that are continuous in $\lambda_{hh'}^{\theta}$. Payoffs follow the continuity requirement.

Next, I demonstrate that payoffs $\mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)$ is concave in $\lambda_{hh'}^{\theta}$. To do this, first take the first derivative:

$$\begin{aligned}\frac{\partial}{\partial\lambda_{hh'}^{\theta}}\left(\frac{\mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)}{\Gamma\left(1-1/\theta\right)}\right) &= \frac{1}{\theta}\bar{S}_{h}^{1/\theta-1}\left(\boldsymbol{\lambda}\right)\bar{\varphi}_{h}^{+}\left(\boldsymbol{\lambda}\right)\tau_{\ell'\ell}^{\theta}p_{\ell'}^{\theta}z_{h'}A_{\ell'}-\tau_{\ell\ell'}^{\theta-1}p_{\ell}^{\theta}z_{h}A_{\ell}\bar{\varphi}_{hh'}^{-}\left(\boldsymbol{\lambda}\right)\cdot\\ &\quad\frac{\partial}{\partial\lambda_{hh'}^{\theta}}\left(\left[\lambda_{hh'}^{\theta}+\bar{c}\left(\lambda_{hh'}^{\theta}\right)^{\frac{\gamma+\theta}{\theta}}\right]\bar{S}_{h'}^{1/\theta-1}\right)\\ &= \frac{1}{\theta}\bar{S}_{h}^{1/\theta-1}\left(\boldsymbol{\lambda}\right)\bar{\varphi}_{h}^{+}\left(\boldsymbol{\lambda}\right)\tau_{\ell'\ell}^{\theta}p_{\ell'}^{\theta}z_{h'}A_{\ell'}-\tau_{\ell\ell'}^{\theta-1}p_{\ell}^{\theta}z_{h}A_{\ell}\bar{\varphi}_{hh'}^{-}\left(\boldsymbol{\lambda}\right)\bar{S}_{h'}^{1/\theta-1}\left(\boldsymbol{\lambda}\right)\cdot\\ &\quad\left[\left(1+\bar{c}\frac{\gamma+\theta}{\theta}\left(\lambda_{hh'}^{\theta}\right)^{\frac{\gamma}{\theta}}\right)+\left(\frac{1}{\theta}-1\right)\kappa_{hh'}\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right]\end{aligned}$$

Let us sign this derivative as $\lambda_{hh'}\to^{R}0$. The expression is positive if:

$$\begin{aligned}\frac{1}{\theta}\left(\frac{\bar{S}_{h'}\left(\boldsymbol{\lambda}\right)}{\bar{S}_{h}\left(\boldsymbol{\lambda}\right)}\right)^{1-1/\theta}\frac{\bar{\varphi}_{h}^{+}\left(\boldsymbol{\lambda}\right)}{\bar{\varphi}_{hh'}^{-}\left(\boldsymbol{\lambda}\right)}\tau_{\ell\ell'}\left(\frac{p_{\ell'}^{\theta}z_{h'}A_{\ell'}}{p_{\ell}^{\theta}z_{h}A_{\ell}}\right) &> \left(1+\bar{c}\frac{\gamma+\theta}{\theta}\left(\lambda_{hh'}^{\theta}\right)^{\frac{\gamma}{\theta}}\right)\\ &\quad+\left(\frac{1}{\theta}-1\right)\kappa_{hh'}\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\end{aligned}$$

The right-hand-side approaches one as $\lambda_{hh'}\to^{R}0$. In the absence of inflow and outflow spatial risk adjustments, respectively $\bar{\varphi}_{h}^{+}\left(\boldsymbol{\lambda}\right)$ and $\bar{\varphi}_{hh'}^{-}\left(\boldsymbol{\lambda}\right)$, this condition implies that if $\frac{\partial\mathbb{E}(C_{h\ell}(\boldsymbol{\lambda}))}{\partial\lambda_{hh'}^{\theta}}>0$, then $\frac{\partial\mathbb{E}(C_{h'\ell'}(\boldsymbol{\lambda}))}{\partial\lambda_{h'h}^{\theta}}<0$, and vice versa. To see this, note that if $NPR_{h'h}\left(\boldsymbol{\lambda}\right)IPR_{h'h}\geq\frac{\theta}{\tau_{\ell\ell'}}>1$, then $NPR_{hh'}\left(\boldsymbol{\lambda}\right)IPR_{hh'}<\frac{\theta}{\tau_{\ell\ell'}}$ because $NPR_{h'h}=1/NPR_{hh'}$ and $IPR_{h'h}=1/IPR_{hh'}$, and vice versa, where $NPR_{h'h}$ and $IPR_{h'h}$ are defined according to Proposition 1. The condition that $\lambda_{hh'}\geq\underline{\lambda}$ is important to bind risk-adjustment terms $\bar{\varphi}_{h}^{+}\left(\boldsymbol{\lambda}\right)$ and $\bar{\varphi}_{hh'}^{-}\left(\boldsymbol{\lambda}\right)$ away from 1 and facilitate the formation of the transfer network.

Before calculating the second derivative, let $\mathcal{F}\left(\boldsymbol{\lambda}\right)=1+\bar{c}\frac{\gamma+\theta}{\theta}\left(\lambda_{hh'}^{\theta}\right)^{\frac{\gamma}{\theta}}+\left(\frac{1}{\theta}-1\right)\kappa_{hh'}\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)$. Evaluate

$$\begin{aligned}\frac{\partial\mathcal{F}\left(\boldsymbol{\lambda}\right)}{\partial\lambda_{hh'}^{\theta}} &= \bar{c}\frac{\gamma+\theta}{\theta}\frac{\gamma}{\theta}\left(\lambda_{hh'}^{\theta}\right)^{\frac{\gamma-\theta}{\theta}}+\left(\frac{1}{\theta}-1\right)\frac{\kappa_{hh'}}{\lambda_{hh'}^{\theta}}\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\left(1-\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)\\ &\quad+\bar{c}\left(\frac{1}{\theta}-1\right)\frac{\gamma}{\theta}\left(\lambda_{hh'}^{\theta}\right)^{\frac{\gamma-\theta}{\theta}}\\ &= \bar{c}\frac{\gamma}{\theta}\left(\frac{\gamma+1}{\theta}\right)\left(\lambda_{hh'}^{\theta}\right)^{\frac{\gamma-\theta}{\theta}}+\left(\frac{1}{\theta}-1\right)\frac{\kappa_{hh'}}{\lambda_{hh'}^{\theta}}\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\left(1-\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)\end{aligned}$$

Then,

$$\begin{aligned}
\frac{\partial^2 \mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)}{\partial\left(\lambda_{hh'}^{\theta}\right)^2} \propto & \frac{1}{\theta}\left(\frac{1}{\theta}-1\right)\bar{S}_h^{1/\theta-2}\left(\boldsymbol{\lambda}\right)\bar{\varphi}_h^{+}\left(\boldsymbol{\lambda}\right)\tau_{\ell'\ell}^{2\theta}p_{\ell'}^{2\theta}z_{h'}^2A_{\ell'}^2-\tau_{\ell\ell'}^{\theta-1}p_{\ell}^{\theta}z_hA_{\ell}\cdot \\
& \bar{\varphi}_{hh'}^{-}\left(\boldsymbol{\lambda}\right)\bar{S}_{h'}^{1/\theta-1}\left(\boldsymbol{\lambda}\right)\left[\left(\frac{1}{\theta}-1\right)\bar{S}_{h'}^{-1}\left(\boldsymbol{\lambda}\right)\tau_{\ell'\ell}^{\theta}p_{\ell}^{\theta}z_hA_{\ell}\mathcal{F}\left(\boldsymbol{\lambda}\right)+\frac{\partial\mathcal{F}\left(\boldsymbol{\lambda}\right)}{\partial\lambda_{hh'}^{\theta}}\right] \\
= & \frac{1}{\theta}\left(\frac{1}{\theta}-1\right)\bar{\varphi}_h^{+}\left(\boldsymbol{\lambda}\right)\bar{S}_h^{1/\theta}\left(\boldsymbol{\lambda}\right)\frac{\pi_{h'\ell'h\ell}^2\left(\boldsymbol{\lambda}\right)}{\lambda_{hh'}^{2\theta}}-\tau_{\ell\ell'}^{-1}\bar{S}_{h'}^{1/\theta}\left(\boldsymbol{\lambda}\right)\frac{\pi_{h\ell h'\ell'}}{\lambda_{hh'}^{\theta}}\cdot \\
& \left(\left(\frac{1}{\theta}-1\right)\frac{\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)}{\lambda_{hh'}^{\theta}}\left(1+\bar{c}\frac{\gamma+\theta}{\theta}\left(\lambda_{hh'}^{\theta}\right)^{\frac{\gamma}{\theta}}+\left(\frac{1}{\theta}-1\right)\kappa_{hh'}\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)\right. \\
& \left.+\bar{c}\frac{\gamma}{\theta}\left(\frac{\gamma+1}{\theta}\right)\left(\lambda_{hh'}^{\theta}\right)^{\frac{\gamma-\theta}{\theta}}+\left(\frac{1}{\theta}-1\right)\frac{\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)}{\lambda_{hh'}^{\theta}}\kappa_{hh'}\left(1-\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)\right) \\
= & \frac{1}{\theta}\left(\frac{1}{\theta}-1\right)\bar{\varphi}_h^{+}\left(\boldsymbol{\lambda}\right)\bar{S}_h^{1/\theta}\left(\boldsymbol{\lambda}\right)\frac{\pi_{h'\ell'h\ell}^2\left(\boldsymbol{\lambda}\right)}{\lambda_{hh'}^{2\theta}}-\tau_{\ell\ell'}^{-1}\bar{S}_{h'}^{1/\theta}\left(\boldsymbol{\lambda}\right)\frac{\pi_{h\ell h'\ell'}^2\left(\boldsymbol{\lambda}\right)}{\lambda_{hh'}^{2\theta}}\cdot \\
& \bar{\varphi}_{hh'}^{-}\left(\boldsymbol{\lambda}\right)\left[\left(\frac{1}{\theta}-1\right)\left(\left[2\left(1-\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)+\frac{1}{\theta}\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right]\kappa_{hh'}+\bar{c}\frac{\gamma}{\theta}\lambda_{hh'}^{\gamma}\right)\right] \\
& -\tau_{\ell\ell'}^{-1}\bar{S}_{h'}^{1/\theta}\left(\boldsymbol{\lambda}\right)\bar{c}\frac{\gamma}{\theta}\left(\frac{\gamma+1}{\theta}\right)\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\lambda_{hh'}^{\gamma-2\theta},
\end{aligned}$$

where the first term is negative, the second term is positive, and the third term is negative. The overall sign is negative if

$$\begin{aligned}
& \frac{1}{\theta}\bar{\varphi}_h^{+}\left(\frac{\bar{S}_{h'}\left(\boldsymbol{\lambda}\right)}{\bar{S}_h\left(\boldsymbol{\lambda}\right)}\right)^{-1/\theta-2}\left(\frac{p_{\ell'}^{\theta}z_{h'}A_{\ell'}}{p_{\ell}^{\theta}z_hA_{\ell}}\right)^2\tau_{\ell\ell'}+\frac{\bar{c}\gamma\left(\gamma+1\right)}{\theta\left(\theta-1\right)}\frac{\lambda_{hh'}^{\gamma}}{\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)} \\
& >\bar{\varphi}_{hh'}^{-}\left(\left[2\left(1-\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)+\frac{1}{\theta}\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right]\kappa_{hh'}+\bar{c}\frac{\gamma}{\theta}\lambda_{hh'}^{\gamma}\right).
\end{aligned}$$

If $\gamma<\theta$, then as $\lambda_{hh'}\to^R 0$, the left-hand-side of the inequality approaches positive infinity. The right-hand-side, however, approaches a constant bounded away from 0, as $\lim_{\lambda_{hh'}\to^R 0}\bar{\varphi}_{hh'}^{-}\left(\lambda_{hh'}\cup\boldsymbol{\lambda}_{-hh'}\right)=C>0$ and the parenthetical term approaches two at the limit. The condition is satisfied for $\lambda_{hh'}$ close to zero.

I have shown that payoffs $\mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)$ is continuous and concave in $\lambda_{hh'}^{\theta}$ if $\gamma<\theta$, satisfying the conditions for existence of pairwise-stable equilibria in this setting.

Next, I show that given two preferred partnership levels $\lambda_{hh'}^{*}$ and $\lambda_{h'h}^{*}$ between households pairs h and h', the realized partnership level in a pairwise-stable equilibrium between the pair should be $\lambda_{hh'}=\lambda_{h'h}=\min\left\{\lambda_{hh'}^{*},\lambda_{h'h}^{*}\right\}$. To do so, I must show that: (i) there is no level $\lambda<\min\left\{\lambda_{hh'}^{*},\lambda_{h'h}^{*}\right\}$ such that $\mathbb{E}\left(C_{h\ell}\left(\lambda\cup\boldsymbol{\lambda}_{-hh'}\right)\right)\geq\mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)$ or $\mathbb{E}\left(C_{h'\ell'}\left(\lambda\cup\boldsymbol{\lambda}_{-hh'}\right)\right)\geq\mathbb{E}\left(C_{h'\ell'}\left(\boldsymbol{\lambda}\right)\right)$, and (ii) there is no level $\lambda>\min\left\{\lambda_{hh'}^{*},\lambda_{h'h}^{*}\right\}$ such that $\mathbb{E}\left(C_{h\ell}\left(\lambda\cup\boldsymbol{\lambda}_{-hh'}\right)\right)\geq$

$\mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)$ and that $\mathbb{E}\left(C_{h'\ell'}\left(\lambda \cup \boldsymbol{\lambda}_{-hh'}\right)\right) \geq \mathbb{E}\left(C_{h'\ell'}\left(\boldsymbol{\lambda}\right)\right)$.

In Section A.3, I show that payoffs $\mathbb{E}\left(C_{h\ell}\left(\boldsymbol{\lambda}\right)\right)$ are continuous and concave in $\lambda_{hh'}$. In Section A.4, I restrict attention to payoffs that are initially increasing in $\lambda_{hh'}$. Therefore, when $\lambda < \lambda^*_{hh'}$, then payoffs $\mathbb{E}\left(C_{h\ell}\left(\lambda \cup \boldsymbol{\lambda}_{-hh'}\right)\right)$ are increasing, and when $\lambda > \lambda^*_{hh'}$, payoffs $\mathbb{E}\left(C_{h\ell}\left(\lambda \cup \boldsymbol{\lambda}_{-hh'}\right)\right)$ are decreasing. Through this observation, we know that condition (i) is satisfied: there is no profitable unilateral, downwards deviation of either household, because for payoffs are increasing in weight λ for both households in the interval $[0, \min\left\{\lambda^*_{hh'}, \lambda^*_{h'h}\right\}]$. To show (ii), suppose there is a $\lambda > \min\left\{\lambda^*_{hh'}, \lambda^*_{h'h}\right\}$ that is mutually profitable for households. This would imply that both payoffs $\mathbb{E}\left(C_{h\ell}\left(\lambda \cup \boldsymbol{\lambda}_{-hh'}\right)\right)$ and $\mathbb{E}\left(C_{h'\ell'}\left(\lambda \cup \boldsymbol{\lambda}_{-h'h}\right)\right)$ are increasing in weight λ for the interval $[\min\left\{\lambda^*_{hh'}, \lambda^*_{h'h}\right\}, 1]$. Without loss, suppose $\lambda^*_{hh'} = \min\left\{\lambda^*_{hh'}, \lambda^*_{h'h}\right\}$. This implication would violate the assumption that payoffs $\mathbb{E}\left(C_{h\ell}\left(\lambda \cup \boldsymbol{\lambda}_{-hh'}\right)\right)$ are decreasing in λ when $\lambda > \lambda^*_{hh'}$. So, there is no mutually profitable, upwards deviation in weight λ for household pairs.

A.5 Mobile Money and Cross-Productivity Group Links

In this section, I demonstrate that mobile money facilitates partnerships with more-productive partners. To do so, I note that from Equation (11), a household h is more likely to realize a transfer source h' if its partnership level $\lambda_{z\ell z'\ell'}$ exceeds a certain threshold ϵ. I call partnerships that exceed this threshold *substantial* and likely to be reported if requested by an enumerator.

Corollary 2 considers the highest and lowest idiosyncratic productivity ratios $\frac{p^{\theta}_{\ell'} z' A_{\ell'}}{p^{\theta}_{\ell} z A_{\ell}}$ found in substantial partnerships under pairwise stability. The corollary demonstrates that partner productivities found in equilibrium are sensitive to reductions in transport frictions in the model.

Corollary 2. *Suppose Equation (15) holds. Define the partnership between households h and h' as "substantial" if the level $\lambda_{z'\ell' z\ell} = \lambda_{z\ell z'\ell'}$ exceeds a threshold ϵ. Consider a pairwise stable network $\boldsymbol{\lambda}$. Conditional on pair characteristics, idiosyncratic productivity ratios $\frac{p^{\theta}_{\ell'} z' A_{\ell'}}{p^{\theta}_{\ell} z A_{\ell}}$ found in "substantial" partnerships falls in the interval:*

$$\left(\varphi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right)\tau_{\ell\ell'}\right)^{-1}\left(\frac{S^{(1)}_{z'\ell'}\left(\boldsymbol{\lambda}\right)}{S^{(1)}_{z\ell}\left(\boldsymbol{\lambda}\right)}\right)^{1/\theta-1}\mathcal{F}\left(\pi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right)\right) \leq \frac{p^{\theta}_{\ell'} z_{h'} A_{\ell'}}{p^{\theta}_{\ell'} z_{h'} A_{\ell'}} \leq \varphi_{z'\ell' z\ell}\left(\boldsymbol{\lambda}\right)\tau_{\ell'\ell}\left(\frac{S^{(1)}_{z'\ell'}\left(\boldsymbol{\lambda}\right)}{S^{(1)}_{z\ell}\left(\boldsymbol{\lambda}\right)}\right)^{1/\theta-1}\mathcal{F}^{-1}\left(\pi_{z'\ell' z\ell}\left(\boldsymbol{\lambda}\right)\right) \quad (31)$$

where $\mathcal{F}\left(x\right) = \epsilon^{\gamma}\bar{c}\gamma + \left(\epsilon^{\gamma}\bar{c}+1\right)\left[\theta - \left(\theta-1\right)x\right]$.

Proof. The proof is found in the Appendix A.5.1. □

The lower-bound of Equation (31) dictates the lowest-productivity partner h' a household h substantially connects to. The inequality follows from a condition on the household's preferences that $\lambda^*_{z\ell z'\ell'} \geq \epsilon$. The upper-bound of Equation (31) dictates the highest-productivity partner h' a household h substantially connects to. It follows from a condition on the partner's preferences that $\lambda^*_{z'\ell' z\ell} \geq \epsilon$.

How does the interval of idiosyncratic productivity ratios in Corollary 2 change under mobile money? As before, suppose money transport costs for a location ℓ has lowered, while costs in other locations ℓ' remain constant. Under Equation (15), a household's own preferred partnership level $\lambda^*_{z\ell z'\ell'}$ declines after a shock to money transport costs, which raises the lower-bound. Due to partner substitutability, a household who enhances network access becomes less willing to substantially connect with a low productivity partner.

A partner, however, increases its preferred partnership level with the household, which raises the upper-bound of the interval. From strategic complementarities, the household experiencing a decline in money transport costs becomes a more attractive partner to others: it relies less on high-productivity partners for payments. Households simultaneously add more productive partners while culling marginal, lower-productivity partnerships. Overall, the two forces combine so that households *increase* their partners' productivities on average. Note that productivities are both geographic $A_{\ell'}$ and idiosyncratic $z_{h'}$, containing both real $A_{\ell'}$ and nominal $p_{\ell'}$ determinants.

A.5.1 Proof of Corollary 2

Now, we show the main claim of the Corollary 2. For the relationship to be "substantial", or $\lambda_{hh'} = \lambda_{h'h} \geq \epsilon$, we must have the $\lambda^*_{hh'} \geq \epsilon$ and $\lambda^*_{h'h} \geq \epsilon$. The first inequality, $\lambda^*_{hh'} \geq \epsilon$, is:

$$\frac{\left(\frac{p^\theta_{\ell'} z_{h'} A_{\ell'}}{p^\theta_\ell z_h A_\ell}\right)\left(\frac{\bar{S}_{h'}(\boldsymbol{\lambda})}{\bar{S}_h(\boldsymbol{\lambda})}\right)^{1-1/\theta} \tau_{\ell\ell'} \frac{\bar{\varphi}^+_h(\boldsymbol{\lambda})}{\bar{\varphi}^-_{hh'}(\boldsymbol{\lambda})} - \mathcal{H}\left(\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)}{\bar{c}\left(\gamma + \mathcal{H}\left(\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)\right)} \geq \epsilon^\gamma, \text{ where } \mathcal{H}\left(x\right) = \theta - (\theta - 1)\, x.$$

This inequality can be rearranged as such:

$$\frac{p^\theta_{\ell'} z_{h'} A_{\ell'}}{p^\theta_\ell z_h A_\ell} \geq \left(\frac{\bar{\varphi}^+_h\left(\boldsymbol{\lambda}\right)}{\bar{\varphi}^-_{hh'}\left(\boldsymbol{\lambda}\right)} \tau_{\ell\ell'}\right)^{-1} \left(\frac{\bar{S}_{h'}\left(\boldsymbol{\lambda}\right)}{\bar{S}_h\left(\boldsymbol{\lambda}\right)}\right)^{1/\theta - 1} \left[\epsilon^\gamma \bar{c}\left(\gamma + \mathcal{H}\left(\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)\right) + \mathcal{H}\left(\pi_{h\ell h'\ell'}\left(\boldsymbol{\lambda}\right)\right)\right].$$

This inequality places a lower-bound on the idiosyncratic productivity ratio $IPR_{h'h}$. The second inequality, $\lambda^*_{h'h} \geq \epsilon$, is:

$$\frac{\left(\frac{p^\theta_\ell z_h A_\ell}{p^\theta_{\ell'} z_{h'} A_{\ell'}}\right)\left(\frac{\bar{S}_h(\boldsymbol{\lambda})}{\bar{S}_{h'}(\boldsymbol{\lambda})}\right)^{1-1/\theta} \tau_{\ell'\ell} \frac{\bar{\varphi}^+_{h'}(\boldsymbol{\lambda})}{\bar{\varphi}^-_{h'h}(\boldsymbol{\lambda})} - \mathcal{H}\left(\pi_{h'\ell' h\ell}\left(\boldsymbol{\lambda}\right)\right)}{\bar{c}\left(\gamma + \mathcal{H}\left(\pi_{h'\ell' h\ell}\left(\boldsymbol{\lambda}\right)\right)\right)} \geq \epsilon^\gamma.$$

Rearranging:

$$\frac{p_{\ell}^{\theta} z_h A_{\ell}}{p_{\ell'}^{\theta} z_{h'} A_{\ell'}} \geq \left(\frac{\bar{\varphi}_{h'}^{+}(\boldsymbol{\lambda})}{\bar{\varphi}_{hh'}^{-}(\boldsymbol{\lambda})}\tau_{\ell\ell'}\right)^{-1}\left(\frac{\bar{S}_h(\boldsymbol{\lambda})}{\bar{S}_{h'}(\boldsymbol{\lambda})}\right)^{1/\theta-1}\left[\epsilon^{\gamma}\bar{c}\left(\gamma+\mathcal{H}\left(\pi_{h'\ell'h\ell}(\boldsymbol{\lambda})\right)\right)+\mathcal{H}\left(\pi_{h'\ell'h\ell}(\boldsymbol{\lambda})\right)\right]$$

$$\frac{p_{\ell'}^{\theta} z_{h'} A_{\ell'}}{p_{\ell}^{\theta} z_h A_{\ell}} \leq \frac{\bar{\varphi}_{h'}^{+}(\boldsymbol{\lambda})}{\bar{\varphi}_{hh'}^{-}(\boldsymbol{\lambda})}\tau_{\ell\ell'}\left(\frac{\bar{S}_{h'}(\boldsymbol{\lambda})}{\bar{S}_h(\boldsymbol{\lambda})}\right)^{1/\theta-1}\left[\epsilon^{\gamma}\bar{c}\left(\gamma+\mathcal{H}\left(\pi_{h'\ell'h\ell}(\boldsymbol{\lambda})\right)\right)+\mathcal{H}\left(\pi_{h'\ell'h\ell}(\boldsymbol{\lambda})\right)\right]^{-1}.$$

This inequality places an upper-bound on the idiosyncratic productivity ratio $IPR_{h'h}$. Placing the two inequalities together yields the expression in Corollary 2:

$$\left(\frac{\bar{\varphi}_{h}^{+}(\boldsymbol{\lambda})}{\bar{\varphi}_{hh'}^{-}(\boldsymbol{\lambda})}\tau_{\ell\ell'}\right)^{-1}\left(\frac{\bar{S}_{h'}(\boldsymbol{\lambda})}{\bar{S}_h(\boldsymbol{\lambda})}\right)^{1/\theta-1}\mathcal{F}\left(\pi_{h\ell h'\ell'}(\boldsymbol{\lambda})\right) \leq \frac{p_{\ell}^{\theta} z_h A_{\ell}}{p_{\ell'}^{\theta} z_{h'} A_{\ell'}} \leq \frac{\bar{\varphi}_{h'}^{+}(\boldsymbol{\lambda})}{\bar{\varphi}_{hh'}^{-}(\boldsymbol{\lambda})}\tau_{\ell\ell'}\left(\frac{\bar{S}_{h'}(\boldsymbol{\lambda})}{\bar{S}_h(\boldsymbol{\lambda})}\right)^{1/\theta-1}\mathcal{F}^{-1}\left(\pi_{h'\ell'h\ell}(\boldsymbol{\lambda})\right)$$

where $\mathcal{F}(x) = \epsilon^{\gamma}\bar{c}\left(\gamma+\mathcal{H}(x)\right)+\mathcal{H}(x)$.

A.6 Idiosyncratic Shocks and Transfer Span

Mobile money facilitates transfers over distances. However, the distances transfers travel are also sensitive to household characteristics and change according to household circumstances. To examine this sensitivity, I derive the distance between pairs in substantial partnerships under pairwise stable networks according to Corollary 3.

Corollary 3. *Define the partnership between households h and h' as "substantial" if the level $\lambda_{z'\ell'z\ell}$ exceeds a threshold ϵ. Consider a pairwise stable network $\boldsymbol{\lambda}$. Conditional on pair characteristics, the distance between pairs (h,h') in substantial partnerships follows:*

$$d(\ell,\ell') \leq \min\left\{\left(\frac{\mathcal{F}\left(\pi_{h\ell h'\ell'}\right)}{\frac{p_{\ell'}^{\theta} z_{h'} A_{\ell'}}{p_{\ell'}^{\theta} z_{h'} A_{\ell'}}\left(\frac{S_{z'\ell'}^{(1)}(\boldsymbol{\lambda})}{S_{z\ell}^{(1)}(\boldsymbol{\lambda})}\right)^{1-1/\theta}\varphi_{z\ell z'\ell'}(\boldsymbol{\lambda})}\right)^{-\frac{1}{\delta}}, \left(\frac{\mathcal{F}\left(\pi_{z'\ell'z\ell}\right)\varphi_{z'\ell'z\ell}(\boldsymbol{\lambda})}{\left(\frac{p_{\ell'}^{\theta} z_{h'} A_{\ell'}}{p_{\ell'}^{\theta} z_{h'} A_{\ell'}}\right)^{-1}\left(\frac{S_{z'\ell'}^{(1)}(\boldsymbol{\lambda})}{S_{z\ell}^{(1)}(\boldsymbol{\lambda})}\right)^{1/\theta-1}}\right)^{-\frac{1}{\delta}}\right\} = \tilde{\tau}_{z\ell z'\ell'} \quad (32)$$

where $\mathcal{F}(x) = \epsilon^{\gamma}\bar{c}\gamma + (\epsilon^{\gamma}\bar{c}+1)\left[\theta-(\theta-1)x\right]$.

Denote the idiosyncratic productivity of a household h as $\tilde{A}_{z\ell} = zA_{\ell}p_{\ell}^{\theta}$. The comparative statics are as follows: (a) if $\lambda_{z\ell z'\ell'} = \lambda_{z'\ell' z\ell} = \lambda^{*}_{z\ell z'\ell'}$, then $\frac{\partial\tilde{\tau}_{z\ell z'\ell'}}{\partial\tilde{A}_{z\ell}} > 0$ and $\frac{\partial^2\tilde{\tau}_{z\ell z'\ell'}}{\partial\tilde{A}_{z\ell}\partial\delta} < 0$, and (b) if $\lambda_{z\ell z'\ell'} = \lambda_{z'\ell' z\ell} = \lambda^{*}_{z'\ell' z\ell}$ then $\frac{\partial\tilde{\tau}_{z\ell z'\ell'}}{\partial\tilde{A}_{z\ell}} < 0$ and $\frac{\partial^2\tilde{\tau}_{z\ell z'\ell'}}{\partial\tilde{A}_{z\ell}\partial\delta} > 0$.

Proof. The proof is found in the Appendix A.6.1. □

The term $\tilde{\tau}_{z\ell z'\ell'}$ in Equation (32) determines the maximum distance a substantial partnership can sustain under pairwise stability. The term is the minimum of two expressions.

Rearranging $\lambda^*_{z'\ell' z\ell} \geq \epsilon$, the first expression is the maximum distance dictated by the preferences of the partner. Rearranging $\lambda^*_{hh'} \geq \epsilon$, the second expression is the maximum distance dictated by the preferences of the household. Transfer distance $\tilde{\tau}_{z\ell z'\ell'}$ responds in opposite ways to persistent shifts in household productivity $\tilde{A}_{z\ell}$ depending on which expression binds. I give an economic interpretation of the comparative statics of Corollary 3 below.

Suppose a pair's partnership level is constrained by the preferences of a household's partner, or $\lambda_{z\ell z'\ell'} = \lambda_{z'\ell' z\ell} = \lambda^*_{z'\ell' z\ell}$. The first expression in Equation (32) binds. The household has difficulty raising the partnership's intensity to its desired level because it asks for too many payments from partners in expectation. This concern is embedded in a positive relationship between preferred partnership levels $\lambda^*_{z'\ell' z\ell}$ and the idiosyncratic productivity ratio $\frac{p^{\theta}_{\ell'} z_{h'} A_{\ell'}}{p^{\theta}_{\ell'} z_{h'} A_{\ell'}}$ in Proposition 1. Suppose a household experiences a negative shock to its productivity $\tilde{A}_{z\ell}$, which causes its relative productivity to decline. The pair's sustainable transfer distance $\tilde{\tau}_{z\ell z'\ell'}$ lowers because the household's matching friction has worsened: from Equation (11), a household's smaller network access $S^{(1)}_{z\ell}(\boldsymbol{\lambda})$ from a negative shock to productivity $\tilde{A}_{z\ell}$ leaves the household asking for *more* payments in expectation than before. Mobile money causes contractions in $\tilde{\tau}_{z\ell z'\ell'}$ to be more pronounced.

The opposite matching friction dictates partnership levels when constrained by the preferences of a household, or $\lambda_{z\ell z'\ell'} = \lambda_{z'\ell' z\ell} = \lambda^*_{z\ell z'\ell'}$. In this case, the second expression in Equation (32) binds. Households have difficulty raising the intensities of their partnerships because they expect others to ask for too many payments: the expected costs of entering partnerships are very high. If this household experiences a shock to its productivity $\tilde{A}_{z\ell}$, its matching friction alleviates. Under productivity changes that decreases a household's expected income, partners ease expected transfer duties on the household, which attracts the household into more substantial partnerships. Partnerships are formed with more distant types, and the sustainable transfer distance $\tilde{\tau}_{z\ell z'\ell'}$ widens. As before, mobile money causes expansions in $\tilde{\tau}_{z\ell z'\ell'}$ to be more pronounced.[29]

A.6.1 Proof of Corollary 3

I use the same insight that the realized partnership level in a pairwise-stable equilibrium between pair h and h' should be $\lambda_{hh'} = \lambda_{h'h} = \min\{\lambda^*_{hh'}, \lambda^*_{h'h}\}$ to derive this result. The

[29]The prediction that partnership levels $\lambda_{z\ell z'\ell'}$, and thus recipient transfers $R^{+}_{z\ell}(h|\boldsymbol{\lambda})$, *increase* after permanent household shocks contradicts the main supposition of limited commitment models of village insurance, as those found in Ligon, Thomas, and Worrall (2000). These models assume a positive correlation between households' autarky levels and transfer inflows, particularly among high productivity households. Empirically, however, this correlation does not hold.

inequality $\lambda^*_{hh'} \geq \epsilon$ states

$$\frac{\left(\frac{p^\theta_{\ell'} z_{h'} A_{\ell'}}{p^\theta_\ell z_h A_\ell}\right)\left(\frac{\bar{S}_{h'}(\boldsymbol{\lambda})}{\bar{S}_h(\boldsymbol{\lambda})}\right)^{1-1/\theta} \tau_{\ell\ell'} \frac{\bar{\varphi}^+_h(\boldsymbol{\lambda})}{\bar{\varphi}^-_{hh'}(\boldsymbol{\lambda})} - \mathcal{H}\left(\pi_{h\ell h'\ell'}(\boldsymbol{\lambda})\right)}{\bar{c}\left(\gamma + \mathcal{H}\left(\pi_{h\ell h'\ell'}(\boldsymbol{\lambda})\right)\right)} \geq \epsilon^\gamma, \text{ where } \mathcal{H}(x) = \theta - (\theta - 1)x,$$

which can be rearranged as

$$\begin{aligned}
\tau_{\ell\ell'} &\geq \mathcal{F}\left(\pi_{h\ell h'\ell'}(\boldsymbol{\lambda})\right)\left(\frac{p^\theta_{\ell'} z_{h'} A_{\ell'}}{p^\theta_\ell z_h A_\ell}\right)^{-1}\left(\frac{\bar{S}_{h'}(\boldsymbol{\lambda})}{\bar{S}_h(\boldsymbol{\lambda})}\right)^{1/\theta-1}\frac{\bar{\varphi}^+_h(\boldsymbol{\lambda})}{\bar{\varphi}^-_{hh'}(\boldsymbol{\lambda})} \\
1 + d(\ell,\ell') &\leq \left[\mathcal{F}\left(\pi_{h\ell h'\ell'}(\boldsymbol{\lambda})\right)\left(\frac{p^\theta_{\ell'} z_{h'} A_{\ell'}}{p^\theta_\ell z_h A_\ell}\right)^{-1}\left(\frac{\bar{S}_{h'}(\boldsymbol{\lambda})}{\bar{S}_h(\boldsymbol{\lambda})}\right)^{1/\theta-1}\frac{\bar{\varphi}^+_h(\boldsymbol{\lambda})}{\bar{\varphi}^-_{hh'}(\boldsymbol{\lambda})}\right]^{-1/\delta},
\end{aligned}$$

where $\mathcal{F}(x) = \epsilon^\gamma \bar{c}\left(\gamma + \mathcal{H}(x)\right) + \mathcal{H}(x)$ and the second inequality uses the PayPal assumption.

Likewise, the inequality $\lambda^*_{h'h} \geq \epsilon$ states

$$\frac{\left(\frac{p^\theta_\ell z_h A_\ell}{p^\theta_{\ell'} z_{h'} A_{\ell'}}\right)\left(\frac{\bar{S}_h(\boldsymbol{\lambda})}{\bar{S}_{h'}(\boldsymbol{\lambda})}\right)^{1-1/\theta} \tau_{\ell'\ell} \frac{\bar{\varphi}^+_{h'}(\boldsymbol{\lambda})}{\bar{\varphi}^-_{h'h}(\boldsymbol{\lambda})} - \mathcal{H}\left(\pi_{h'\ell' h\ell}(\boldsymbol{\lambda})\right)}{\bar{c}\left(\gamma + \mathcal{H}\left(\pi_{h'\ell' h\ell}(\boldsymbol{\lambda})\right)\right)} \geq \epsilon^\gamma.$$

Rearranging:

$$\begin{aligned}
\tau_{\ell'\ell} &\geq \mathcal{F}\left(\pi_{h'\ell' h\ell}(\boldsymbol{\lambda})\right)\left(\frac{p^\theta_\ell z_h A_\ell}{p^\theta_{\ell'} z_{h'} A_{\ell'}}\right)\left(\frac{\bar{S}_{h'}(\boldsymbol{\lambda})}{\bar{S}_h(\boldsymbol{\lambda})}\right)^{1-1/\theta}\frac{\bar{\varphi}^+_{h'}(\boldsymbol{\lambda})}{\bar{\varphi}^-_{h'h}(\boldsymbol{\lambda})} \\
1 + d(\ell,\ell') &\leq \left[\mathcal{F}\left(\pi_{h'\ell' h\ell}(\boldsymbol{\lambda})\right)\left(\frac{p^\theta_\ell z_h A_\ell}{p^\theta_{\ell'} z_{h'} A_{\ell'}}\right)\left(\frac{\bar{S}_{h'}(\boldsymbol{\lambda})}{\bar{S}_h(\boldsymbol{\lambda})}\right)^{1-1/\theta}\frac{\bar{\varphi}^+_{h'}(\boldsymbol{\lambda})}{\bar{\varphi}^-_{h'h}(\boldsymbol{\lambda})}\right]^{-1/\delta}.
\end{aligned}$$

Given the productivity and network characteristics of pairs h and h', the maximum distance $d(\ell,\ell')$ between locations ℓ and ℓ' for the relationship to be "substantial" is the minimum of the two upper-bounds derived from $\lambda^*_{hh'} \geq \epsilon$ and $\lambda^*_{hh'} \geq \epsilon$.

B Quantitative Appendix

B.1 Partial Equilibrium Algorithm

The partial equilibrium algorithm takes as inputs: (1) an $L \times 1$ local productivity vector $\boldsymbol{A}$, (2) an $L \times L$ variance-covariance vector $\boldsymbol{\Sigma}$, (3) an $L \times 1$ local price vector $\boldsymbol{p}$, (4) a $Z \times 1$ household productivity vector $\boldsymbol{z}$, and (5) parameter values θ, δ, $\bar{c}$, γ, $\overline{\lambda}$, and $\underline{\lambda}$. The algorithm generates as an output the $L \times Z \times L \times Z$ network $\boldsymbol{\lambda}$. The steps are as follows:

1. First, initialize the algorithm. These steps include:

   (a) Randomly generate a "queue"—this "queue" constitutes a list of household pairs and dictates the sequence with which household pairs best-respond to the existing network. Call this $\binom{L\times Z\times L\times Z}{2}\times 1$ "queue" vector $\boldsymbol{Q}$.

   (b) Calculate $L\times L$ matrix $\boldsymbol{\tau}$ such that the (ℓ,ℓ') entry is $\tau_{\ell\ell'}=\left(1+d\left(\ell,\ell'\right)\right)^{-\delta}$.

   (c) Construct an initial guess of $L\times Z\times L\times Z$ weights $\boldsymbol{\lambda}$. Set self-weights ("diagonals" of network $\boldsymbol{\lambda}$) to $\bar{\lambda}$, and other partnership levels ("off-diagonals") to $\frac{1-\bar{\lambda}}{|L\times Z|-1}$. Calculate a corresponding $L\times Z\times L\times Z$ matrix $\boldsymbol{\kappa}$ of transfer friction wedges, where $\kappa_{\ell z\ell' z'}=1+\bar{c}\,\lambda_{\ell z\ell' z'}^{\gamma}$.

   (d) Initialize a counter and set error to a level greater than the tolerance.

2. Store the current $\boldsymbol{\lambda}$ as $\boldsymbol{\lambda}^{OLD}$.

3. For each element of $\boldsymbol{Q}$:

   (a) Calculate the mean $\bar{\boldsymbol{S}}$ and variance $\boldsymbol{\sigma_S^2}$ of network access terms for each household type. Both of these vectors should be an $L\times Z$ sized matrix. The (ℓ,z) entry of $\bar{\boldsymbol{S}}$ is

$$\bar{S}_{\ell z}=\sum_{\ell',z'}\left(\lambda_{\ell z\ell' z'}\tau_{\ell\ell'}p_{\ell'}\right)^{\theta}z'A_{\ell'}$$

   and the (ℓ,z) entry of $\boldsymbol{\sigma_S^2}$ is

$$\sigma_{S_{\ell z}}^2=\sum_{\ell',z',\ell'',z''}\left(\lambda_{\ell z\ell' z'}\lambda_{\ell z\ell'' z''}\tau_{\ell\ell'}\tau_{\ell\ell''}p_{\ell'}p_{\ell''}\right)^{\theta}z'z''\sigma_{\ell''\ell'}.$$

   (b) Calculate an adjusted "shares" matrix $\boldsymbol{\pi}$ (written in terms of the mean of stochastic terms Φ_ℓ and $S_{\ell' z'}$) of size $L\times Z\times L\times Z$. The (ℓ,z,ℓ',z') entry is the non-stochastic likelihood a household of type z' in location ℓ' will call on a household of type z in location ℓ for help and is given by

$$\pi_{\ell z\ell' z'}=\lambda_{\ell z\ell' z'}^{\theta}\tau_{\ell'\ell}^{\theta}p_{\ell}^{\theta}zA_{\ell}\bar{S}_{\ell' z'}^{-1}.$$

   (c) Calculate the diversification matrix $\tilde{\boldsymbol{S}}$ of size $L\times Z\times L$. The (ℓ,z,ℓ') entry is the covariance of network access $S_{\ell z}$ with a location ℓ' spatial shock Φ_ℓ and is given by the expression

$$\mathrm{Cov}\left(S_{\ell z},\Phi_{\ell'}\right)=\sum_{\ell'',z''}\left(\lambda_{\ell z\ell'' z''}\tau_{\ell\ell''}p_{\ell''}\right)^{\theta}z''\sigma_{\ell''\ell'}.$$

(d) With these terms in hand, calculate the idiosyncratic productivity ratio $\boldsymbol{IPR}$ and the network productivity ratio $\boldsymbol{NPR}$. The matrix $\boldsymbol{IPR}$ is of size $L \times Z \times L \times Z$ whose (ℓ, z, ℓ', z') entry is the ratio of non-network income determinants of type z' in location ℓ' households with respect to type z in location ℓ:

$$IPR_{\ell z \ell' z'} = \frac{p^{\theta}_{\ell'} z_{h'} A_{\ell'}}{p^{\theta}_{\ell} z_h A_{\ell}}.$$

The matrix $\boldsymbol{NPR}$ of size $L \times Z \times L \times Z$ whose (ℓ, z, ℓ', z') entry is the ratio of network income determinants of type z' in location ℓ' households with respect to type z in location ℓ:

$$NPR_{\ell z \ell' z'} = \frac{\bar{S}_{\ell' z'}}{\bar{S}_{\ell z}}.$$

(e) Calculate the risk-adjustment terms. The inflow risk-adjustment terms $\bar{\boldsymbol{\varphi}}^{+}$ is an $L \times Z$ matrix whose (ℓ, z) entry is

$$\bar{\varphi}^{+}_{\ell z} = 1 - \frac{\theta - 1}{2\theta} \frac{\sigma^2_{S_{\ell z}}}{\bar{S}^2_{\ell z}}.$$

The outflow risk-adjustment term $\bar{\boldsymbol{\varphi}}^{-}$ is an $L \times Z \times L \times Z$ matrix whose (ℓ, z, ℓ', z') entry is

$$\bar{\varphi}^{-}_{\ell z \ell' z'} = 1 + \frac{(\theta - 1)(2\theta - 1)}{2\theta^2} \frac{\sigma^2_{S_{\ell' z'}}}{\bar{S}^2_{\ell' z'}} - \frac{\theta - 1}{\theta} \frac{\tilde{S}_{\ell' z' \ell}}{\bar{S}_{\ell' z'} A_{\ell}}.$$

(f) Calculate the maximum partnership level that can sustained under the feasibility constraint for each household. Construct an $L \times Z \times L \times Z$ matrix $\boldsymbol{\lambda}^{MAX}$ with the (ℓ, z, ℓ', z') entry

$$\lambda^{MAX}_{\ell z \ell' z'} = 1 - \sum_{\ell'', z''} \kappa_{\ell z \ell' z'} \lambda_{\ell z \ell'' z''} + \kappa_{\ell z \ell' z'} \lambda_{\ell z \ell' z'}.$$

(g) Calculate the preferred partnership level matrix $\boldsymbol{\lambda}^{*}$. This matrix is of size $L \times Z \times L \times Z$, and the (ℓ, z, ℓ', z') entry corresponds to the preferred partnership level of a type z household in location ℓ with a type z' household in location ℓ'. Initially, construct an interior "indicator" matrix $\boldsymbol{IntInd}$ that equals one if $\boldsymbol{\lambda}^{*}$ has an interior solution, zero otherwise. The (ℓ, z, ℓ', z') of the $\boldsymbol{IntInd}$ matrix is

$$IntInd_{\ell z \ell' z'} = \begin{cases} 1 & \text{if } NPR^{1-1/\theta}_{\ell z \ell' z'} IPR_{\ell z \ell' z'} \frac{\bar{\varphi}^{+}_{\ell z}}{\bar{\varphi}^{-}_{\ell z \ell' z'}} \geq \frac{\theta}{\tau_{\ell \ell'}} \\ 0 & \text{else} \end{cases}.$$

Calculate the $L \times Z \times L \times Z$ unconstrained preferred partnership level matrix $\boldsymbol{\lambda}^{\boldsymbol{U}}$, whose (ℓ, z, ℓ', z') entry is

$$\lambda^{U}_{\ell z \ell' z'} = \left(\frac{IPR_{\ell z \ell' z'} NPR^{1-1/\theta}_{\ell z \ell' z'} \tau_{\ell \ell'} \frac{\bar{\varphi}^{+}_{\ell z}}{\bar{\varphi}^{-}_{\ell z \ell' z'}} - \theta + (\theta - 1)\, \pi_{\ell z \ell' z'}}{\bar{c}\,(\gamma + \theta - (\theta - 1)\, \pi_{\ell z \ell' z'})} \right)^{\frac{1}{\gamma}}$$

Then, the preferred partnership level matrix $\boldsymbol{\lambda}^{*}$ is

$$\lambda^{*}_{\ell z \ell' z'} = \begin{cases} \underline{\lambda} & \text{if } IntInd_{\ell z \ell' z'} = 0 \text{ or } \lambda^{U}_{\ell z \ell' z'} < \underline{\lambda} \\ \overline{\lambda} & \text{if } \lambda^{U}_{\ell z \ell' z'} \geq \overline{\lambda} \\ \lambda^{U}_{\ell z \ell' z'} & \text{else.} \end{cases}$$

(h) Update $\boldsymbol{\lambda}$ link-by-link. For an element (ℓ, z, ℓ', z') in the queue:

$$\lambda_{\ell z \ell' z'} = \min \left\{ \lambda^{*}_{\ell z \ell' z'}, \lambda^{*}_{\ell' z' \ell z} \right\}.$$

4. Calculate the error between $\boldsymbol{\lambda}^{OLD}$ and $\boldsymbol{\lambda}$, as $\max \left\{ |\lambda^{OLD}_{\ell z \ell' z'} - \lambda_{\ell z \ell' z'}| \right\}$.

5. Repeat steps 2 to 4 until convergence.

B.2 General Equilibrium Algorithm

The general equilibrium algorithm takes as inputs: (1) an $L \times 1$ local productivity vector $\boldsymbol{A}$, (2) an $L \times L$ variance-covariance vector $\boldsymbol{\Sigma}$, (3) a $Z \times 1$ household productivity vector $\boldsymbol{z}$, (4) an $L \times 1$ spatial shock realization $\boldsymbol{\Phi}$, and (5) parameter values θ, δ, $\bar{c}$, γ, $\overline{\lambda}$, and $\underline{\lambda}$. The algorithm generates as an output: (1) the $L \times Z \times L \times Z$ network $\boldsymbol{\lambda}$, and (2) an $L \times 1$ local price vector $\boldsymbol{p}$. The steps are as follows:

1. Begin with an initial guess of $\boldsymbol{p}$.

2. Using this $\boldsymbol{p}$ as an input, run the algorithm in Section B.1 and obtain $\boldsymbol{\lambda}$.

3. Store $\boldsymbol{p}$ as $\boldsymbol{p}^{OLD}$.

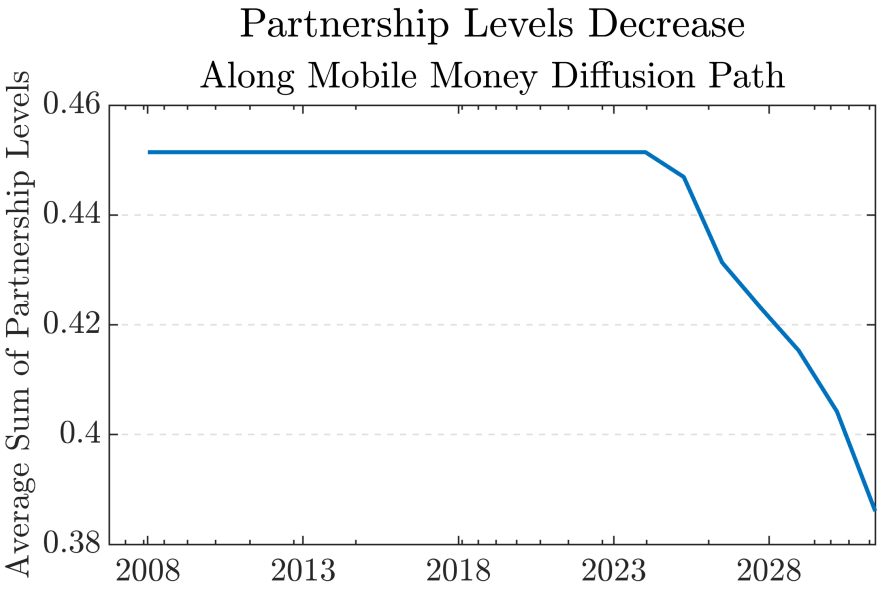
4. Using $\boldsymbol{\lambda}$, update $L \times 1$ vector $\boldsymbol{p}$ as

$$p_{\ell} = \left(\frac{\Phi_{\ell} \sum_{z} \Omega_{z\ell} \sum_{z', \ell'} z \kappa_{z\ell z'\ell'} \lambda^{\theta}_{z\ell z'\ell'} \tau^{\theta-1}_{\ell\ell'} \bar{S}^{1/\theta-1}_{z'\ell'}}{\sum_{z} \Omega_{z\ell} \bar{S}^{1/\theta}_{z\ell}} \right)^{\frac{1}{\theta}}.$$

5. Calculate error between $\boldsymbol{p}^{OLD}$ and $\boldsymbol{p}$, as $\max\left\{|p_\ell^{OLD} - p_\ell|\right\}$. Update $\boldsymbol{p} = 0.25 \cdot \boldsymbol{p} + (1 - .25) \cdot \boldsymbol{p}^{OLD}$. Repeat steps 2 to 4 until convergence.

B.3 Additional Graphs

Figure B1: Partnership Levels Over Mobile Money Diffusion Path



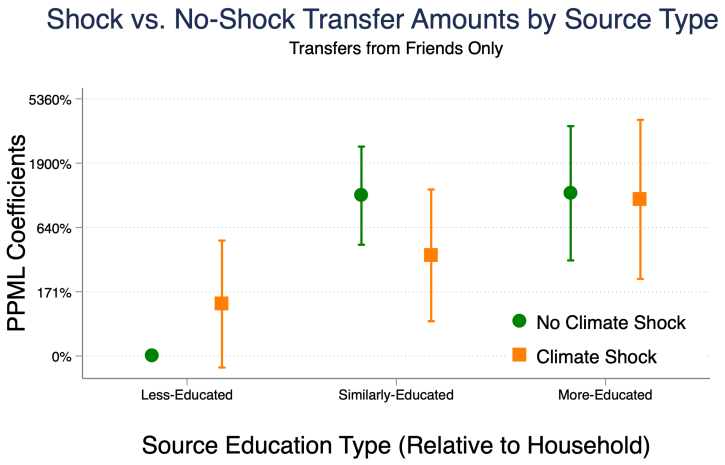
C Empirical Appendix

C.1 Robustness Checks on Fact 3

Figure C2: Transfers Amounts (TZS) from Friends After Climate Shocks

	From Friends (1) PPML
Shock=1	0.809
	(0.504)
More=1	2.531***
	(0.533)
More=1 × Shock=1	-0.904*
	(0.468)
Same=1	2.494***
	(0.389)
Same=1 × Shock=1	-1.737***
	(0.441)
N	7796

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

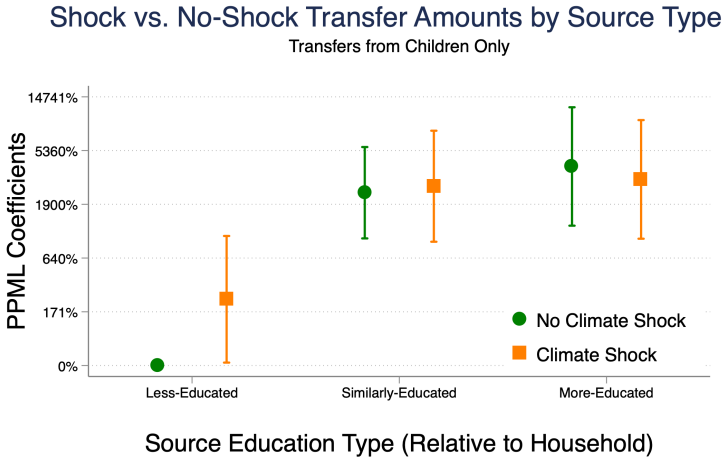


Note: The outcome variable is transfer amounts arising from friends. A household who experiences a shock reports being "severly impacted" by a "drought or flood" in the past year. We include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard errors clustered at the household level are shown in parentheses.

Figure C3: Transfers Amounts (TZS) from Children After Climate Shocks

	From Childen (1) PPML
Shock=1	1.232**
	(0.601)
More=1	3.704***
	(0.562)
More=1 × Shock=1	-1.473***
	(0.561)
Same=1	3.216***
	(0.434)
Same=1 × Shock=1	-1.111**
	(0.541)
N	6700

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

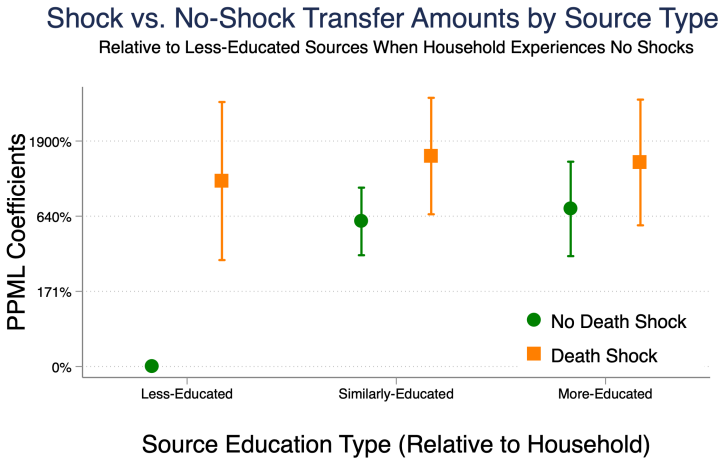


Note: The outcome variable is transfer amounts arising from children. A household who experiences a shock reports being "severly impacted" by a "drought or flood" in the past year. We include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard errors clustered at the household level are shown in parentheses.

Figure C4: Transfers Amounts (TZS) After Household Death Shocks

	From Friends (1) PPML
Shock=1	2.468***
	(0.536)
More=1	2.097***
	(0.321)
More=1 × Shock=1	-1.850***
	(0.415)
Same=1	1.930***
	(0.229)
Same=1 × Shock=1	-1.598***
	(0.419)
N	20040

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

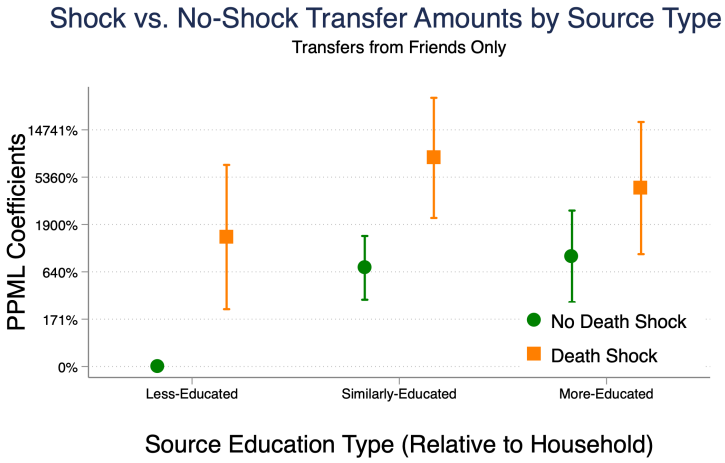


Note: The outcome variable is total transfer amounts. A household who experiences a shock reports being "severly impacted" by a "death of a household member" in the past year. We include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard errors clustered at the household level are shown in parentheses.

Figure C5: Transfers Amounts (TZS) from Friends After Household Death Shocks

	From Friends (1) PPML
Shock=1	2.735***
	(0.778)
More=1	2.326***
	(0.494)
More=1 × Shock=1	-1.292*
	(0.682)
Same=1	2.084***
	(0.344)
Same=1 × Shock=1	-0.412
	(0.678)
N	7796

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

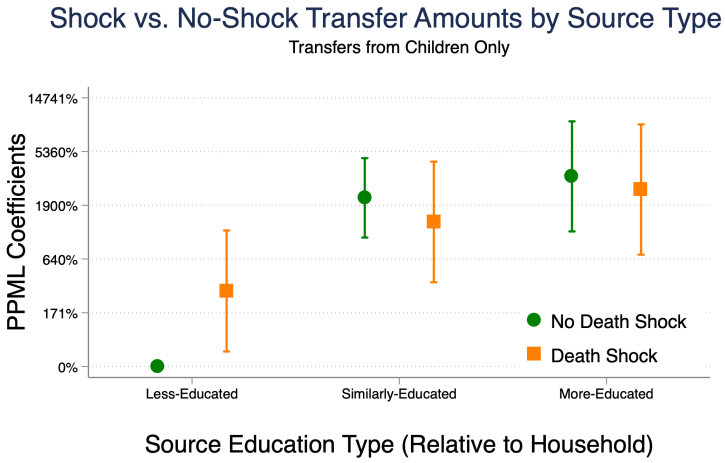


Note: The outcome variable is transfer amounts arising from friends. A household who experiences a shock reports being "severly impacted" by a "death of a household member" in the past year. We include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard errors clustered at the household level are shown in parentheses.

Figure C6: Transfers Amounts (TZS) from Children After Household Death Shocks

	From Children (1) PPML
Shock=1	1.406**
	(0.575)
More=1	3.538***
	(0.523)
More=1 × Shock=1	-1.650***
	(0.503)
Same=1	3.139***
	(0.377)
Same=1 × Shock=1	-1.854***
	(0.493)
N	6700

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

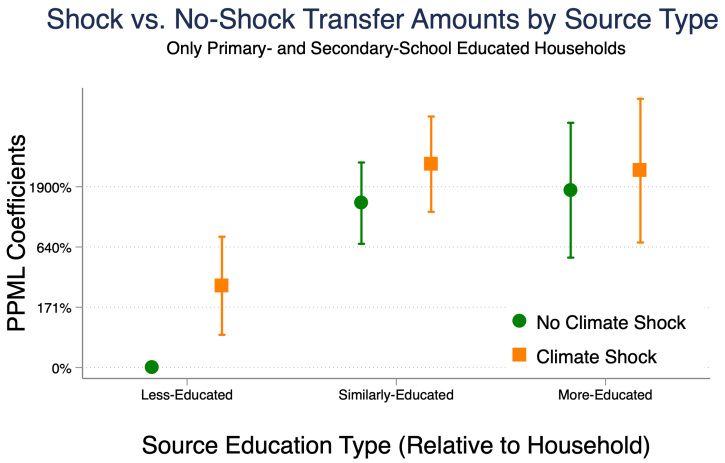


Note: The outcome variable is transfer amounts arising from children. A household who experiences a shock reports being "severly impacted" by a "death of a household member" in the past year. We include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard errors clustered at the household level are shown in parentheses.

Figure C7: Transfers Amounts (TZS) After Climate Shocks in Truncated Sample

	Transfer Amount (1) PPML
Shock=1	1.357***
	(0.415)
More=1	2.942***
	(0.571)
More=1 × Shock=1	-1.032***
	(0.362)
Same=1	2.727***
	(0.344)
Same=1 × Shock=1	-0.710**
	(0.352)
N	13144

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

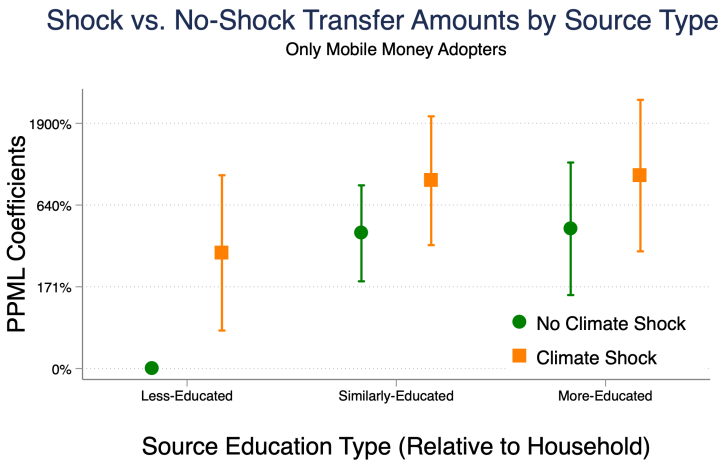


Note: The outcome variable is total transfer amounts. We restrict the sample to only primary- and secondary-school educated households. A household who experiences a shock reports being "severly impacted" by a "drought or flood" in the past year. We include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard errors clustered at the household level are shown in parentheses.

Figure C8: Transfers Amounts (TZS) After Climate Shocks Among Mobile Money Adopters

	Transfer Amount (1) PPML
Shock=1	1.415***
	(0.485)
More=1	1.709***
	(0.414)
More=1 × Shock=1	-0.764*
	(0.402)
Same=1	1.654***
	(0.300)
Same=1 × Shock=1	-0.771**
	(0.390)
N	10328

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

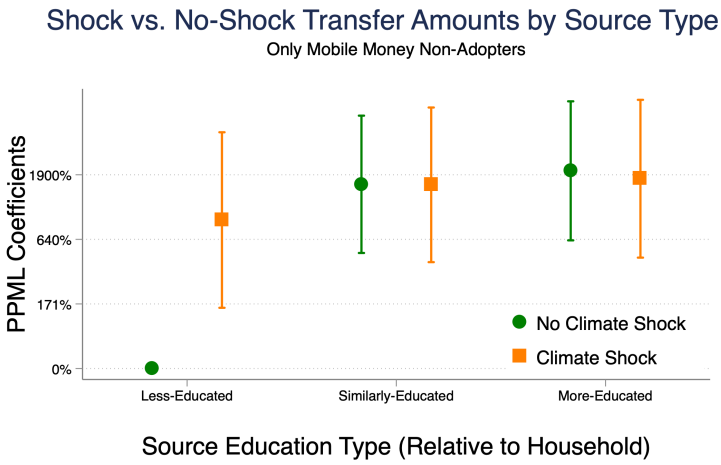


Note: The outcome variable is total transfer amounts. We restrict the sample to only mobile money adopters. A household who experiences a shock reports being "severly impacted" by a "drought or flood" in the past year. We include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard errors clustered at the household level are shown in parentheses.

Figure C9: Transfers Amounts (TZS) After Climate Shocks Among Non-Adopters

	Transfer Amount (1) PPML
Shock=1	2.299***
	(0.693)
More=1	3.061***
	(0.549)
More=1 × Shock=1	-2.421***
	(0.672)
Same=1	2.852***
	(0.542)
Same=1 × Shock=1	-2.307***
	(0.672)
N	7724

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



Note: The outcome variable is total transfer amounts. We restrict the sample to only non-adopters. A household who experiences a shock reports being "severly impacted" by a "drought or flood" in the past year. We include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard errors clustered at the household level are shown in parentheses.

Table C1: Geographic Frictions in the Transfer Networks

	Total Transfer Amount (TZS)			Transfers From Friend	Transfers From Child
	All	*MM Users*	*Non-Users*		
	(1)	(2)	(3)	(4)	(5)
	PPML	PPML	PPML	PPML	PPML
Distance (100 km)	-0.453***	-0.380***	-0.895***	-0.661***	-0.346***
	(0.0309)	(0.0332)	(0.0562)	(0.0533)	(0.0426)
N	111318	65656	42314	43328	40842
Household FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Source Region FE	✓	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the results of Equation (33). The outcome variable is the total transfer amount a household receives from a potential source region. The main independent variable is the kilometer distance between a potential source region and a household's region of residence. Huber-White standard errors are in parentheses and clustered at the household level.

C.2 Stylized Facts

Fact 1. Geographic frictions in the transfer network exist, even among mobile money users.

Frictions associated with making transfers—like the costs of money transport, relationship formation, or information verification—may scale with distance (Economides and Jeziorski 2017). The presence of geographic frictions would yield a gravity-like pattern in transfer flows, where households receive transfer from geographically proximate social contacts.

To test for geographic frictions in the transfer network, I run the following PPML regression for a household h in region ℓ at interview year t given source region ℓ':

$$Y_{h\ell\ell' t} = \exp\left[\alpha + \beta \cdot d\left(\ell, \ell'\right) + \gamma_h + \gamma_t + \gamma_{\ell'}\right] + \epsilon_{h\ell\ell' t}, \tag{33}$$

where $Y_{h\ell\ell' t}$ are the total transfer received by the household h in region ℓ from source region ℓ' at time t, $d\left(\ell, \ell'\right)$ is the distance between region ℓ and source region ℓ' in hundreds of kilometers, γ_h are household fixed effects, γ_t are interview time fixed effects, $\gamma_{\ell'}$ are source region fixed effects, and $\epsilon_{h\ell\ell' t}$ is an error term. The coefficient of interest β is negative if larger distances between regions are associated with lower transfer amounts, indicating the presence of geographic frictions.

Table C1 reports estimates from Equation (33) across different respondent subsets and specifications of the outcome variable. In column (1), I examine total transfer amounts from all households in the NPS. A 100-kilometer increase in distance between the recipient household and the potential source region is associated with an average 36.4% decline in transfers. Column (2) restricts the sample to households using mobile money. Geographic

frictions decline substantially but remain nontrivial: among mobile money users, a 100-kilometer increase in distance corresponds to a 31.6% reduction in transfer amounts. Column (3) limits the sample to households that do not use mobile money, for whom geographic frictions are even stronger than in column (1). Columns (4) and (5) redefine the outcome as transfers from friends and from children, respectively.[30] Geographic frictions are more pronounced for transfers from friends than from children. Across all specifications, the coefficient of interest remains statistically significant at the 1% level.

Fact 2. A household's geographic transfer span acts as insurance against climate (i.e., spatial) shocks.

A household's geographic transfer span is defined as the maximum centroid-to-centroid distance (in kilometers) between the household's region of residence and that of any source region from which it actually receives transfers. I examine the role of span in facilitating transfers following spatial shocks using the following PPML specification for household h at interview time t:

$$Y_{ht} = \exp\left[\alpha + \beta \cdot Shock_{ht} + \delta \cdot Span_{ht} + \xi \cdot (Shock_{ht} \times Span_{ht}) + \gamma_h + \gamma_t\right] + \epsilon_{ht}, \qquad (34)$$

where Y_{ht} are total transfers household h receives at time t, $Shock_{ht}$ is an indicator variable that equals one when a household h reports a shock at time t, $Span_{ht}$ is the geographic transfer span a household h reports at time t, γ_h are household fixed effects, γ_t are time fixed effects, and ϵ_{ht} is an error term.

A positive δ indicates that households receive larger transfers when they access more geographically distant sources, though this relationship is not interpreted causally since realized span is endogenous. A positive β suggests that households receive more transfers following a shock, consistent with transfers serving an insurance function even without distant sources. A positive ξ implies that households with broader geographic reach receive greater post-shock transfers—indicating that geographic span itself enhances informal insurance.

I focus on two types of shocks when running specification (34). First, I consider an indicator variable that equals one if a household reports being severely affected by a drought or flood in the previous year. From Figure 4, climate shocks display spatial correlation: geographically proximate households are likely to report experiencing droughts or flood at similar times. Second, I consider an indicator variable that equals one if a household reports experiencing the death of a member in the previous year. This shock is not spatial because

[30] I classify a "friend" as a source relationship the household head describes as either a friend, other relative, or other. I classify a "child" as a source relationship the household head describes as "son" or "daughter".

Table C2: Geographic Transfer Span as Insurance

	Panel A. Transfer Amount (TZS)	
	(1)	(2)
	PPML	PPML
Span (100 km)	0.199***	0.126***
	(0.0450)	(0.0464)
Death Shock=1	1.301***	
	(0.419)	
Death Shock=1 × Span (100 km)	-0.262**	
	(0.114)	
Climate Shock=1		0.167
		(0.231)
Climate Shock=1 × Span (100 km)		0.261***
		(0.0632)
N	2835	2835
Household FE	✓	✓
Quarter FE	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the results of Equation (34). The outcome variable is the total transfer amount a household receives at a particular interview time. Huber-White standard errors are in parentheses and clustered at the household level.

responses display no salient geographic patterns.

The results of specification (34) are displayed in Table C2. For both specifications, the coefficient in front of transfer span is *positive* and statistically significant at the 1% level, indicating that households who access geographically distant sources receive more transfers. A few within-household, across-time mechanisms can explain this relationship. For example, in the face of geographic transfer frictions, households may only activate particularly profitable transfer opportunities, inducing a positive relationship between realized span and transfer amounts. Similarly, a household may strategically alleviate geographic transfer frictions by adopting mobile money precisely when it requires transfers.

Column (1) displays results for non-spatial death shocks. On average, households receive 267.3% more transfers after the death of a household member. This estimate is statistically significant at the 1% level, suggesting that even households with limited span use transfers to insure against non-spatial shocks. Geographic span does not facilitate more transfers after non-spatial death shocks. Instead, a 100 kilometer increase in a household's transfer span is associated with a 23.0% decline in its transfer amounts, which is statistically significant at the 5% level.

Column (2) displays results for spatial climate shocks. The coefficient in front of the shock indicator is not statistically significantly different from zero, suggesting that transfer

networks without span do not help households insure against spatial shocks. However, a 100 kilometer increase in a household's transfer span is associated with 29.8% increase in transfer amounts, which is statistically significant at the 1% level. A household's geographic transfer span determines the level of received transfers after shocks, suggesting that span itself may act as a form of insurance under spatial shocks. These results are consistent with Riley (2018), who documents that mobile money users in Tanzania see lower pass-throughs of village-level shocks to consumption.

C.3 Shift-share IV

The micro-level implications of Section 3.4 establish *ceteris paribus* causal links between a household's money transport costs and transfer outcomes. To test these implications, I use the advent of mobile money during the NPS survey period as a negative shock to an adopter's money transport costs. I construct a shift-share IV for a household's use of mobile money. I use the instrument to quantify the causal effect of mobile money on outcomes such as network density, partner productivity, and transfer distance after shocks.

There are many reasons the exclusion restriction for regression specification (16) is unlikely to hold. First, one may worry about *reverse causality*, where particularly profitable transfer opportunities induce shifts into adoption. This concern has an ambiguous effect on correlation between a structural error term and the mobile money adoption decision. On one hand, households with robust and extant networks are likely to adopt, causing positive correlation. On the other hand, households adopt during times of need—under correlated shocks, its potential partners experience concomitantly low income realizations. This situation yields negative correlation. Second, one may be concerned about *selection into adoption*. This concern also has an ambiguous effect. On one hand, transfer networks smooth consumption: they depress the impact of high shocks while lowering the pass-through of low shocks. This dynamic yields negative selection into adoption, which brings about negative correlation (Borjas 1987). On the other hand, households may wait for high income realizations to sink fixed costs associated with mobile money adoption, such as obtaining a mobile phone or downloading an app. This dynamic causes positive correlation.

The instrument's first stage specification for a household h at interview time t is

$$MM_{ht} = \alpha + \beta \cdot Z_{ht} + \Gamma' \boldsymbol{\omega_{ht}} + \gamma_h + \gamma_t + \epsilon_{ht}, \tag{35}$$

where γ_h and γ_t are household and interview time fixed effects. The vector $\boldsymbol{\omega_{ht}}$ includes leave-one-out time-varying averages of village characteristics.

First-stage results are displayed in column (1) of Table C3. The instrument Z_{ht} statisti-

Table C3: First-stage IV Results

	Mobile Money	
	(1)	(2)
	OLS	Logit
Shift-Share IV	0.726***	
	(0.0459)	
Log Village Avg. Income	0.00283	0.123***
	(0.00364)	(0.0178)
Village Avg. Transfer Source	0.0558**	0.341**
	(0.0265)	(0.139)
Village Avg. Transfer Distance	0.000131	0.00243***
	(0.000123)	(0.000619)
Head Education Years		0.136***
		(0.00563)
Head Age		-0.00125
		(0.00165)
Household Size		0.0139**
		(0.00692)
Female Head		0.0770
		(0.0577)
N	15158	16287
F-statistic	65.14	
Household FE	✓	
Region FE		✓
Quarter FE	✓	✓
Village Characteristics	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Huber-White standard errors clustered at the household level are in parentheses.

cally significantly predicts mobile money use. Keeping household characteristics and other time trends constant, a 10.0% increase in the imputed village-level adoption rate from Equation (17) increases the average probability a household uses mobile money by 7.3%. This relationship is statistically significant at the 1% level. In column (2), I run a logit specification of a household's mobile money use on a variety of village and household characteristics to investigate demographic predictors of adoption. Larger households with more educated heads are statistically significantly more likely to use mobile money. Households in villages with greater incomes, denser transfer networks, and larger transfer distances are similarly more likely to adopt.

C.4 Empirical Results

In this section, I use the strategy outlined in Section C.3 to examine the causal relationship between mobile money and transfer outcomes.

C.4.1 Mobile Money and Network Density

I examine whether mobile money increases the number of distinct transfer sources reported by a household in a year. The number of realized sources increases in the size of its set of substantial partnerships. I consider a household's number of transfer sources as the outcome variable in Equation (16) and instrument for mobile money use with the shift-share in Equation (17). I say that a household adopts mobile money if it reports using M-Pesa, ezyPesa, Airtel Money, Tigo Pesa, Z-Pesa, or Zap to transfer money over the past twelve months.[31]

From Section 3.4, the exogenous network perspective states that $\beta > 0$. Mobile money relaxes money transport costs, permitting households to reach its furthest partners with ease. However, the endogenous network perspective states that the coefficient of interest has an ambiguous sign. Mobile money increases a household's network access, which reduces its desire to partner with others while increasing its desirability as a partner. If, on average, a household's preferences constrain its partnership levels, mobile money decreases the household's number of substantial partners and yields sparser networks. If, on average, partners' preferences constrain a household's partnership levels, mobile money increases the household's number of substantial partners and yields denser networks.

OLS and IV results are shown in Table C4. With the full vector of controls, mobile money adoption is associated with an average 0.1 increase in the number of transfer sources. This

[31]Households do not use mobile money exclusively to receive transfers. Of mobile money users, 34.5% report sending money as the service's most important use, 10.2% report saving, and 8.0% report buying airtime.

Table C4: The Impact of Mobile Money on Network Density

	Panel A. Number of Transfer Sources	
	(1)	(2)
	OLS	IV
Mobile Money	0.0983***	-0.0275
	(0.0157)	(0.0822)
N	15158	15158
Wald F		249.4
Household FE	✓	✓
Quarter FE	✓	✓
Village Characteristics	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Huber-White standard errors clustered at the household level are in parentheses. Village characteristics include leave-one-out averages of log income, number of transfer sources, and transfer distance.

relationship is statistically significant at the 1% level. Under the instrument, the relationship between mobile money and number of transfer sources falls out of statistical significance. The IV results imply that there is no causal relationship between mobile money and network density, which places empirical results at odds with the exogenous network perspective.

C.4.2 Mobile Money and Transfer Distance

I additionally examine the impact of mobile money on post-shock fluctuations in transfer distance. Corollary 3 suggests that reductions in money transport costs enhance the magnitude of these fluctuations. To test this prediction, I separate the sample into low and high-productivity households based on the education level of the household head. For each subset of the sample, I run the following regression for household h at interview time t

$$Y_{ht} = \alpha + \beta \cdot Shock_{ht} + \zeta \cdot MM_{ht} + \delta \cdot (Shock_{ht} \times MM_{ht}) + \Gamma' \boldsymbol{\omega_{ht}} + \gamma_h + \gamma_t + \epsilon_{ht},$$

where variables are defined as before. I instrument a household h's mobile money use at time t with the shift-share from Equation (17) and the interaction term with the product of the shock indicator and shift-share. The model predicts that $\beta < 0$ and $\delta < 0$ for low-productivity households. For high-productivity households, the model predicts that $\beta > 0$ and $\delta > 0$. I additionally run the regression on a "placebo" shock.

The results of the exercise are found in Table C5. There are a few observations to note about this table. First, the instrument is much stronger for the high-productivity subset of the sample. Second, the impact of mobile money on transfer distance is never statistically

Table C5: The Impact of Mobile Money on Post-Shock Transfer Distance

	Panel A. Transfer Distance (km)							
	Below-Median Educ. (< 9 Years)		Above-Median Educ. (>= 9 Years)		Below-Median Educ. (< 9 Years)		Above-Median Educ. (>= 9 Years)	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
MM=1	81.59***	101.4	30.87***	-22.92	58.20***	30.88	31.94***	-22.54
	(11.13)	(71.89)	(5.076)	(20.81)	(10.57)	(59.50)	(5.534)	(21.90)
Pers. Shock=1	2.292	11.08	-4.327	-15.47				
	(5.587)	(11.11)	(5.066)	(10.01)				
MM=1 × Pers. Shock=1	-62.13***	-113.7**	6.085	32.58				
	(22.17)	(52.25)	(11.53)	(22.45)				
Temp. Shock=1					-4.379	-6.776	1.702	-3.934
					(4.846)	(7.451)	(4.527)	(7.541)
MM=1 × Temp. Shock=1					58.44**	78.64*	0.138	16.60
					(23.16)	(46.17)	(8.912)	(15.96)
N	5349	5349	7503	7503	5349	5349	7503	7503
First-stage F		13.44		80.12		16.51		77.05
Household FE	✓	✓	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Village Characteristics	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

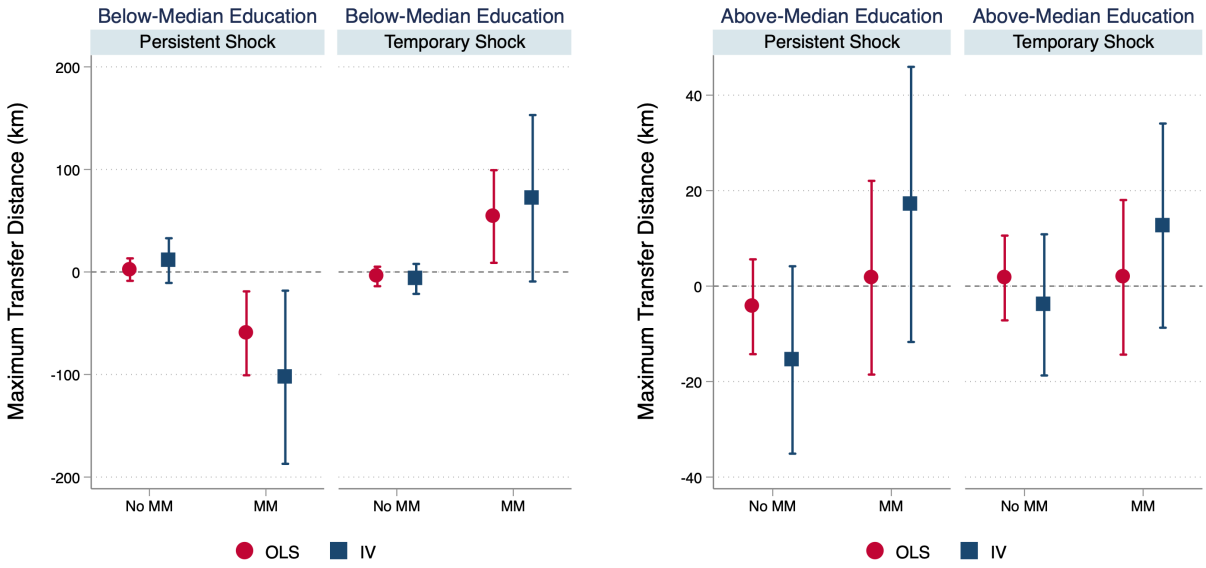
Note: Huber-White standard errors clustered at the household level are in parentheses. Village characteristics include leave-one-out averages of log income, number of transfer sources, and transfer distance.

significant in the absence of shocks. Third, for the low-productivity subset of the sample, mobile money contracts a household's transfer distance after persistent shocks by 113.7 km. This effect is statistically significant at the 5% level. Without mobile money, households do not change their transfer span. The opposite is true when considering low-productivity households' responses to "placebo" (i.e., temporary) shocks. Under "placebo" shocks, mobile money *increases* a household's transfer distance by 78.6 km more than without mobile money. This effect is statistically significant at the 10% level. Fourth, though positive, the impact of mobile money on transfer distance is not statistically significant for high-productivity households experiencing persistent shocks. The results partially support model predictions.

In Figure C10, I plot 95% confidence intervals around the post-shock response of low and high-productivity households with and without mobile money. In these plots, one can see that mobile money accounts for most of the contractions in transfer distance of low-productivity households under persistent shocks. However, under temporary shocks, low-productivity households expand their transfer distance. This post-shock expansion is mostly accounted for by mobile money.

In this section, I have demonstrated that empirical patterns conform more with the endogenous than exogenous network perspective. In particular, changes in transfer distance and partner productivity are responsive to shifts in money transport costs, for which the new

Figure C10: Coefficient Plots of Household Response of Transfer Outcomes After Shocks



Note: The figure displays coefficient plots for regression results of Equation (24). The response for "No MM" correspond with estimates for β and associated standard errors. The response for "MM" corresponds to a linear combination of estimates $\beta + \delta$ and associated standard errors.

availability of mobile money acts as a shock. The model qualitatively explains micro-level patterns in the data.

D Limited Commitment Extension

A defining feature of cash transfers in developing economies is that they occur informally, via social connections rather than government intervention. In the main text, I examine how this informality shapes the relationships that arise in equilibrium *before* shocks are realized, as informal bilateral contracts must be privately optimal for both contracting parties. In the baseline model, I largely abstract away from the ex-post actions households can take, assuming full-commitment to agreed-upon contracts. By contrast, much of the existing literature emphasizes the ex-post un-enforceability of informal contracts as the key friction in preventing the implementation of perfect risk-sharing within social groups (Coate and Ravallion 1993; Ligon, Thomas, and Worrall 2000; Genicot and Ray 2003; Bold 2009).

In this Appendix chapter, I place both of these frictions—ex-ante network re-organization and ex-post limited commitment—in a unified quantitative framework to study how these two perspectives on informality interact. Using this extension of the baseline model, I address three questions. Does the ability of households to renege from payment duties facilitate or inhibit the formation of transfer partnerships? Which households benefit the most from the

network changes induced by limited commitment? And does limited commitment allow the networks to sustain more or less insurance?

The chapter proceeds as follows. In Section D.1, I extend the baseline model in Chapter 1 to allow households to deviate from agreed-upon payments after the realization of shocks, in which case the offended partner to sever its ties with the deviating household for the foreseeable future. Payments must be incentive-compatible: a household deviates when the costs from not paying a transfer, net of a punishment for deviation, exceeds the dynamic marginal valuation of maintaining relationship, which depends on the household's and its partners' other linking choices. The incentive-compatibility constraint implies a pairwise and potentially asymmetric upper-bound on the income draw for which a household honors payment requests. These upper-bounds form an outer fixed point that interacts with equilibrium transfer partnership levels under pairwise-stability.

In Section D.2, I perform a quantitative exercise that sheds light on the motivating questions. I examine how limited commitment changes the structure of transfer partnerships and compare the welfare gains generated by the network under full versus limited commitment. Networks are less-connected, more spatially-concentrated, and less volatile under limited commitment relative to the full commitment benchmark. As in the main text, I decompose these gains into those attributable to redistribution—i.e., consumption allocations when spatial shocks realize their expectation—and insurance—i.e., additional welfare gains that occur due to uncertainty around the spatial shock.

The ability to deviate from agreed-upon transfers reduces the redistributive costs of participation in transfer partnerships for high-productivity households—which, in turn, reduces the redistributive benefits accrued to low-productivity households. Because high-productivity households mostly form relationships for insurance purposes, limited commitment *increases* the amount of insurance the network can sustain in equilibrium. These additional insurance gains nearly fully compensate for redistributive losses experienced by low-productivity households. Counterintuitively, limited commitment sustains the risk-sharing role of the network in the face of new technologies by reducing costs high-productivity households face when forming transfer partnerships.

D.1 Theory

In this section, I describe a model of endogenous network formation under limited commitment. I take the static setting described in the main text as the stage game of an infinitely repeated game and borrow the notation from this section. In this setting, households are differentiated by their location ℓ and productivity z. Suppose under income realizations

$I_{z\ell}(h)$ and $I_{z'\ell'}(h')$, a household h' in location ℓ' with productivity z' asks its partner h in location ℓ of productivity z for a payment of $\lambda_{z\ell z'\ell'} I_{z\ell}(h)$, which requires the partner to pay $\kappa_{z\ell z'\ell'}\lambda_{z\ell z'\ell'} I_{z\ell}(h)$, as $\kappa_{z\ell z'\ell'}$ denotes the presence of sender-borne transfer frictions. Because the household bears costs of transporting money, it receives the amount $\tau_{\ell\ell'}\lambda_{z\ell z'\ell'} I_{z\ell}(h)$ if the requested payment is made.

Households can take additional, ex-post actions governed by a "grim-trigger" strategies: the household h can either honor or renege in its payments to a household h'. If the household h chooses to defect in its payment to its partner h', then h' sever ties to h—i.e., setting $\lambda_{z\ell z'\ell'} = 0$—for the foreseeable future. In response, it is optimal for the household h to sever its relationship to h'—i.e., $\lambda_{z'\ell' z\ell} = 0$.

Let β be a temporal discount factor. Under partnerships $\boldsymbol{\lambda}$, denote the dynamic payoffs of a household h as

$$\begin{aligned}\mathcal{V}_h(\boldsymbol{\lambda}) &= \mathbb{E}\left(\sum_{t=0}^{\infty}\beta^t C_{z\ell}(h|\boldsymbol{\lambda})\right)\\ &= \frac{1}{1-\beta}\mathbb{E}\left(C_{z\ell}(h|\boldsymbol{\lambda})\right),\end{aligned} \tag{36}$$

where the expectation is taken over realizations of a spatial shock $\boldsymbol{\Phi}$.

Denote as $\boldsymbol{\lambda} \setminus (z,\ell,z',\ell')$ the matrix of partnerships when $\lambda_{z\ell z'\ell'}$ and $\lambda_{z'\ell' z\ell}$ are set to zero but all other partnerships are the same as in $\boldsymbol{\lambda}$. In order for a payment to be incentive compatible, the static benefits accrued to h of not paying the requested amount, net of a punishment for deviation $\mathcal{F}$, must exceed the dynamic gains it receives from its relationship with h'.[32] The household h defects if

$$I_{z\ell}(h) > \frac{\delta\left[\mathcal{V}_h(\boldsymbol{\lambda}) - \mathcal{V}_h(\boldsymbol{\lambda}\setminus(z,\ell,z',\ell'))\right] + \mathcal{F}}{\kappa_{z\ell z'\ell'}\lambda_{z\ell z'\ell'}} \equiv \bar{I}_{z\ell z'\ell'}. \tag{37}$$

Equation (37) amounts to an incentive compatibility constraint. The right-hand-side $\bar{I}_{z\ell z'\ell'}$ amounts to an upper-bound of partner h income realizations for which the household h' can expect h not to deviate in its requests. This upper-bound is pair-specific and can be asymmetric. Note that the upper-bound depends on a household h's marginal dynamic valuation of relationship with h', which I denote as $\mathcal{MV}_h((z,\ell,z',\ell'),\boldsymbol{\lambda})$.

I assume the sequence of actions occurs as follows. First, after observing the income draws of others, a household chooses to request a payment from the partner in its network who will give it the most money if asked, as dictated by the contracted partnership levels $\boldsymbol{\lambda}$.

[32] Such punishments for deviation $\mathcal{F}$ are common in this literature, and can represents conflict, reputation loss, or psychological discomfort. I show that under endogenous partnership levels $\boldsymbol{\lambda}$, these negative costs of deviation are necessary to sustain transfer relationships in equilibrium.

Second, upon receiving the request, the partner chooses whether to honor the payment or renege. Under this sequence of actions, when making a payment request, the household does not consider whether the requested amount is incentive-compatible for its partner and bears the risk that the partner refuses to pay. The upper-bounds $\bar{\boldsymbol{I}}$ effectively act as a partner's private information over which the household cannot optimize.[33]

Relative to the full-commitment benchmark of Chapter 1, the upper-bounds $\bar{\boldsymbol{I}}$ of Equation (37) impact $\mathcal{MV}_h\left((z,\ell,z',\ell'),\boldsymbol{\lambda}\right)$ by reducing both the expected recipient and sender transfers. I adjust the recipient transfer definition to reflect this type of limited commitment, such that the transfer inflow of a household in location ℓ with productivity z is

$$R^{+}_{z\ell}(\boldsymbol{\lambda}) = \sum_{h'\in\mathcal{H}} \tau_{\ell'\ell}\lambda_{z'\ell'z\ell} I_{z'\ell'}(h')\,\mathbf{1}\left(h' = \arg\max_{h''\in\mathcal{H}} \tau_{\ell''\ell}\lambda_{z''\ell''z\ell} I_{z''\ell''}(h'')\right)\cdot \\ \mathbf{1}\left(I_{z'\ell'}(h') \leq \bar{I}_{z'\ell'z\ell}\right). \tag{38}$$

Similarly, I adjust the sender transfer definition to reflect the possibility the household in location ℓ of productivity z reneges in its payment responsibilities

$$R^{-}_{z\ell}(\boldsymbol{\lambda}) = \sum_{h'\in\mathcal{H}} \kappa_{z\ell z'\ell'}\lambda_{z\ell z'\ell'} I_{z'\ell'}(h')\,\mathbf{1}\left(h' = \arg\max_{h''\in\mathcal{H}} \tau_{\ell''\ell}\lambda_{z''\ell''z\ell} I_{z''\ell''}(h'')\right)\cdot \\ \mathbf{1}\left(I_{z\ell}(h) \leq \bar{I}_{z\ell z'\ell'}\right) \tag{39}$$

Similarly to the main text, I solve the game under limited commitment via backwards induction. First, in Section D.1.1, conditional on partnership levels $\boldsymbol{\lambda}$, I derive each household's expected recipient and sender transfers subject to the incentive compatibility of payments under condition (37). Second, in Section D.1.2, I formalize how limited commitment enters into households' decisions to connect with others, thus making partnership levels $\boldsymbol{\lambda}$ endogenous. Third, I define a pairwise-stable equilibrium under limited commitment in Section D.1.3.

D.1.1 Expected Transfers under Fixed $\boldsymbol{\lambda}$ and Limited Commitment

The definition of transfer inflows and outflows in Equations (38) and (39) yield tractable expectations. These are defined in the following Lemma 2.

Lemma 2. *Consider a household in location ℓ of productivity z facing the limited-commitment network payment game. Given partnership levels $\boldsymbol{\lambda}$ and upper-bounds $\bar{\boldsymbol{I}}$ and approximating*

[33] One can interpret this assumption as the presence zero-mean uncertainty around a household's dynamic valuation $\mathcal{MV}_h\left((z,\ell,z',\ell'),\boldsymbol{\lambda}\right)$ of the partnership or pair-specific noise around the partner's cost of deviation $\mathcal{F}$.

with second-order Taylor expansion around the vector of local productivities $\boldsymbol{A} = \mathbb{E}(\boldsymbol{\Phi})$*:*

(a) The household's expected sender transfer is

$$\mathbb{E}\left(R^{+}_{z\ell}(\boldsymbol{\lambda})\right) = \sum_{h' \in \mathcal{H}} \pi_{z'\ell' z\ell}(\boldsymbol{\lambda})\, \bar{S}^{1/\theta}_{z\ell}(\boldsymbol{\lambda})\, \varphi^{-}_{z\ell z'\ell'}(\boldsymbol{\lambda})\, \Gamma\left(1 - 1/\theta; \bar{I}^{-\theta}_{z'\ell' z\ell}\right),$$

where $\Gamma(\vartheta; x) \equiv \int_x^{\infty} t^{\vartheta - 1} \exp(-t)\, dt$ *is an upper-incomplete Gamma function and* $\varphi^{-}_{z\ell z'\ell'}(\boldsymbol{\lambda})$ *is a risk-adjustment term.*

(b) The household's expected recipient transfer is

$$\mathbb{E}\left(R^{-}_{z\ell}(\boldsymbol{\lambda})\right) = \sum_{h' \in \mathcal{H}} \kappa_{z\ell z'\ell'} \tau^{-1}_{\ell\ell'} \pi_{z\ell z'\ell'}(\boldsymbol{\lambda})\, \bar{S}^{1/\theta}_{z'\ell'}(\boldsymbol{\lambda})\, \varphi^{-}_{z\ell z'\ell'}(\boldsymbol{\lambda})\, \Gamma\left(1 - 1/\theta; \bar{I}^{-\theta}_{z'\ell' z\ell}\right).$$

Proof. The proof is found in Section D.3.1. □

The probability that a partner honors its payment duties to the household is given by the expression $\frac{\Gamma\left(1-1/\theta;\bar{I}^{-\theta}_{z'\ell' z\ell}\right)}{\Gamma(1-1/\theta)}$. When the matrix of upper-bounds $\bar{\boldsymbol{I}}$ approach infinity, the probability approaches one, and the expected transfer terms approach those under full commitment derived in the main text.

Lemma 2 makes explicit that expected transfers are additively separable across partners, so that each term represents the marginal contribution of a partner. This observation yields a tractable expression for a household's dynamic marginal valuation of its partners, which yields the following fixed point for $\bar{\boldsymbol{I}}$,

$$\begin{aligned}\bar{I}_{z\ell z'\ell'} = \frac{1-\delta}{\delta}\left(\kappa_{z\ell z'\ell'}\lambda_{z\ell z'\ell'}\right)^{-1}\Bigg[&\tau^{\theta}_{\ell'\ell}\lambda^{\theta}_{z'\ell' z\ell} p^{\theta}_{\ell'} z' A_{\ell'} \bar{S}^{1/\theta-1}_{z\ell}(\boldsymbol{\lambda})\; \varphi^{-}_{z'\ell' z\ell}(\boldsymbol{\lambda})\; \Gamma\left(1-1/\theta; \bar{I}^{-\theta}_{z\ell z'\ell'}\right) \\ &- \kappa_{z\ell z'\ell'}\tau^{\theta-1}_{\ell\ell'}\lambda^{\theta}_{z\ell z'\ell'} p^{\theta}_{\ell} z A_{\ell} \bar{S}^{1/\theta-1}_{z'\ell'}(\boldsymbol{\lambda})\, \varphi^{-}_{z\ell z'\ell'}(\boldsymbol{\lambda})\; \Gamma\left(1-1/\theta; \bar{I}^{-\theta}_{z'\ell' z\ell}\right)\Bigg] + \mathcal{F}. \end{aligned} \tag{40}$$

This expression arises from applying the definition of $\bar{I}_{z\ell z'\ell'}$ in Equation (37).

The household h's marginal valuation of its relationship with partner h'—embedded in the variable $\bar{I}_{z\ell z'\ell'}$—hinges on the partner h''s marginal valuation $\bar{I}_{z'\ell' z\ell}$ of the household h, infinitely iterated. The expression in Equation (37) formalizes this notion of reciprocity in relationships: as a household, I value my partners in part because they value me.

D.1.2 Household Optimization Under Limited Commitment

Households bear the risk that partners default in payments, which impacts the partnership levels they wish to have with others. The desired partnership level $\lambda^{*}_{z\ell z'\ell'}$ a household has in

its relationship with another is given by Corollary 4.

Corollary 4. *The desired partnership level $\lambda^*_{z\ell z'\ell'}$ of a household in location ℓ of productivity z with another household in location ℓ' of productivity z' in the limited commitment network payment game is given by the fixed point*

$$\lambda^*_{z\ell z'\ell'} = \left(\frac{\chi_{z\ell z'\ell'}(\boldsymbol{\lambda})\left(\theta - (\theta-1)\,\pi_{z'\ell' z\ell}(\boldsymbol{\lambda})\right) - \theta + (\theta-1)\,\pi_{z\ell z'\ell'}(\boldsymbol{\lambda})}{\bar{c}\left(\theta + \gamma - (\theta-1)\,\pi_{z\ell z'\ell'}(\boldsymbol{\lambda})\right)} \right)^{\frac{1}{\gamma}}, \tag{41}$$

where the pairwise constant $\chi_{z\ell z'\ell'}(\boldsymbol{\lambda})$ is

$$\chi_{z\ell z'\ell'}(\boldsymbol{\lambda}) \equiv \tau_{\ell'\ell} \frac{\Gamma\left(1-1/\theta; \bar{I}^{-\theta}_{z'\ell' z\ell}\right)}{\Gamma\left(1-1/\theta; \bar{I}^{-\theta}_{z\ell z'\ell'}\right)} \left(\frac{p^\theta_{\ell'} z' A_{\ell'}}{p^\theta_\ell z A_\ell}\right) \left(\frac{\bar{S}_{z'\ell'}(\boldsymbol{\lambda})}{\bar{S}_{z\ell}(\boldsymbol{\lambda})}\right)^{1-1/\theta} \frac{\bar{\varphi}_{z\ell z'\ell'}(\boldsymbol{\lambda})}{\bar{\varphi}_{z'\ell' z\ell}(\boldsymbol{\lambda})}. \tag{42}$$

Proof. The proof is found in Section D.3.2. □

The desired partnership levels $\boldsymbol{\lambda}$ under limited commitment closely resembles those under full commitment with a few adjustments. The main adjustment is that the desired partnership level increases in the ratio $\frac{\Gamma\left(1-1/\theta;\bar{I}^{-\theta}_{z'\ell' z\ell}\right)}{\Gamma\left(1-1/\theta;\bar{I}^{-\theta}_{z\ell z'\ell'}\right)}$ of a partner's ability to commit to its payments to the household over the household's ability to commit to its payments to the partner. A relatively more trustworthy partner is a more attractive partner, since expected recipient transfers increase in the partner's trustworthiness, as dictated by $\bar{I}_{z'\ell' z\ell}$, and expected sender transfers increase in the household's trustworthiness, as dictated by $\bar{I}_{z\ell z'\ell'}$.

D.1.3 Limited Commitment Network Equilibrium

In Definition 4, I consider the following equilibrium for the network under limited commitment. This equilibrium notion takes into account both the notion reciprocity inherent in the determination of upper-bounds $\bar{\boldsymbol{I}}$ and the commitment-adjusted strategic considerations that determine partnerships $\boldsymbol{\lambda}$.

Definition 4. Let $|\mathcal{H}|$ denote the number of household types. A *limited commitment network equilibrium* is a (i) $|\mathcal{H}| \times |\mathcal{H}|$ matrix of transfer partnerships $\boldsymbol{\lambda}$, and a (ii) $|\mathcal{H}| \times |\mathcal{H}|$ matrix of upper-bound income draws $\bar{\boldsymbol{I}}$, such that:

(a) Given upper-bounds $\bar{\boldsymbol{I}}$, partnership levels $\boldsymbol{\lambda}$ are pairwise-stable with respect to the payoffs of Equation (36).

(b) Given partnership levels $\boldsymbol{\lambda}$, upper-bounds $\bar{\boldsymbol{I}}$ satisfy Equation (40).

I quantify this type of equilibrium in Section D.2 and show how limited commitment interacts with endogenous network formation in the provision of informal insurance.

Table D6: Summary Statistics of Networks Under Limited Commitment

	Full	Limited	
	$\mathcal{F}=\infty$	$\mathcal{F}=1$	$\mathcal{F}=.5$
Percentage Pairs Constrained	0.00%	0.84%	13.15%
Average Sum of $\boldsymbol{\lambda}$	0.451	0.354	0.176
Average Spatial Herfindahl	0.130	0.144	0.175
Average Change in Network Volatility		–0.174	–0.531

D.2 Quantitative Exercise

I quantify the model using the same parameter values uncovered in the main text. I set the distance discount $\log \delta = -2.5$. Additional to these model inputs, I consider a "high" ($\mathcal{F}=1$) and a "low" ($\mathcal{F}=.5$) cost of deviation. These punishments amount to approximately 15% and 30% of a university-educated household's expected income in Dar es Salaam.

How do networks change under limited commitment relative to full commitment? Table D6 documents these changes across four summary statistics. The first is the percentage of household type pairings whose transfers are constrained by limited commitment.[34] As the costs of deviation decrease, the proportion of constrained pairs increase. The second statistic is the unweighted average of the sum of partnership levels $\sum_{z',\ell'} \lambda_{z\ell z'\ell'}$ across household types, corresponding to a node's degree in a weighted network. The third statistic is an adjusted spatial Herfindahl of transfer inflow shares, in which self-shares are excluded.[35] Transfer networks concentrate spatially as concerns of limited commitment become more binding. Households maintain fewer connections as the costs of deviation decrease. In all, limited commitment yields less-connected, more spatially-concentrated networks. This change in network structure may reflect difficulty in enforcing payments across distant partners, as all else equal, dynamic marginal valuations are lower for more distant than proximate partners.

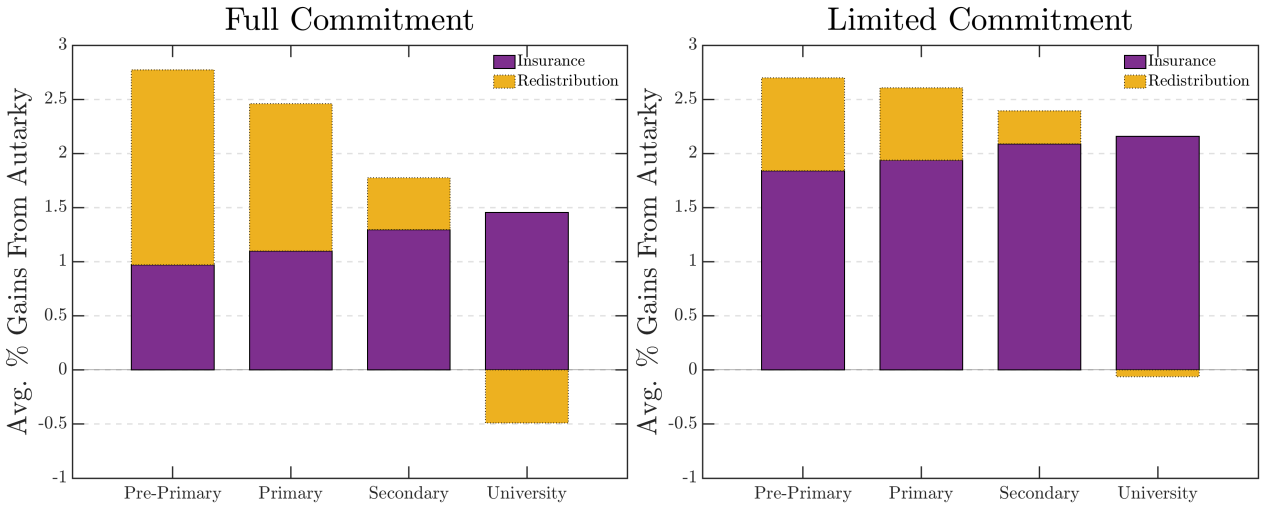
I also examine changes in size-adjusted network access volatility.[36] As the costs of devia-

[34] This statistic is given by the number of pairs (ℓ, z) and (ℓ', z') for which $\min\left\{\Gamma\left(1-1/\theta; \bar{I}^{-\theta}_{z\ell z'\ell'}\right), \Gamma\left(1-1/\theta; \bar{I}^{-\theta}_{z'\ell' z\ell}\right)\right\} < \Gamma\left(1-1/\theta\right)$ over the total number of pairs in the network.

[35] For a household in location ℓ of productivity z, this measure is $\sum_{\ell'}\left(\sum_z \pi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right)\right)^2$, where we set exogenously $\pi_{z\ell z\ell} = 0$.

[36] This statistic is given by $\log\left(\sigma_S^{LC}/\bar{S}^{LC}\right) - \log\left(\sigma_S^{FC}/\bar{S}^{FC}\right)$.

Figure D11: Welfare Gains From Transfer Network Under Full vs. Limited Commitment



Note: This graph shows the unweighted average of welfare gains of the transfer network relative to autarky by education group under full commitment (the left panel) and limited commitment (the right panel). This average is taken over 50 random draws of the queue in which household pairs best-respond.

tion decline, this volatility reduces in equilibrium, indicating that transfers—and therefore, consumption—become more stable despite the contraction in network size.

In Figure D11, I examine the impacts of limited commitment on informal insurance when transfer networks are endogenously formed. In this graph, I consider only the case when costs of deviation are low, where limited commitment is a key determinant of realized transfers. I perform the same insurance vs. redistribution decomposition of network gains in the main text. Under full commitment, network gains form a clear progressive pattern: averaging across locations, non-educated households receive average welfare gains of 2.8% under the network relative to autarky and university-educated households receive gains of 1.0%. This progressivity reflects the redistributive role of the network: more-productive households send transfers on net—effectively absorbing redistributive losses—to realize the insurance benefits of the network. At the same time, insurance benefits are regressive, indicating that insuransce gains drive network participation particularly strongly among more-educated households

Limited commitment induces large changes in network structure. When households can renege on transfers ex-post, the redistributive role of the network weakens and the progressivity of gains declines. More productive households benefit substantially from this change: averaged across locations, welfare gains for university-educated households nearly double under limited commitment relative to full commitment. Because these households are no longer required to absorb large redistributive losses when forming partnerships, their willingness to participate in transfer partnerships increase. Net givers' increased willingness to participate in partnerships improves the network's ability to deliver insurance in equilibrium.

As a result, despite experiencing substantial redistributive losses when moving from full to limited commitment, non-educated households see only slight declines in network gains of 0.07 percentage points.

The results highlight a striking contrast with the standard exogenous network perspective. When risk-sharing groups are fixed, limited commitment typically acts as a friction that prevents perfect risk-sharing (Ligon, Thomas, and Worrall 2000; Morten 2019; Kinnan 2022). When networks are endogenous, the same friction plays an opposite role and can potentially increase the amount of insurance transfer partnerships provide. By limiting the redistributive burden borne by more-productive households, the possibility of reneging increases their willingness to participate in cross-spatial transfer partnerships. In equilibrium, more-productive households' enhanced participation sustains the provision of informal insurance within the network.

D.3 Limited Commitment Extension Proofs

D.3.1 Proof of Lemma 2

Conditional on realizations of $\mathbf{\Phi}$, we start with expected recipient transfers under limited commitment:

$$\begin{aligned}
\mathbb{E}\left[R^{+}_{z\ell}\left(\boldsymbol{\lambda}\right)\right] &= \sum_{h'\in\mathcal{H}} \tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\mathbb{E}\left(I_{z'\ell'}\prod_{h''\neq h'}\Pr\left(I_{z''\ell''}\leq I_{z'\ell'}\frac{\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}}{\tau_{\ell''\ell}\lambda_{z''\ell''z\ell}}\right)\middle| I_{z'\ell'}\leq \bar{I}_{z'\ell'z\ell}\right)\\
&\quad\cdot\Pr\left(I_{z'\ell'}\leq\bar{I}_{z'\ell'z\ell}\right)\\
&= \sum_{h'\in\mathcal{H}} \tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\mathbb{E}\left[I_{z'\ell'}\exp\left(-\sum_{h''\neq h'}\left(I_{z'\ell'}\frac{\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}}{\tau_{\ell''\ell}\lambda_{z''\ell''z\ell}}\right)^{-\theta}\cdot\right.\right.\\
&\quad\left.\left. p^{\theta}_{\ell''}z''\Phi_{\ell''}\right)\middle| I_{z'\ell'}\leq\bar{I}_{z'\ell'z\ell}\right]\cdot\Pr\left(I_{z'\ell'}\leq\bar{I}_{z'\ell'z\ell}\right)\\
&= \sum_{h'\in\mathcal{H}} \tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\left[\int_0^{\bar{I}_{z'\ell'z\ell}}\mathcal{I}\exp\left(-\mathcal{I}^{-\theta}\left(\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\right)^{-\theta}\cdot\right.\right.\\
&\quad\left.\left.\sum_{h''\neq h'}\tau^{\theta}_{\ell''\ell}\lambda^{\theta}_{z''\ell''z\ell}p^{\theta}_{\ell''}z''\Phi_{\ell''}\right)dI_{z'\ell'}\left(\mathcal{I}\right)\right]\\
&= \sum_{h'\in\mathcal{H}} \tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\left[\int_0^{\bar{I}_{z'\ell'z\ell}}\mathcal{I}\exp\left(-\mathcal{I}^{-\theta}\left(\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\right)^{-\theta}\sum_{h''\neq h'}\tau^{\theta}_{\ell''\ell}\lambda^{\theta}_{z''\ell''z\ell}p^{\theta}_{\ell''}z''\Phi_{\ell''}\right)\cdot\right.\\
&\quad\left.\theta\mathcal{I}^{-\theta-1}p^{\theta}_{\ell'}z'\Phi_{\ell'}\exp\left(-\mathcal{I}^{-\theta}p^{\theta}_{\ell'}z'\Phi_{\ell'}\right)d\mathcal{I}\right]\\
&= \sum_{h'\in\mathcal{H}} \tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\left[\int_0^{\bar{I}_{z'\ell'z\ell}}\theta\mathcal{I}^{-\theta}p^{\theta}_{\ell'}z'\Phi_{\ell'}\exp\left(-\mathcal{I}^{-\theta}\frac{S_{z\ell}\left(\boldsymbol{\lambda}\right)}{\left(\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\right)^{\theta}}\right)d\mathcal{I}\right].
\end{aligned}$$

Let

$$t=\mathcal{I}^{-\theta}\frac{S_{z\ell}\left(\boldsymbol{\lambda}\right)}{\left(\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\right)^{\theta}}.$$

Then

$$dt=-\theta\mathcal{I}^{-\theta-1}\frac{S_{z\ell}\left(\boldsymbol{\lambda}\right)}{\left(\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\right)^{\theta}}d\mathcal{I}.$$

Substituting in and continuing:

$$\begin{aligned}
\mathbb{E}\left[R^{+}_{z\ell}\left(\boldsymbol{\lambda}\right)\right] &= \sum_{h'\in\mathcal{H}} \tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\cdot\left[\int_0^{\bar{I}_{z'\ell'z\ell}} \frac{\theta\mathcal{I}^{-\theta}p^{\theta}_{\ell'}z'\Phi_{\ell'}}{\theta\mathcal{I}^{-\theta-1}\frac{S_{z\ell}(\boldsymbol{\lambda})}{\left(\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\right)^{\theta}}}\exp\left(-\mathcal{I}^{-\theta}\frac{S_{z\ell}\left(\boldsymbol{\lambda}\right)}{\left(\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\right)^{\theta}}\right)\right.\\
&\qquad\left.\theta\mathcal{I}^{-\theta-1}\frac{S_{z\ell}\left(\boldsymbol{\lambda}\right)}{\left(\tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\right)^{\theta}}d\mathcal{I}\right]\\
&= \sum_{h'\in\mathcal{H}} \tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\left(\int_{\bar{I}^{-\theta}_{z'\ell'z\ell}}^{\infty}\mathcal{I}\frac{\tau^{\theta}_{\ell'\ell}\lambda^{\theta}_{z'\ell'z\ell}p^{\theta}_{\ell'}z'\Phi_{\ell'}}{S_{z\ell}\left(\boldsymbol{\lambda}\right)}\exp\left(-t\right)dt\right)\\
&= \sum_{h'\in\mathcal{H}} \tau_{\ell'\ell}\lambda_{z'\ell'z\ell}\left(\int_{\bar{I}^{-\theta}_{z'\ell'z\ell}}^{\infty} t^{\frac{\theta-1}{\theta}-1}\exp\left(-t\right)dt\right)p^{\theta}_{\ell'}z'\Phi_{\ell'}\tau^{\theta-1}_{\ell'\ell}\lambda^{\theta-1}_{z'\ell'z\ell}S^{1/\theta-1}_{z\ell}\left(\boldsymbol{\lambda}\right)\\
&= \sum_{h'\in\mathcal{H}} \tau^{\theta}_{\ell'\ell}\lambda^{\theta}_{z'\ell'z\ell}p^{\theta}_{\ell'}z'\Phi_{\ell'}S^{1/\theta-1}_{z\ell}\left(\boldsymbol{\lambda}\right)\Gamma\left(1-\frac{1}{\theta};\bar{I}^{-\theta}_{z'\ell'z\ell}\right)\\
&= \sum_{h'\in\mathcal{H}} \pi_{z'\ell'z\ell}\left(\boldsymbol{\lambda}\right)S^{1/\theta}_{z\ell}\left(\boldsymbol{\lambda}\right)\Gamma\left(1-1/\theta;\bar{I}^{-\theta}_{z'\ell'z\ell}\right)
\end{aligned}$$

where $\Gamma\left(\vartheta;x\right)\equiv\int_x^{\infty}t^{\vartheta-1}\exp\left(-t\right)dt$ is an upper-incomplete Gamma function.

Now, consider expected sender transfers. Conditional on realizations of $\boldsymbol{\Phi}$ and using the same argument as before, these are given by

$$\mathbb{E}\left[R^{-}_{z\ell}\left(\boldsymbol{\lambda}\right)\right] = \sum_{h'\in\mathcal{H}}\kappa_{z\ell z'\ell'}\tau^{-1}_{\ell\ell'}\pi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right)S^{1/\theta}_{z'\ell'}\left(\boldsymbol{\lambda}\right)\Gamma\left(1-1/\theta;\bar{I}^{-\theta}_{z\ell z'\ell'}\right).$$

Unconditional on realizations of $\boldsymbol{\Phi}$, the marginal dynamic value of a household h's relationship with h' is given by the fixed point

$$\begin{aligned}
\mathcal{MV}_h\left(\left(z,\ell,z',\ell'\right),\boldsymbol{\lambda}\right) \approx\ & \tau^{\theta}_{\ell'\ell}\lambda^{\theta}_{z'\ell'z\ell}p^{\theta}_{\ell'}z'A_{\ell'}\bar{S}^{1/\theta-1}_{z\ell}\left(\boldsymbol{\lambda}\right)\varphi^{-}_{z'\ell'z\ell}\left(\boldsymbol{\lambda}\right)\Gamma\left(1-1/\theta;\bar{I}^{-\theta}_{z\ell z'\ell'}\right)\\
&-\kappa_{z\ell z'\ell'}\tau^{\theta-1}_{\ell\ell'}\lambda^{\theta}_{z\ell z'\ell'}p^{\theta}_{\ell}zA_{\ell}\bar{S}^{1/\theta-1}_{z'\ell'}\left(\boldsymbol{\lambda}\right)\varphi^{-}_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right)\Gamma\left(1-1/\theta;\bar{I}^{-\theta}_{z'\ell'z\ell}\right),
\end{aligned}$$

where $\varphi^{-}_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right)$ is a risk-adjustment term given by

$$\varphi^{-}_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right) = 1+\frac{\left(1-\theta\right)\left(1-2\theta\right)}{2\theta^2}\frac{\sigma^2_{S_{z'\ell'}}\left(\boldsymbol{\lambda}\right)}{\bar{S}^2_{z'\ell'}\left(\boldsymbol{\lambda}\right)}+\frac{1-\theta}{\theta}\frac{\mathrm{Cov}\left(S_{z'\ell'}\left(\boldsymbol{\lambda}\right),\Phi_{\ell}\right)}{\bar{S}_{z'\ell'}\left(\boldsymbol{\lambda}\right)A_{\ell}}.$$

D.3.2 Proof of Corollary 4

The incentive compatibility constraint of Equation (37) can influence the transfer partnerships $\boldsymbol{\lambda}$. Let us derive the desired transfer partnership level. To do so, consider the following

derivatives

$$\begin{aligned}
\frac{\partial \mathbb{E}\left[R_{z\ell}^{+}\left(\boldsymbol{\lambda}\right)\right]}{\partial \lambda_{z'\ell'z\ell}} &= \tau_{\ell'\ell}^{\theta} p_{\ell'}^{\theta} z' A_{\ell'} \Gamma\left(1-1/\theta;\bar{I}_{z'\ell'z\ell}^{-\theta}\right) \varphi_{z'\ell'z\ell}^{-}\left(\boldsymbol{\lambda}\right) \cdot \frac{\partial}{\partial \lambda_{z'\ell'z\ell}} \left(\lambda_{z'\ell'z\ell}^{\theta} \bar{S}_{z\ell}^{1/\theta-1}\left(\boldsymbol{\lambda}\right)\right) \\
&= \tau_{\ell'\ell}^{\theta} p_{\ell'}^{\theta} z' A_{\ell'} \Gamma\left(1-1/\theta;\bar{I}_{z'\ell'z\ell}^{-\theta}\right) \varphi_{z'\ell'z\ell}^{-}\left(\boldsymbol{\lambda}\right) \cdot \\
&\quad \left(\theta \lambda_{z'\ell'z\ell}^{\theta-1} \bar{S}_{z\ell}^{1/\theta-1}\left(\boldsymbol{\lambda}\right) + \left(1/\theta-1\right) \lambda_{z'\ell'z\ell}^{\theta} \bar{S}_{z\ell}^{1/\theta-2}\left(\boldsymbol{\lambda}\right) \frac{\partial \bar{S}_{z\ell}\left(\boldsymbol{\lambda}\right)}{\partial \lambda_{z'\ell'z\ell}}\right) \\
&= \tau_{\ell'\ell}^{\theta} p_{\ell'}^{\theta} z' A_{\ell'} \lambda_{z'\ell'z\ell}^{\theta-1} \bar{S}_{z\ell}^{1/\theta-1}\left(\boldsymbol{\lambda}\right) \Gamma\left(1-1/\theta;\bar{I}_{z'\ell'z\ell}^{-\theta}\right) \varphi_{z'\ell'z\ell}^{-}\left(\boldsymbol{\lambda}\right) \cdot \\
&\quad \left(\theta + \left(1/\theta-1\right) \tau_{\ell'\ell}^{\theta} p_{\ell'}^{\theta} z' A_{\ell'} \theta \lambda_{z'\ell'z\ell}^{\theta} \bar{S}_{z\ell}^{-1}\left(\boldsymbol{\lambda}\right)\right) \\
&= \Gamma\left(1-1/\theta;\bar{I}_{z'\ell'z\ell}^{-\theta}\right) \tau_{\ell'\ell}^{\theta} p_{\ell'}^{\theta} z' A_{\ell'} \lambda_{z'\ell'z\ell}^{\theta-1} \bar{S}_{z\ell}^{1/\theta-1}\left(\boldsymbol{\lambda}\right) \varphi_{z'\ell'z\ell}^{-}\left(\boldsymbol{\lambda}\right) \cdot \\
&\quad \left(\theta - \left(\theta-1\right) \pi_{z'\ell'z\ell}\left(\boldsymbol{\lambda}\right)\right)
\end{aligned}$$

Additionally,

$$\begin{aligned}
\frac{\partial \mathbb{E}\left[R_{z\ell}^{-}\left(\boldsymbol{\lambda}\right)\right]}{\partial \lambda_{z\ell z'\ell'}} &= \Gamma\left(1-1/\theta;\bar{I}_{z\ell z'\ell'}^{-\theta}\right) \tau_{\ell\ell'}^{\theta-1} p_{\ell}^{\theta} z A_{\ell} \lambda_{z\ell z'\ell'}^{\theta-1} \bar{S}_{z'\ell'}^{1/\theta-1}\left(\boldsymbol{\lambda}\right) \varphi_{z\ell z'\ell'}^{-}\left(\boldsymbol{\lambda}\right) \cdot \\
&\quad \left[\left(\theta - \left(\theta-1\right) \pi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right)\right) + \bar{c} \lambda_{z\ell z'\ell'}^{\gamma} \left(\theta+\gamma-\left(\theta-1\right) \pi_{z\ell z'\ell'}\right)\right].
\end{aligned}$$

Define a pairwise constant as

$$\chi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right) \equiv \tau_{\ell'\ell} \frac{\Gamma\left(1-1/\theta;\bar{I}_{z'\ell'z\ell}^{-\theta}\right)}{\Gamma\left(1-1/\theta;\bar{I}_{z\ell z'\ell'}^{-\theta}\right)} \left(\frac{p_{\ell'}^{\theta} z' A_{\ell'}}{p_{\ell}^{\theta} z A_{\ell}}\right) \left(\frac{\bar{S}_{z'\ell'}\left(\boldsymbol{\lambda}\right)}{\bar{S}_{z\ell}\left(\boldsymbol{\lambda}\right)}\right)^{1-1/\theta} \frac{\bar{\varphi}_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right)}{\bar{\varphi}_{z'\ell'z\ell}\left(\boldsymbol{\lambda}\right)}.$$

The first order condition is

$$\chi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right) \left[\theta - \left(\theta-1\right) \pi_{z'\ell'z\ell}\left(\boldsymbol{\lambda}\right)\right] = \theta - \left(\theta-1\right) \pi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right) + \bar{c} \lambda^{\gamma} \left(\theta+\gamma-\left(\theta-1\right) \pi_{z\ell z'\ell'}\right).$$

Solving for λ, we get

$$\lambda = \left(\frac{\chi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right) \left(\theta - \left(\theta-1\right) \pi_{z'\ell'z\ell}\left(\boldsymbol{\lambda}\right)\right) - \theta + \left(\theta-1\right) \pi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right)}{\bar{c}\left(\theta+\gamma-\left(\theta-1\right) \pi_{z\ell z'\ell'}\left(\boldsymbol{\lambda}\right)\right)}\right)^{\frac{1}{\gamma}}.$$