Cover Letter: NBER Workshop on Development Economics and Networks for Early-Career Researchers

Christina Qiu

I am an Assistant Professor of Economics at the University of Miami applying to participate in the NBER Workshop on Development Economics and Networks for Early-Career Researchers. I received my PhD from Yale University in May 2026. Attached, you can find: (i) an updated CV, (ii) a personal statement on my motivation for attending the workshop, and (iii) a manuscript of my job market paper, entitled "Endogenous Transfer Networks Under Spatial Risk."

My email address is cmq28@miami.edu. My phone number is +1(973)906-5296.

My PhD advisor, Ahmed Mushfiq Mobarak, can provide a reference for me. His email address is ahmed.mobarak@yale.edu.

Personal Statement: NBER Workshop on Development Economics and Networks for Early-Career Researchers

Christina Qiu

I work at the intersection of development and trade economics. I use quantitative methods to examine the economic impacts of social networks, with a particular interest in settings where network formation is endogenous and embeds strategic considerations (i.e., the high-order links of one agent impact the outcomes of another). In my job market paper, I examine the role of digital payment technologies in the provision of informal insurance when transfer networks endogenously form. In recent works in progress, I explore how the network of geopolitical alliances impacts the probability of war and how AI technologies impact labor markets given rapidly developing capabilities and complementary tasks.

While the literature on social networks has advanced on both the theoretical and empirical front, quantitative work embedding those advances remains limited. For instance, my job market paper is, to the best of my knowledge, the only implementation of a pairwise-stable equilibrium in a quantitative spatial model. I take the stance that developing quantitative methodologies around strategic network formation is valuable because it permits economists to conduct counterfactuals, which can (i) identify explanatory mechanisms in networked settings, (ii) create projections that take into account equilibrium effects, and (iii) establish the conditions under which a theoretical possibility is practically relevant. However, conventional quantitative approaches are unequipped to handle the complex and non-linear nature of networks—which generically include equilibrium multiplicity or non-existence; network links as discrete yet interdependent choices; and the dependence of payoffs on an adjacency matrix, where the space of possible networks grows exponentially in the number of nodes. Moreover, credible quantitative exercises require high quality data as inputs and serious engagement with the institutional context in which networks form. Building coherent quantitative implementations of economic networks demands both theoretical and empirical expertise, and therefore, conversation and collaboration across different fields.

I hope to attend this workshop to lay the groundwork for future collaborations that quantify the economic impacts of networks. The question I would most like to work through is which features of a network are worth the cost of measuring. The scope of quantitative models depends on what the empirical frontier can credibly recover, which I hope to learn from the lectures and other participants' work. In return, quantitative methods offer a way to assess the generality of an empirical finding once equilibrium effects are accounted for. This exchange seems particularly useful in development settings, where networks often structure the informal institutions that formal markets provide elsewhere.

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Fields
International Trade, Development Economics, Macroeconomics, Networks

Employment

2026– **University of Miami Business School**
Assistant Professor of Economics

Education

2019–2026 **Yale University**
Ph.D. in Economics
M.Phil. in Economics, 2022
M.A. in Economics, 2021

2019–2020 **University of Oxford**
M.Sc. Global Governance and Diplomacy (distinction)

2015–2019 **Harvard College**
B.A. Applied Mathematics, magna cum laude

Working Papers
"Endogenous Transfer Networks Under Spatial Risk" (Job Market Paper), September 2026
"AI, Scale, and Skills: A Quantitative Task-Based Theory of Automation" with Danial Lashkari, Wensu Li, and Neil Thompson, July 2025

Publications
Qiu, C. M. (2022) Regionalized liquidity: A cross-country analysis of mobile money deployment and inflation in developing economies. *World Development*, 152, 105781.

Fellowships, Honors, and Awards

2024–2025 Carl Arvid Anderson Prize Fellowship ($19,000), Yale University
2022–2024 Sasakawa Young Leaders Fellowship ($4,000), Yale University
2020–2025 NSF Graduate Research Fellowship
2024 Sloan Foundation Minor Research Grant in Mesoeconomics ($5,000)
2020 Outstanding Academic Achievement Prize, Oxford University
2019 Clarendon Fellowship, Oxford University
2019 Phi Beta Kappa, Harvard College
2019 John Dunlop Thesis Prize (honorable mention), Harvard Kennedy School
2018 Kenneth I. Juster Fellowship, Harvard University
2018 Distinction in Teaching Award, Harvard College
2017 Region 1 Mark of Excellence Award, Society of Professional Journalists
2016 Cyrilly Abels Short Story Prize (2nd place), Harvard College

2015 U.S. Presidential Scholar in the Arts (writing)

Research Experience

2023–2024 Research Assistant to Teresa Fort, Dartmouth College
2022 Research Assistant to Costas Arkolakis, Yale University
2022 Research Assistant to Orazio Attanasio, Yale University
2019 Data Science Fellow, Bureau of Labor Statistics

Teaching

2024 TA for Ana Cecilia Fieler, Growth & Macroeconomics (Yale)
2025–2026 Grader for Kaivan Munshi, Social Networks and Development (Yale)
2021 TA for Jonathan Hawkins, Intermediate Microeconomics (Yale Summer Session)
2018 Classroom Assistant for Jeremy Hahn, Linear Algebra (Harvard)

Seminars and Conferences (* denotes scheduled)

2026 University of Toronto, Penn State, University of South Carolina, Bocconi, MIT FutureTech, University of Miami, BI Norwegian Business School, Network Science in Economics, New Jersey Institute of Technology, ThReD, BSE Summer Forum (Development), SED, Southern Economic Association*, University of Hong Kong*
2025 NEUDC
2024 G-TAP
2023 EEA

Refereeing

Journal of Development Economics, AEJ: Micro, Journal of International Economics, World Development

Languages

English (native), French (intermediate)

PhD Courses

General Economic Theory: Microeconomics; General Economic Theory: Macroeconomics; Econometrics I; Econometrics II; Computational Methods in Economics; Advanced Macroeconomics I & II; Topics in Empirical Economics & Public Policy; International Trade I & II; Industrial Organization I & II; International Trade Policy; American Economic History

Endogenous Transfer Networks Under Spatial Risk*

Christina Qiu
University of Miami

September 15, 2026

Please click here for the most recent draft.

Abstract

I study informal insurance when transfer networks endogenously form. In the model, heterogeneous households form partnerships over space, treating their own links as substitutes and others' as strategic complements. I quantify the model using Tanzanian microdata following mobile money's 2008 introduction, which lowered geographic transfer costs. Reorganization is itself a form of consumption risk: net givers weaken partnerships precisely when expected obligations rise. Before mobile money, welfare gains over autarky hover around 2.8% across groups and stem almost entirely from insurance. By 2028, they reach 4.1% for non-educated but 1.3% for university-educated households, arising mostly from redistribution.

*I am indebted to my advisors Costas Arkolakis and Ahmed Mushfiq Mobarak for their guidance and support. I thank Mayara Felix and Joel Flynn for their detailed comments. For very helpful suggestions, I am thankful to S. Nageeb Ali, Kevin Donovan, Doireann Fitzgerald, Teresa Fort, Amit Khandelwal, Rachel Kranton, Danial Lashkari, Debraj Ray, Daniel Trefler, as well as seminar participants at the University of Toronto, Penn State, Bocconi University, University of South Carolina, MIT FutureTech, University of Miami, BI Norwegian Business School, the 2026 Network Science in Economics conference, the 2026 ThReD conference, and the 2026 BSE Summer Forum in Development. I thank numerous former colleagues at Yale for valuable feedback.

1 Introduction

Households in developing countries face volatile incomes but limited access to formal insurance mechanisms. To smooth consumption, households often rely on cash gifts from relatives, friends, and other social contacts. A large literature in development economics studies these informal transfers as a form of risk-sharing (Townsend, 1994; Udry, 1994). Yet most of this work assumes that transfers occur among fixed members of a group, such as a village. This approach takes each household's set of potential partners—or the *transfer network* itself—as exogenous. Departing from this assumption raises a natural question: how do informal networks help households manage risk when economic conditions alter the value of maintaining links?

This paper studies the provision of informal insurance when transfer networks are endogenous. The empirical setting is Tanzania, where the diffusion of mobile money, a digital payment system, lowered the economy-wide costs of sending cash, which changed the value of maintaining network links across space (Jack and Suri, 2014; Economides and Jeziorski, 2017; Riley, 2018). These reductions in distance-dependent frictions matter for risk-sharing because households face spatially correlated shocks (Rosenzweig and Stark, 1989; Balboni et al., 2026)—e.g., droughts and floods. I develop a quantitative model in which heterogeneous households manage spatial risk by forming mutually beneficial, bilateral transfer partnerships. These partnerships are interdependent and create a network: households view their own links as substitutable but treat others' links as strategic complements. As a result, changes in the economic environment reshape the transfer network itself, creating an additional source of consumption risk.

Quantitatively, mobile money increases transfer activity. Because the average household sends out more transfers than it receives, its net outflows in 2028 grow by 2.3% of its baseline consumption in 2013. Without network reorganization, this magnitude would be 3.0%, suggesting that a fixed-network approach overstates the rise by roughly a quarter. Despite increased transfers, mobile money *reduces* the insurance function of transfer networks. While the impacts of the technology are strongly progressive, poor households gain not because networks provide more smoothing across spatial shocks, but because partnerships are activated more often and generate transfers that are typically redistributive (i.e., arising from more-productive sources). Informal insurance remains incomplete not only because transfers are costly to send, but also because potential insurers weaken partnerships precisely when their expected obligations rise.

The rest of the paper proceeds as follows. To begin, I use a household-level panel survey that tracks a nationally representative sample of Tanzanian households from 2008

to 2016. In Section 2, I establish three motivating facts about households' transfer networks. 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, after such shocks, households rely disproportionately on sources that are *less-productive* than they are, where the education level of the household head proxies for productivity. This pattern suggests that, in contrast to canonical frameworks of risk-sharing where households equalize marginal utilities of consumption (e.g., Townsend, 1994), insurance-like transfers systematically arise from sources with *higher* marginal utilities of consumption than the recipient household. Endogenous network adjustment can account for this fact: when a household's expected income falls, its anticipated transfer needs rise, which makes links with that household more costly for partners. In response, more-productive partners scale back their engagement, leaving the household dependent on less-productive sources. This observation motivates a model of informal insurance in which the transfer network is endogenously determined rather than a fixed feature of the environment.

In Section 3, 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. Households face both idiosyncratic and spatially correlated income shocks. After shocks are realized, households choose one partner from whom to demand payments. Aggregating these requests determines transfer flows. Payments are subject to distance-dependent transfer frictions, which mobile money reduces. I study the pairwise-stable equilibria of this network formation game: all partnerships are mutually beneficial, and no pair can jointly 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. A deepened 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 *strategic complementarities*: households prefer partners with strong connections, since these types are otherwise well-insured and demand less transfers. Third, under spatially correlated 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 es-

tablish that a pairwise-stable equilibrium exists in my setting using recent results on the existence of weighted, pairwise-stable networks (Bich and Morhaim, 2020). In Section 3.4, I test the model's within-equilibrium micro-level predictions using the survey data.

I quantify the model to assess the impact of mobile money on economic outcomes for heterogeneous households in Section 4.1. I separate households into four discrete education levels, corresponding to a household's productivity type. Equipped with household consumption and price data from the survey, I estimate the dispersion of households' agricultural production using a model-implied relationship that maps asymmetries in the cross-region transfer share matrix to differences in regional price levels. I use real income data to directly estimate parameters of the spatial shock distribution across household types.

I then calibrate remaining structural parameters. A key quantitative challenge is that the model generates multiple equilibria. To address this model feature, I propose an equilibrium selection procedure that characterizes a distribution of outcomes under endogenous networks. Variation in outcomes arises from randomness in the order in which pairs best-respond to the current network. For each selected equilibrium, the model generates aggregate transfer inflow shares, which can be directly observed in the data. I discipline model parameters such that the average selected equilibrium matches key empirical moments of these shares. The spatial, across-region transfer source Herfindahl disciplines the costs of transporting money over space. Changes in this measure over the survey period identify the five-year rate of decline in costs. The local, within-region transfer source Herfindahl disciplines the costs of intensifying transfer partnerships. An exogenous self-weight and minimum partnership level are calibrated to match the empirical prevalence and size of transfer inflows. I use the calibrated model to assess the impact of mobile money on network structure, transfers, and welfare.

I discuss quantitative results in Section 4.2. The first series of quantitative results highlights that endogenous network adjustment forms an additional source of consumption risk. In the model, insurance motives lead households to form mutually beneficial partnerships across productivity types, even though transfer flows between partners are asymmetric in expectation. The higher-productivity partner typically sends more to the other and acts as a net giver; the lower-productivity partner acts as a net receiver. I consider two types of shocks: shocks to regions composed primarily of net receivers (e.g., poor regions) and shocks to regions composed primarily of net givers (e.g., rich regions). For net-receiver regions, the distribution of real consumption under fixed networks stochastically dominates that under endogenous networks. Fixed networks preserve access to high-productivity partners, while endogenous adjustment allows those

partners to reduce their engagement as the relationship becomes more costly in expectation. Consistent with this mechanism, consumption losses from endogenous adjustment are strongly correlated with declines in network connectivity. For net-giver regions, the opposite pattern emerges: these households fare better under endogenous networks because they can reorganize links to reduce transfer obligations after negative shocks. Negative shocks cause the partnerships of net receivers to weaken while the partnerships of net givers strengthen. Network reorganization is thus itself a source of consumption risk, and in particular, amplifies the negative effects of shocks for poor households.

Next, I trace the evolution of household welfare along the diffusion path of mobile money as average geographic transfer frictions decline. Assuming the same five-year rate of decline from 2008 to 2013, I project households' outcomes forward. By 2028, transfer activities increase: the average household raises its net outflows, which—across the distribution of spatial shocks—reduces its expected real consumption by 2.3% of its 2013 level. I decompose these losses into two effects: (i) a *direct mechanical effect*, as households more easily access payments from geographically distant partners under the existing network, and (ii) an *indirect network effect*, as households adjust the intensity of transfer partnerships. Quantitatively, the indirect effect reduces average consumption losses by roughly a quarter. This exercise suggests that a fixed-network perspective overstates the increase in transfer activity 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, the transfer network is primarily a risk-sharing institution: gains from the network stem almost entirely from insurance, display no clear progressive pattern, and hover around 2.8% across productivity groups. By 2028, the role of the network changes substantially. Insurance gains decline relative to 2008, as fewer partnerships are maintained. Instead, redistribution accounts for nearly nine-tenths of gains for non-educated households and one-quarter for university-educated types. Network gains follow a progressive pattern: non-educated types see an average welfare improvement of 4.1% relative to autarky, while university types see improvements of only 1.3%.

This change reflects a shift in which partnerships are sustained in equilibrium. By lowering transfer frictions, mobile money makes cross-productivity partnerships more attractive to poor households, since these links generate transfers that are typically redistributive. The same partnerships become less attractive to high-productivity house-

holds, whose expected transfer obligations rise. As high-productivity households reduce their participation in cross-spatial partnerships, the network sustains less insurance than in 2008. The transfer network therefore shifts from an institution organized primarily around risk-sharing to one that systematically facilitates redistribution across household types. These results show that mobile money changes not only the magnitude of network gains, but also the economic mechanism through which those gains arise.

Related Literature The paper relates to literatures spanning the fields of development and spatial economics. 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 (e.g., Coate and Ravallion, 1993; Attanasio and Rıos-Rull, 2000; Ligon et al., 2000; Ambrus et al., 2014), information asymmetry (e.g., Ligon, 1998; Bloch et al., 2008; Attanasio and Krutikova, 2020; Ambrus et al., 2022), autarkic spatial hedging (e.g., Rosenzweig and Stark, 1989; Munshi and Rosenzweig, 2016; Morten, 2019; Meghir et al., 2022), and endogenous group formation arising from ex-post contract deviations (e.g., Genicot and Ray, 2003; Bloch et al., 2007; Bold, 2009). Though I largely abstract away from these frictions, my paper joins a few exceptions in this literature that treat the transfer network itself as an endogenous equilibrium object (Bramoullé and Kranton, 2007a,b; Billand et al., 2012; Gao and Moon, 2016; Ambrus and Elliott, 2021). In this paper, network formation is governed by households' ex-ante evaluations of net benefits in transfer partnerships: households choose both whom to partner with and how intensively to maintain each partnership, allowing for different and overlapping sets of transfer partners as observed empirically in village networks (De Weerdt and Dercon, 2006). This approach permits the examination of additional economic considerations in transfer arrangements—such as partner selection, indirect exposure to risk through social connections, and motives of spatial diversification.[1]

Previous papers on pairwise-stable networks in the context of informal insurance are mostly theoretical, examining equilibrium properties of stable networks and contrasting them to efficient ones. My paper departs from this literature in two ways. First, relative to these papers, my framework is quantitative and can be used to evaluate counterfactual changes in welfare across heterogeneous households embedded in space. Second, I incorporate a realistic intensive margin of network formation. This margin serves two distinct purposes. On an economic level, I can map changes in transfer activities among house-

[1] Ex-ante and ex-post contracting frictions can interact. In Section 3.5, I extend the framework to include limited commitment, and in Section B.4, I quantify this version of the model. The ability to deviate from agreed-upon transfer obligations reduces a net-sender's projected costs of staying in partnerships, which counterintuitively *raises* the amount of insurance the transfer network can provide.

holds that remain connected to relational changes in the network. On a technical level, this formulation moves the problem to a class of weighted networks, where conditions for equilibrium existence are weaker (Bich and Morhaim, 2020).[2]

Second, the paper is situated in a growing literature about mobile money and digital payment systems in developing countries (Yang, 2008; Jack and Suri, 2014; Riley, 2018; Batista and Vicente, 2020a,b; Alvarez and Argente, 2022; Alvarez et al., 2023; Blumenstock et al., 2025; Batista and Vicente, 2025; Houeix, 2025). The paper quantifies the impacts of mobile money diffusion for heterogeneous households across locations and shows that the technology's effects are progressive. Importantly, for poor households, the driver of welfare gains under mobile money is not an improvement in insurance but an increased frequency of transfers that are usually redistributive.

Third, the paper contributes to a growing literature on endogenous network formation in quantitative spatial models (Lim, 2017; Kopytov et al., 2024; Bernard et al., 2022; Eaton et al., 2022; Arkolakis et al., 2023; Fontaine 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 links of others payoff-relevant, internalizing others' linking decisions when forming their own. To the best of my knowledge, this is the first implementation of a pairwise-stable equilibrium in a quantitative spatial model. Relatedly, the paper adds a strategic dimension to a rapidly growing literature in trade that quantifies interdependent choices (Alfaro-Urena et al., 2023; Sabal, 2025; Arkolakis et al., 2026; Head et al., 2026). In this literature, "interdependence" refers to how an agent's valuation of an additional option depends on the other options it has chosen. In my setting, this valuation also hinges on the choices of others, and this strategic interaction is internalized by agents when making their own decisions. The paper also speaks to a literature on risk and uncertainty in quantitative spatial models (Burgess and Donaldson, 2010; Fitzgerald, 2012; Brooks and Donovan, 2020; Allen and Atkin, 2022; Castro-Vincenzi et al., 2024; Fan and Luo, 2025; Fitzgerald, 2025; Dunn and Leibovici, 2026). To this literature, I introduce a set of *strategic* spatial risk considerations, where an agent's exposure to risk depends on the links of its partners and determines its own linking choices.

[2]The strategic considerations in this paper—*partner substitutability* and *strategic complementarity*, in tandem, among arbitrarily many players—is theoretically distinct from those typically considered in the literature. Celebi (2023) examines unweighted networks with the same strategic considerations. An equilibrium does not always exist in his setting, which makes his model difficult to adapt for quantitative analysis.

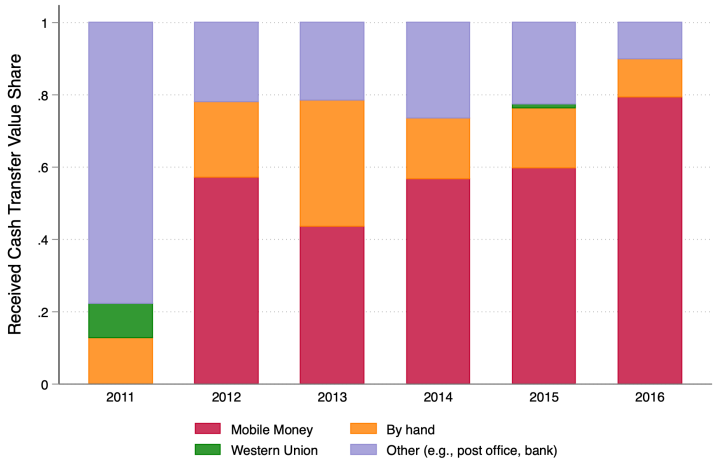
2 Data & Motivating Facts

In this section, I introduce the Tanzania National Panel Survey (NPS), which is publicly available on the World Bank Microdata Library (National Bureau of Statistics, 2020). I use the NPS to establish three facts about households' transfer networks. These facts motivate a model of risk-sharing in geography with endogenous network formation.

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, 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]

Figure 1: Modes of Domestic Cash Transfers 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."

[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.

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 households as using mobile money if respondents report 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 received via mobile money.

The NPS asks households about transfers, including transfer amounts and 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 fewer 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) and constitutes 12.2% of a household's yearly income. The median source has lived in his current location of residence for 15 years, indicating limited inter-regional migration during the sample period, and has nine years of education. Of the 4,517 transfers reported across rounds, 82.3% were used for "household consumption."

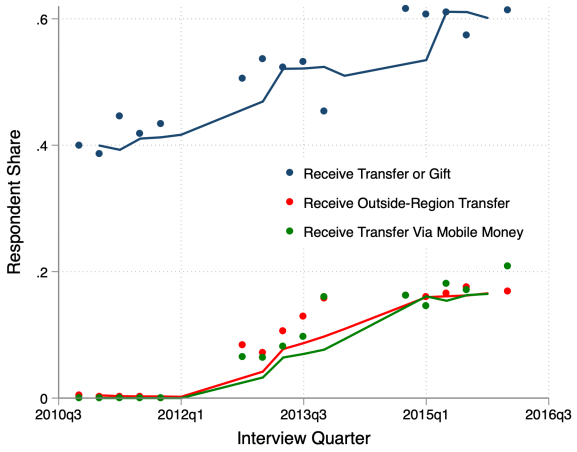
The NPS also asks households how they respond to negative shocks.[5] The three most common ways households cope with shocks are: (i) doing nothing, constituting 54.2% of responses, (ii) relying on own-savings, constituting 21.0%, and (iii) receiving unconditional help from relatives and friends, constituting 9.6%. 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 insurance. The dominance of this 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 fewer 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).

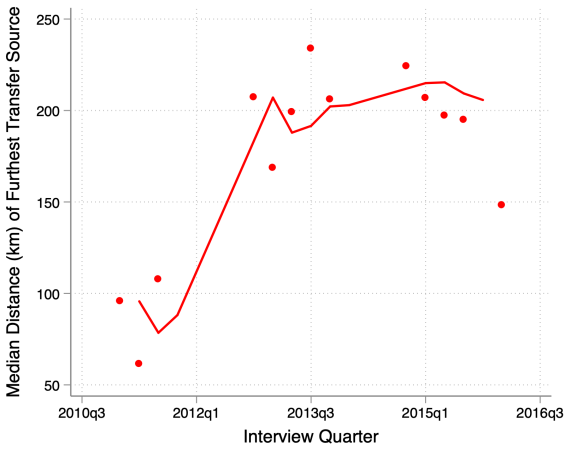
[5]78.9% of respondents report being affected by a shock. The five most commonly cited shocks include: (i) a large rise in the price of food, composing 20.2% of recorded shocks; (ii) death of a non-household family member, composing 13.8%; (iii) a severe water shortage, composing 10.9%; (iv) droughts 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 NPS

(a) Transfer Network Participation Over Time



(b) Median Payment Distance Among Recipients



Note: Quarters with fewer than ten respondents are dropped. Smoothed time series, indicated with lines, 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

I present three motivating facts about the transfer network.

Fact 1. The transfer network spatially expanded after mobile money.

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 it 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 coincides with the new receipt of outside-region transfers. Furthermore, the increase in receipt of outside-region transfers corresponds to the increase in the respondent share receiving transfers via mobile money.

The spatial configuration of transfer networks also changed in this period. In Figure 2b, I show that, conditional on receiving transfers, households obtain cash from geographically further origins. I define transfer distance as the centroid-to-centroid kilometer span between a household and its 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 Section C.1.1, I show that transfers follow a gravity-like pattern, where households receive more transfers from geographically proximate social contacts. Among mobile money users, this geographic pattern remains but is substantially attenuated. In Figure A7, I display average mobile phone and computer ownership, as well as median household technology expenditure, during the time period. There is no clear time trend for these outcomes, suggesting that mobile money is a more likely explanation for the expansion.

Fact 2. Households face spatially correlated shocks.

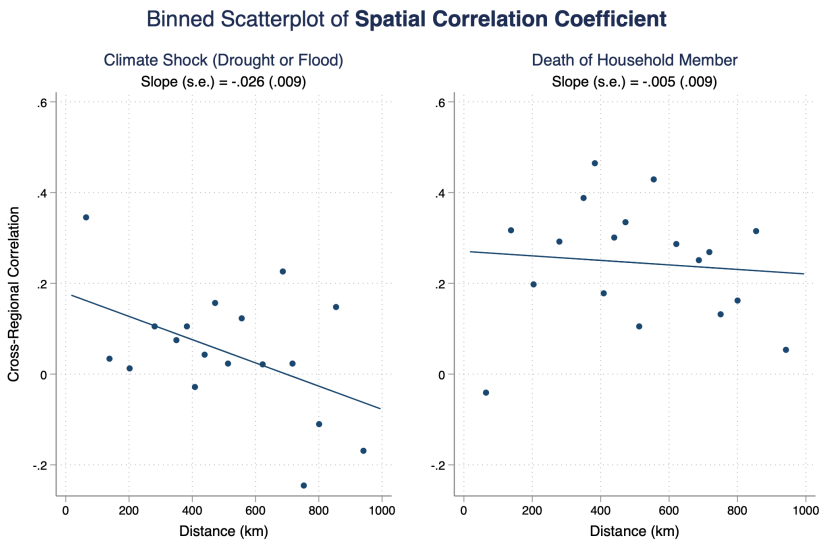
If distant locations experience different shock patterns, the relaxation of distance-dependent transfer frictions can help households stabilize consumption. Here, I show that households face spatially correlated shocks. To do so, I focus on households' experience of climate-related shocks.

Pooling across rounds and regions, approximately 38.1% of households report being "severely affected negatively by droughts or floods". Additionally, substantial spatial and temporal heterogeneity exists in the reported salience of these climate shocks, shown in Figure A8. In the left panel of Figure 3, I plot a binned scatterplot of the pairwise correlations of regional respondent shares reporting climate shocks against the centroid-to-centroid kilometer distance between region pairs.[6] A 100-kilometer increase in the distance between regions is associated with an average 0.03-point decline in the correlation of respondent shares, indicating that households living closer together exhibit more agreement on whether they were impacted by droughts or floods. This association is statistically significant at the 1% confidence level. In summary, households face spatially correlated shocks, the presence of which suggests insurance gains from spatially diversifying transfer sources.

In the right panel of Figure 3, I contrast the spatial correlation of droughts and floods with the spatial pattern of reported deaths of household members. The death shock im-

[6] 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 3: Geographic Distance and Respondent Share Shock Correlations



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.

pacts 8.3% of NPS respondents and does not display spatial correlation.

In Section C.1.2, I show that transfer distance acts as insurance against the spatially correlated climate shock. In particular, households that can access more distant sources receive more transfers after the climate shocks, 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 reorganization as another potential feature. To do so, I document a robust empirical pattern about who insures households when they experience negative shocks.

Fact 3. Most insurance-like transfers arise from less-productive sources.

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 are already fixed at the time the shock occurs. A tight, positive relationship between household income and the head's years of education

is shown in Figure A9.

I separate out household heads into four productivity types, corresponding to discrete education levels. These groups are non-educated or pre-primary, some primary school, some secondary school, and some university or more.[7] Pooling across rounds and households, 51.3% of the value of total transfers arise from sources that are more-educated than the household head, while 9.2% arise from sources that are less-educated than the household head. Unsurprisingly, across Tanzania, transfers redistribute funds from higher- 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. Insurance-like transfers are particularly salient economic objects because transfer networks have canonically been conceived as risk-sharing institutions (Fafchamps, 2011). To show this pattern, I run the following PPML regression for a household h of type s at interview time t given source type s',

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

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

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, $\mathbf{1}\left(s' > s\right)$ is an indicator that equals one when a source type s' is more-educated than the household's type s, $\mathbf{1}\left(s' = s\right)$ is an indicator that equals one when a source type s' is similarly educated to the household's type s, γ_h are household fixed effects, $\gamma_{s'}$ are source type fixed effects, γ_t are interview quarter fixed effects, and $\epsilon_{hss't}$ is an error term. Transfers from less-educated sources when households do not experience shocks compose the outcome associated with the omitted group. I focus on shock indicators generated by self-reported climate shocks.

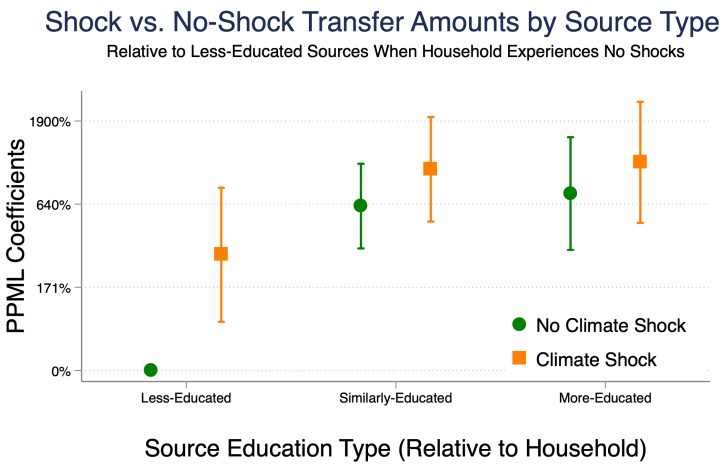
The left panel of Table 1 displays the regression results of Equation (1). Households roughly quadruple transfers from less-educated sources when reporting climate shocks.

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

Table 1: All Transfer Amounts (TZS) After Climate Shocks By Source Type

	Transfer Amount (1) PPML
Shock=1	1.392***
	(0.411)
More-Educ.=1	2.128***
	(0.346)
More-Educ.=1 × Shock=1	-1.017***
	(0.347)
Same-Educ.=1	1.977***
	(0.260)
Same-Educ.=1 × Shock=1	-0.950***
	(0.338)
N	20040
Household FE	✓
Quarter FE	✓
Source Type FE	✓

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



Note for left panel: This table displays the regression results using Equation (1) as a specification. Indicator variables equal one if (i) a household is less-educated than its source, or (ii) a household is similarly educated to its source. A household that experienced a shock reports being "severely impacted" by a "drought or flood" in the past year. I 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. The outcome is transfers in TZS from all sources. *Note for right panel:* Consider the regression specification 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.

Additionally, in the absence of shocks, coefficient estimates are consistent with redistribution (i.e., $\delta^M \approx \delta^S > 0$), as more- and similarly-educated sources on average give households seven times more than less-educated sources. Interaction coefficients ξ^M and ξ^S, however, are negative, suggesting that transfers from less-educated sources display the largest increases when households report shocks.

In the right panel of Table 1, I plot 95% confidence intervals around the shock-responses of transfers. The only source type from which households receive statistically significantly more transfers when shocked is less-educated sources. The finding is puzzling in light of standard risk-sharing models with fixed network composition, where households aim to equalize marginal utilities of consumption. Given the robust relationship between household income and education in Figure A9, the finding instead suggests that households typically seek insurance-like transfers from partners who, on average, appear to have higher marginal utilities of consumption. In Section C.2, I show that this fact is robust to a variety of alternative specifications—including keeping fixed source relationships (e.g., only transfers from children as an outcome), examining transfer responses to other shocks, and subsetting the sample by mobile money adoption status.

How can a framework in which households re-optimize partnership levels after negative shocks 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 its partners, which raises the partner's expected costs of this relationship. In response, more-productive partners scale back the intensity of their transfer ties, prompting the household to rely on less-productive partners for transfers.

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 backward induction. Section 3.4 summarizes the model's testable implications when applied to the NPS. Section 3.5 describes a limited commitment extension of the model, where households can deviate from their transfer obligations after the realization of income shocks.

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 $\Omega_{\ell z}$, and the sum of measures equals one. I consider an endowment economy in which households produce a stochastic quantity of agricultural goods.

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

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

where Φ_{ℓ} indicates a stochastic local productivity. The distribution $G_{\ell z}(\chi)$ is Fréchet with a shape parameter θ, dictating the dispersion of agricultural yields, and a *stochastic* scale parameter $z\Phi_{\ell}$, amounting to the product of household and local productivities. On average, agricultural yields are larger when households are of higher productivity z and when local productivities realize higher Φ_{ℓ} draws.

Conditional on local shocks $\mathbf{\Phi}$, the variance of quantity draws is positive, indicating the presence of idiosyncratic uncertainty. A household h obtains income $I_{\ell z}(h)$ by selling agricultural goods $\chi_{\ell z}(h)$ for local prices p_{ℓ}, such that $I_{\ell z}(h) = p_{\ell}\chi_{\ell z}(h)$.

Two matrices characterize the distribution of local productivities $\mathbf{\Phi}$. The expectation is denoted by vector $\boldsymbol{A}$, where the ℓth entry A_{ℓ} represents the average local productivity draw of location ℓ and intoduces ex-ante location heterogeneity. The second moments can be summarized by a 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'.

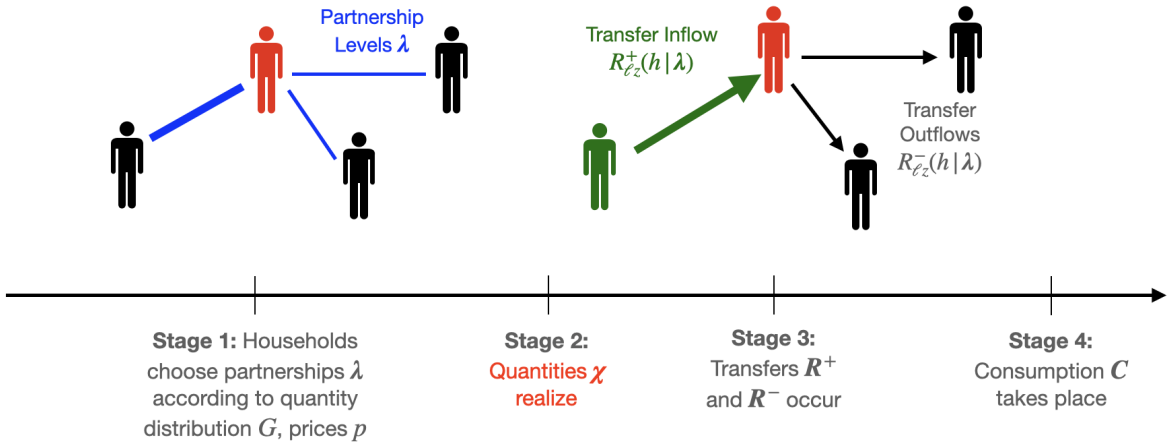
For an economy to exhibit spatial risk, there must be meaningful heterogeneity in the shocks agents experience by the locations they live. Formally, an economy displays *spatial risk* if there is no constant $c \geq 0$ such that $\sigma_{\ell\ell'} = c$ for all location pairs (ℓ, ℓ'). This definition 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 $\mathbf{\Sigma}$.

3.2 The Network Payment Game

Transfers between households are allocated according to a network payment game. Figure 4 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 location-

Figure 4: Timeline Illustration of the Network Payment Game



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

Stage 1: Partnership Formation

Household pairs decide on partnership levels $\boldsymbol{\lambda}$. At this stage, households know the distributions of income $\boldsymbol{G}$, including the expectation vector $\boldsymbol{A}$ and variance-covariance matrix $\boldsymbol{\Sigma}$ of local productivities. The partnership level $\lambda_{\ell' z' \ell z}$ denotes household h's claim on a share of the realized income $I_{\ell' z'}(h')$ of partner h'. Concretely: if approached by household type h at Stage 3, a household h' must pay its partner a portion $\lambda_{\ell' z' \ell z}$ of its realized income $I_{\ell' z'}(h')$.[8] 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

[8] To maintain the tractability of the quantitative model, partnership levels must be multiplicative in income draws. One may alternatively interpret the partnership level $\lambda_{\ell' z' \ell z}$ 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 $\lambda_{\ell' z' \ell z} I_{\ell' z'}(h')$. Similar time-use-based measures of relationship intensity have been collected by Goraya et al. (2025).

may decide to set their partnership levels to zero.

Feasibility The sum of partnerships is 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 $\kappa_{\ell z \ell' z'}$ denote a wedge between sender h's payment and the received transfer of h'.[9] For each household h, the feasibility constraint is

$$\underline{\lambda} \leq \sum_{(\ell',z') \neq (\ell,z)} \kappa_{\ell z \ell' z'} \lambda_{\ell z \ell' z'} \leq 1 - \overline{\lambda}. \tag{3}$$

The right inequality of Equation (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 $1 - \overline{\lambda}$. The "capacity" parameter $\overline{\lambda}$ enters into the feasibility constraint as an exogenous self-weight. When $\overline{\lambda}$ is close to 1, households are unable to form many partnerships with others without violating the feasibility constraint. I set the self-weight $\lambda_{\ell z \ell z} = \overline{\lambda}$ for all $(\ell, z) \in \mathcal{H}$, where $\mathcal{H}$ denotes the set of household types. 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 Equation (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 $\kappa_{\ell z \ell' z'} = 1 + \bar{c} \lambda^{\gamma}_{\ell z \ell' z'}$, 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 $\kappa_{\ell z \ell' z'}$ are increasing in partnership levels $\lambda_{\ell z \ell' z'}$, implying that deeper partnerships are more costly.

[9] From the time use interpretation of partnerships, friction $\kappa_{\ell z \ell' z'}$ is a wedge between the effort of sender h and perceived benefit of receiver h'. One can take the transfer friction $\kappa_{\ell z \ell' z'}$ 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, the friction need 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.

This property induces convexity in the cost of partnerships, which acts as a necessary condition for equilibrium existence. Let $\kappa_{\ell z \ell z} = 1$ for all $(\ell, z) \in \mathcal{H}$.

Desired Partnership Levels 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.

In Section 3.2.1, I will define the relevant equilibrium concept of this game as pairwise stability applied to a weighted network, and in Section 3.3.3, I will show that pairwise-stable networks in this game are symmetric, or that $\lambda_{\ell z \ell' z'} = \lambda_{\ell' z' \ell z}$ for all pairs (ℓ, z) and (ℓ', z'). Importantly, I assume that households internalize this characteristic of the equilibrium network when deciding on their privately optimal partnership levels. Under this assumption, the household's internalized costs of strengthening a relationship scale with its calculated benefits.

I denote $\boldsymbol{\lambda}_{-\ell z \ell' z'}$ as the set of transfer partnerships in the network excluding links $\lambda_{\ell z \ell' z'}$ and $\lambda_{\ell' z' \ell z}$.

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

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

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

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

Stage 2: Shock Realization

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' for $\ell \neq \ell'$, 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 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.[10] A recipient transfer draw of a household h with respect to its partner h' is $\tau_{\ell'\ell}\lambda_{\ell'z'\ell z}I_{\ell'z'}(h')$.

Stage 3: Transfers

A household chooses to receive payments from the partner associated with the highest recipient transfer draw.[11] Conditional on incomes $\boldsymbol{I}$ and partnership levels $\boldsymbol{\lambda}$, the *recipient (positive) transfer* of a household h in location ℓ is

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

Households are more likely to demand payments from those with whom they engage in strong partnerships (high $\lambda_{\ell'z'\ell z}$) and share geographic proximity (high $\tau_{\ell'\ell}$), or who observe high income realizations. Note that a household may generate its own highest recipient transfer draw, the likelihood of which is dictated by capacity parameter $\overline{\lambda}$. If a household generates its own highest recipient transfer draws, or $\overline{\lambda}I_{\ell z}(h) \geq \max_{h'\neq h}\tau_{\ell'\ell}\lambda_{\ell'z'\ell z}I_{\ell'z'}(h')$, a household does not receive a transfer from its partners.

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

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

Crucially, a household's sender transfer depends on its partner's partnership levels among pairs that do not directly involve the household, or $\lambda_{\ell''z''\ell'z'}$ 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 only its own partnership levels.

[10] 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.

[11] 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 fewer transfer sources annually. The NPS permits respondents to report at most four sources.

Stage 4: Consumption

Households consume income net of transfers,

$$C_{\ell z}\left(h|\boldsymbol{\lambda},\boldsymbol{\Phi},\boldsymbol{I}\right)=I_{\ell z}\left(h\right)+R_{\ell z}^{+}\left(h|\boldsymbol{\lambda},\boldsymbol{\Phi},\boldsymbol{I}\right)-R_{\ell z}^{-}\left(h|\boldsymbol{\lambda},\boldsymbol{\Phi},\boldsymbol{I}\right). \tag{7}$$

In my baseline setting, I restrict payoffs to be linear such that households maximize expected transfers. In Section 3.3, I show that motives of spatial diversification still hold under such payoffs.

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 the payment game. I adapt their definition below.

Definition 2. *A network $\widetilde{\boldsymbol{\lambda}}$ is pairwise-stable with respect to payoffs $\mathbb{E}\left[C_{\ell z}\left(h|\boldsymbol{\lambda}\right)\right]$ if:*
(a) for each (h,h') and for $\lambda\in[0,\widetilde{\lambda}_{\ell z\ell' z'})$, $\mathbb{E}\left[C_{\ell z}\left(h|\,\widetilde{\boldsymbol{\lambda}}_{-\ell z\ell' z'}\cup\lambda\right)\right]\leq\mathbb{E}\left[C_{\ell z}\left(h|\,\widetilde{\boldsymbol{\lambda}}\right)\right]$ and $\mathbb{E}\left[C_{\ell' z'}\left(h'|\,\widetilde{\boldsymbol{\lambda}}_{-\ell z\ell' z'}\cup\lambda\right)\right]\leq\mathbb{E}\left[C_{\ell' z'}\left(h'|\,\widetilde{\boldsymbol{\lambda}}\right)\right]$.
(b) for each (h,h') and for $\lambda\in(\widetilde{\lambda}_{\ell z\ell' z'},1]$, at least one of the following two conditions is true: $\mathbb{E}\left[C_{\ell z}\left(h|\widetilde{\boldsymbol{\lambda}}_{-\ell z\ell' z'}\cup\lambda\right)\right]\leq\mathbb{E}\left[C_{\ell z}\left(h|\widetilde{\boldsymbol{\lambda}}\right)\right]$ or $\mathbb{E}\left[C_{\ell' z'}\left(h'|\widetilde{\boldsymbol{\lambda}}_{-\ell z\ell' z'}\cup\lambda\right)\right]\leq\mathbb{E}\left[C_{\ell' z'}\left(h'|\widetilde{\boldsymbol{\lambda}}\right)\right]$.

The first condition requires that households have no incentives to weaken any of their partnerships. The second condition requires that equilibrium partnerships do not admit upward deviations that are profitable to both members of any pair. 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.

3.2.2 Network Access: A Sufficient Statistic

Following Eaton and Kortum (2002), the key assumptions underlying the model's quantitative tractability are (i) the Fréchet-distributed quantity draws of Equation (2) and (ii) the single-sourcing of transfers per income realization in Equation (5). This set of assumptions generate sufficient statistics for households' linking decisions, which reduce the dimensionality of the household's private optimization problem in Equation (4). Though they arise endogenously when solving for households' transfer distributions, I introduce and interpret these statistics in Definition 3.

Definition 3. *The network access of a household in location ℓ with productivity z is*

$$S_{\ell z}\left(\boldsymbol{\lambda}, \boldsymbol{\Phi}\right) = \sum_{\ell', z'} \left(\lambda_{\ell' z' \ell z} \tau_{\ell' \ell} p_{\ell'}\right)^{\theta} z' \Phi_{\ell'}. \tag{8}$$

Resembling deterministic "market access" (see Anderson and Van Wincoop, 2003; Redding and Sturm, 2008; Donaldson and Hornbeck, 2016), the network access term $S_{\ell z}\left(\boldsymbol{\lambda}\right)$ of Equation (8) depends on stochastic, local productivities $\boldsymbol{\Phi}$ and is itself stochastic. Equation (8) has a natural interpretation as a household's valuation of its network, since it describes how closely the household is situated, relationally or geographically, to high-productivity partners. It amounts to a distance $\tau_{\ell' \ell}$ and relationship $\lambda_{\ell' z' \ell z}$ weighted sum of partners' income determinants, where income determinants include both partners' real productivities z' and $\Phi_{\ell'}$ and nominal price levels $p_{\ell'}$.

The mean and variance of network access $S_{\ell z}\left(\boldsymbol{\lambda}\right)$ are

$$S^{(1)}_{\ell z}\left(\boldsymbol{\lambda}\right) = \sum_{\ell', z'} \left(\lambda_{\ell' z' \ell z} \tau_{\ell' \ell} p_{\ell'}\right)^{\theta} z' A_{\ell'} \tag{9}$$

and

$$S^{(2)}_{\ell z}\left(\boldsymbol{\lambda}\right) = \sum_{\ell', z'} \left(\lambda_{\ell' z' \ell z} \tau_{\ell' \ell} p_{\ell'}\right)^{2\theta} z'^{2} \sigma_{\ell' \ell'} + \sum_{(\ell', z') \neq (\ell'', z'')} \left(\lambda_{\ell' z' \ell z} \lambda_{\ell'' z'' \ell z} \tau_{\ell' \ell} \tau_{\ell'' \ell} p_{\ell'} p_{\ell''}\right)^{\theta} z' z'' \sigma_{\ell'' \ell'}. \tag{10}$$

Assuming $\theta > 2$, the variance of network access $S^{(2)}_{\ell z}\left(\boldsymbol{\lambda}\right)$ is low only when households have diversified links. A household's links are diversified when it has strong partnerships with others experiencing negatively correlated shocks, as dictated through the off-diagonal terms of the variance-covariance matrix $\boldsymbol{\Sigma}$. Without spatial correlation, stronger partnerships only make network access more noisy.

3.3 Solving the Model

In this section, I solve the game described in Section 3.2 via backward induction. In Section 3.3.1, I calculate the distribution of transfers for each household type under particular realizations of the spatial shock $\boldsymbol{\Phi}$ and network $\boldsymbol{\lambda}$. In Section 3.3.2, I derive households' privately optimal, preferred partnership levels in each of its relationships with other household types. In Section 3.3.3, I show that pairwise-stable equilibria in the network payment game exist.

3.3.1 Transfer Distribution Given λ

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

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

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

(b) Let $\widetilde{R}^{-}_{\ell z}(h|\boldsymbol{\lambda}, \boldsymbol{\Phi})$ denote a normalized sender transfer $R^{-}_{\ell z}(h|\boldsymbol{\lambda}, \boldsymbol{\Phi})$ scaled by the inverse of income $I_{\ell z}(h)$. This variable is a weighted sum of independent Bernoulli variables, where the success probabilities correspond to the likelihoods that a household h' receives a payment from h and constitute

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

Proof. The proof is found in Section A.1.1 (on page A1). □

The network access term of Equation (8) arises endogenously as a shifter in the distribution of transfer inflows $R^{+}_{\ell z}(h|\boldsymbol{\lambda}, \boldsymbol{\Phi})$ and in the denominator of sender probabilities in Equation (11). Lemma 1 reveals three strategic determinants of households' consumption: partner substitutability, strategic complementarity, and spatial diversification.

Partner Substitutability 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

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

Note that the expression in Equation (12) is an increasing and concave function in own network access conditional on location-specific shocks $S_{\ell z}(\boldsymbol{\lambda}, \boldsymbol{\Phi})$. The concavity arises from the restriction on the Fréchet distribution that $\theta > 1$. Equivalent increases in network access are valued less when the household is initially more connected.

An interpretation of this concavity proceeds as follows. Suppose a household h increases its network access by raising its partnership level $\lambda_{\ell z \ell' z'}$ with h'.[12] At the margin,

[12] 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.

the more valuable partnership with h' is helpful to household h only if h' generates a recipient transfer draw that exceeds the already-existing maximum. The possibility of this marginal benefit declines when network access $S_{\ell z}(\boldsymbol{\lambda}, \boldsymbol{\Phi})$ is large.

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

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

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

Spatial Diversification In a corollary to Lemma 1, I consider a household's expected consumption unconditional on the realization of local productivities $\boldsymbol{\Phi}$. The relaxed information structure temporally places the implications of Corollary 1 at Stage 1 of the game. The corollary describes how expected consumption varies with the first and second moments of network access.

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

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

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

Proof. The proof is found in Section A.1.2 (on page A1). □

I interpret Corollary 1 below. First, expected consumption is higher under smoother network access, or low $S^{(2)}_{\ell z}(\boldsymbol{\lambda})$. 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 implies a high draw of another in expectation. Network access volatility thus

acts as a quality measure of a households' transfer partnerships conditional on partners' productivities.

Second, expected consumption is higher when partners' network access is smoother, or when $S^{(2)}_{\ell' z'}(\boldsymbol{\lambda})$ 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. In other words, 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, as dictated by $\text{Cov}\left(S_{\ell' z'}(\boldsymbol{\lambda}), \Phi_\ell\right)$. When a household's income fluctuations "stick out" relative to its partner's partners, or when $\text{Cov}\left(S_{\ell' z'}(\boldsymbol{\lambda}), \Phi_\ell\right)$ is low, the household acts as its partner's hedge, on which the partner is disproportionately reliant. A partner's portfolio of partners, which determines both $S^{(2)}_{\ell' z'}(\boldsymbol{\lambda})$ and $\text{Cov}\left(S_{\ell' z'}(\boldsymbol{\lambda}), \Phi_\ell\right)$, influences the household's expected consumption.

The discussion above makes explicit that—in the presence of spatial correlation in local productivities $\boldsymbol{\Phi}$—expected net transfers increase when households are spatially diversified and are connected to others that are themselves spatially diversified. Section 2.2 shows that households face spatially correlated shocks, which indicates 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.

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

(a) increases in the network productivity ratio $\frac{S^{(1)}_{\ell' z'}(\boldsymbol{\lambda})}{S^{(1)}_{\ell z}(\boldsymbol{\lambda})}$ 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 $\frac{\partial \lambda^*_{\ell z \ell' z'}}{\partial \delta}\Big|_{\mathbf{S}} < 0$ where $|_{\mathbf{S}}$ keeps network access terms fixed, $\frac{\partial \lambda^*_{\ell z \ell' z'}}{\partial \gamma} < 0$, and $\frac{\partial \lambda^*_{\ell z \ell' z'}}{\partial \bar{c}} < 0$,

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

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

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

Proof. The proof is found in Section A.1.3 (on page A3). □

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 average network access between one's partner and oneself $\frac{S^{(1)}_{\ell' z'}(\boldsymbol{\lambda})}{S^{(1)}_{\ell z}(\boldsymbol{\lambda})}$. 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 level 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 $S^{(1)}_{\ell' z'}(\boldsymbol{\lambda})$ 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 $S^{(1)}_{\ell z}(\boldsymbol{\lambda})$ 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 $S^{(2)}_{\ell' z'}(\boldsymbol{\lambda})$, decreases preferred partnership levels. This relationship reflects strategic complementarities: households prefer partners with higher quality networks. On the other hand, one's own noisy network, or large $S^{(2)}_{\ell z}(\boldsymbol{\lambda})$, increases preferred partnership levels. Reflecting 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 $\text{Cov}\left(S_{\ell' z'}(\boldsymbol{\lambda}), \Phi_\ell\right)$ of a household's income with its partner's network access increases preferred partnership levels.

Furthermore, the preferred partnership level increases in the ratio of a partner's and own non-network income determinants $\frac{p^\theta_{\ell'} z' A_{\ell'}}{p^\theta_\ell z A_\ell}$, or the *idiosyncratic productivity ratio*. The idiosyncratic and network productivity ratios both increase preferred partnership levels. This relationship suggests that a partner can compensate for low idiosyncratic productivity by enhancing its network.

Finally, preferred partnership levels depend directly on transfer frictions. Keeping other terms fixed, high transfer frictions $\bar{c}$ and γ increase expected sender transfers. The same is true for the geographic transfer frictions: when more money is retained in transit from sender to receiver, or $\tau_{\ell\ell'}$ is high, the preferred partnership level increases.

As described in Section 3.2.2, a key quantitative challenge in implementing models of strategic network formation is the high-dimensionality of households' best-response functions. Without the distributional assumption of quantities χ and the single-sourcing of transfer inflows, 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. Proposition 1 shows that the dimensionality of the household's private optimization problem is substantially reduced. Instead, a household need only know: (i) the $|\mathcal{H}| \times 1$ vector of network access expectations $S^{(1)}_{\ell' z'}(\boldsymbol{\lambda})$, (ii) the $|\mathcal{H}| \times 1$ vector of network access volatilities $S^{(2)}_{\ell' z'}(\boldsymbol{\lambda})$, and (iii) its $|\mathcal{H}| \times 1$ diversification vector $\text{Cov}\left(S_{\ell' z'}(\boldsymbol{\lambda}), \Phi_\ell\right)$.

3.3.3 Equilibrium Characterization

The previous section solves the household's private optimization problem. Proposition 2 provides a mapping from privately optimal to equilibrium partnerships levels and establishes that a pairwise-stable equilibrium exists.

Proposition 2. *Consider the game described in Section 3.2. The following is true:*

(a) A pairwise-stable equilibrium exists.

(b) Equilibrium partnership levels 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 Section A.1.4 (on page A4). □

In addition to equilibrium existence, Proposition 2 establishes that the equilibrium partnership level in a link is the minimum of each household's desired partnership level with another. A household can separate its equilibrium partnership levels into two qualitative types: (i) *own-constrained* partnerships whose levels are set to their own preferred intensity, for which $\lambda_{\ell z \ell' z'} = \lambda_{\ell' z' \ell z} = \lambda^*_{\ell z \ell' z'}$, and (ii) *others-constrained partnerships* whose levels are set to others' preferred intensity, for which $\lambda_{\ell z \ell' z'} = \lambda_{\ell' z' \ell z} = \lambda^*_{\ell' z' \ell z}$. Consequently, weighted, pairwise-stable equilibria are endogenously symmetric when payoffs to link intensities are continuous and quasi-concave.

How are equilibrium partnerships consistent with Fact 3 of Section 2.2? Suppose the climate shock in location ℓ results in changes to the $\boldsymbol{\Phi}$ distribution: in particular, the expectation of local productivity A_ℓ declines. The two partnership types respond asymmetrically to this productivity change. 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 $\lambda^*_{\ell z \ell' z'}$ of the household increase, while the preferred levels of its partners $\lambda^*_{\ell' z' \ell z}$ decline with respect to the household. Since the household's relationships with more-productive sources are on average constrained by their partners' preferences, Proposition 2 implies that 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 relationships with these partners are on average own-constrained.

3.4 Testable Implications

The model generates within-equilibrium, micro-level implications that can be tested in the NPS. In this section, I summarize these theoretical predictions and their corresponding empirical evidence. Further details are provided in Section C.3.

Test 1. Mobile money has an ambiguous relationship with network density.

Do households prefer to increase partnership levels under mobile money? Though mobile money's positive impact on network density is the main theoretical finding of Jack and Suri (2014)'s seminal paper, strategic network formation complicates the answer.

To see this point, suppose distance-dependent transfer frictions for a location ℓ have declined, while costs in other locations ℓ' have remained constant. From the chain rule, the derivative of a household h's preferred partnership level $\lambda^*_{\ell z \ell' z'}$ in its relationship to h' with respect to $\tau_{\ell' \ell}$ can be written as

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

This derivative can be decomposed into two additive terms: (i) a direct effect, which keeps network access $S^{(1)}_{\ell z}$ constant, and (ii) an indirect effect, which incorporates the impact of changes to network access $S^{(1)}_{\ell z}$.

Through the direct effect, lower costs increase a household's preferred partnership levels, irrespective of sender characteristics. The indirect network effect, however, places a downward pressure on these levels. In particular, reduced transfer frictions increase expected network access, or $\frac{\partial S^{(1)}_{\ell z}}{\partial \tau_{\ell' \ell}} > 0$. Mobile money allows a household to receive payments more easily from its existing set of partners, which increases how much the household values the transfer network, keeping existing links fixed. Through partner substi-

tutability, preferred partnership levels decline when expected network access is high, or $\frac{\partial \lambda^*_{\ell z \ell' z'}}{\partial S^{(1)}_{\ell z}} < 0$. This observation supports recent empirical findings that network density does not change when the ability to form links is positively shocked (Fleischman, 2025).

Empirical Test and Identification Strategy I directly test the impact of mobile money on network density. I use the household's number of distinct transfer sources reported in a year as a measure of network density. Using the demographic *shares* of co-locating villagers in a base-period and national *shifts* in adoption rate for each demographic group, I implement a shift-share instrument for mobile money adoption. I discuss the instrument's construction and satisfaction of the exclusion restriction in Section C.3.1. Reported in Table A13, the IV displays a strong first-stage F-statistic of 65.1.

The OLS and IV results are displayed in Table A14. With the full vector of controls, under the OLS specification, mobile money adoption is associated with an average 0.1 increase in the number of reported transfer sources. This relationship is statistically significant at the 1% confidence level. Under the IV specification, the relationship between mobile money and the number of transfer sources turns negative and falls out of statistical significance. In line with the above discussion, the IV results are consistent with no causal relationship between mobile money and network density.

Test 2. Mobile money causes households to connect with more productive sources.

As in Test 1 above, suppose that when a household h adopts mobile money, transfer frictions for a location ℓ decline, while frictions in other locations ℓ' remain constant. Once again, mobile money reduces the transfer friction $\tau_{\ell'\ell}$ directly, but also positively shocks network access $S^{(1)}_{\ell z}$ conditional on $\boldsymbol{\lambda}$, as households can more easily access payments from its existing connections.

In this case, the model suggests that mobile money *increases* the average productivity $p^{\theta}_{\ell'} z' A_{\ell'}$ of sources. A formal proof of this result can be found in A.1.5. The intuition proceeds as follows. When a household adopts mobile money, from Proposition 1, the technology reduces the household's network productivity ratio, which lowers its own preferred partnership levels with respect to others $\lambda^*_{\ell z \ell' z'}$, but raises others' preferred partnership levels with respect to the household $\lambda^*_{\ell' z' \ell z}$. In equilibrium, the household strengthens its relationship with others-constrained partners (i.e., higher-productivity sources) and weakens its relationship with own-constrained partners (i.e., lower-productivity sources). In other words, the household becomes a more attractive partner through strategic complementarities, and can reduce its dependence on less-

attractive (i.e., less-productive) sources through partner substitutability.

Empirical Test In Section C.3.3, I adapt the identification strategy in Section 3.4 to test this prediction. I proxy for source productivity with the source's years of education and use this variable as an outcome. The OLS and IV results are displayed in Table A15. The instrument remains strong when adding more controls in the different specifications.

In the OLS specification, under the full vector of controls, mobile money is on average associated with an 1.8-year increase in the source's education level. This relationship is statistically significant at the 1% confidence level. In the IV specification, under the full vector of controls, mobile money brings about an average 2.8-year increase in the source's education level, which is statistically significant at the 10% confidence level. The table provides suggestive evidence that mobile money causes households to connect to more productive sources.

Test 3. Transfer distance responds to 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. Summarized below, the theoretical results in Section A.1.5 explore the impacts of such shocks.

The model incorporates two kinds of shocks. First, a *temporary* shock is a low income realization $I_{\ell z}(h)$ 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 a household's non-spatial, idiosyncratic productivity z. This shock causes a household's idiosyncratic productivity ratio to *increase*, which raises the household's preferred partnership levels $\lambda_{\ell z \ell' z'}$ with all others from Proposition 1. From Proposition 2, in equilibrium, own-constrained partnerships, for which $\lambda_{\ell z \ell' z'} = \lambda^*_{\ell z \ell' z'}$, intensify. Meanwhile, others-constrained partnerships, for which $\lambda_{\ell z \ell' z'} = \lambda^*_{\ell' z' \ell z}$, weaken. 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*.

Mirror-image matching frictions generate this asymmetry. A less-productive household faces more difficulties attracting partners under the shock; they see their networks endogenously thin and lose geographically distant sources. Meanwhile, a more-productive household wishes to intensify its partnerships across the board, including with geographically distance sources. Because its partnerships are on average own-constrained, this post-shock change in preferences typically binds.

Empirical Test Notably, one cannot observe whether a household's partnership levels are constrained by their own or others' preferences.[13] To test the implication, I proxy for own-constrained households as those with a head of an above-median education level (i.e., more-productive) and for others-constrained households as those with a head of below-median education level (i.e., less-productive).[14] The median household head's years of education is nine.[15]

The NPS includes a module on negative household shocks, asking questions about 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.

I provide details about this test in Section C.3.4. Empirical results are shown in Table A16 and provide suggestive evidence for the asymmetry in shock response between more- and less-productive households. A coefficient plot of the shock-response for both transfer distance and transfer amounts is shown in Figure A5.

After a persistent, idiosyncratic shock, less-productive households see an average 9.7 km *decline* in their transfer distances, which is statistically significant at the 5% confidence level. More-productive households do not. By contrast, in response to the same shock, more-productive households see transfer amounts *increase* by nearly two-fold, which is statistically significant at the 1% confidence level. Less-productive households do not. A more detailed discussion of post-shock responses, including those to a "placebo" temporary shock, is included in Section C.3.4.

[13] A 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*.

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

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

3.5 Limited Commitment Extension

Cash transfers in developing economies occur informally. In the previous sections, I examine how this informality shapes the relationships that arise in equilibrium, as informal bilateral contracts must be privately optimal ex-ante for both contracting parties. However, I abstract away from the actions households can take after the realization of income shocks, assuming full commitment to agreed-upon contracts. By contrast, much of the existing literature emphasizes the ex-post unenforceability of informal contracts (Coate and Ravallion, 1993; Ligon et al., 2000; Genicot and Ray, 2003; Bold, 2009).

I incorporate limited commitment into this quantitative framework. To do so, I take the static setting described in Section 3.2 as the stage game of an infinitely repeated game. I assume that, in addition to the ex-ante determination of partnership levels, households can take ex-post actions governed by a "grim-trigger" strategy: the household h can either honor or renege on its payments to its partner h'. If the household h reneges, then h' severs ties to h—i.e., setting $\lambda_{\ell' z' \ell z} = 0$—for the foreseeable future. In response, it is optimal for the household h to sever its relationship to h'—i.e., $\lambda_{\ell z \ell' z'} = 0$.

Let β be a temporal discount factor. Under the network $\boldsymbol{\lambda}$, I denote the dynamic payoffs of a household h as $\mathcal{V}_h(\boldsymbol{\lambda}) = \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t C_{\ell z}(h|\boldsymbol{\lambda})\right]$, where the expectation is taken over realizations of spatial shock $\boldsymbol{\Phi}$. Furthermore, denote as $\boldsymbol{\lambda} \setminus (\ell, z, \ell', z')$ the matrix of partnerships when $\lambda_{\ell z \ell' z'}$ and $\lambda_{\ell' z' \ell z}$ are set to zero but all others are the same as $\boldsymbol{\lambda}$. For the 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'.[16] The household h defects if

$$I_{\ell z}(h) > \frac{\beta\left[\mathcal{V}_h(\boldsymbol{\lambda}) - \mathcal{V}_h(\boldsymbol{\lambda} \setminus (\ell, z, \ell', z'))\right] + \mathcal{F}}{\kappa_{\ell z \ell' z'} \lambda_{\ell z \ell' z'}} \equiv \bar{I}_{\ell z \ell' z'}. \tag{15}$$

Equation (15) is the incentive compatibility constraint, which dictates the upper bound of h's income realization $\bar{I}_{\ell z \ell' z'}$ for which h' can expect h not to deviate in its requests.

The following sequence of actions occurs. First, after observing the income draws of others, a household chooses to request a payment from the partner in its network with the highest recipient transfer draw, as dictated by the contracted partnerships $\boldsymbol{\lambda}$. This decision is the same as the baseline. 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

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

incentive-compatible for its partner and bears the risk that the partner refuses to pay. The upper bounds $\overline{\boldsymbol{I}}$ effectively act as a partner's private information over which the household cannot optimize.[17]

The adjusted recipient transfers of a household in location ℓ with productivity z is

$$R^{+}_{\ell z}(\boldsymbol{\lambda}) = \sum_{h' \in \mathcal{H}} \tau_{\ell' \ell} \lambda_{\ell' z' \ell z} I_{\ell' z'}\left(h'\right) \mathbf{1}\left(h' = \arg\max_{h'' \in \mathcal{H}} \tau_{\ell'' \ell} \lambda_{\ell'' z'' \ell z} I_{\ell'' z''}\left(h''\right)\right) \mathbf{1}\left(I_{\ell' z'}\left(h'\right) \leq \overline{I}_{\ell' z' \ell z}\right). \quad (16)$$

The corresponding sender transfer is

$$R^{-}_{\ell z}(\boldsymbol{\lambda}) = \sum_{h' \in \mathcal{H}} \kappa_{\ell z \ell' z'} \lambda_{\ell z \ell' z'} I_{\ell z}\left(h\right) \mathbf{1}\left(h' = \arg\max_{h'' \in \mathcal{H}} \tau_{\ell'' \ell} \lambda_{\ell'' z'' \ell z} I_{\ell'' z''}\left(h''\right)\right) \mathbf{1}\left(I_{\ell z}\left(h\right) \leq \overline{I}_{\ell z \ell' z'}\right). \quad (17)$$

Derived in Section A.1.6, the upper bounds $\overline{\boldsymbol{I}}$ compose a fixed point. Embedded in the variable $\overline{I}_{\ell z \ell' z'}$, the household h's marginal valuation of its relationship with partner h' hinges on the partner h''s marginal valuation of h, embedded in $\overline{I}_{\ell' z' \ell z}$. This fixed point formalizes a notion of reciprocity in relationships: as a household, I value my partners in part because they value me.

To close this extension, I define a *limited commitment pairwise-stable equilibrium* as two matrices of partnerships $\boldsymbol{\lambda}$ and upper bounds $\overline{\boldsymbol{I}}$, such that: (i) given upper bounds $\overline{\boldsymbol{I}}$, partnerships $\boldsymbol{\lambda}$ are pairwise-stable with respect to the payoffs $\boldsymbol{\mathcal{V}}$, and (ii) given partnerships $\boldsymbol{\lambda}$, upper bounds $\overline{\boldsymbol{I}}$ satisfy Equation (15). Quantitative results are described in Section B.4.

4 Quantitative Exercise

In this section, I quantify the model presented in Section 3. I discuss how the model is calibrated in Section 4.1 and present results in Section 4.2.

4.1 Model Calibration

I calibrate the model in four steps. Parameter values are listed in Table 2. 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, I use the model-implied relationship between real income and household characteristics to obtain productivity estimates. Third, I internally calibrate the distance discount δ, transfer friction convexity γ, capacity parameter $\overline{\lambda}$, and altruism parameter $\underline{\lambda}$ to match relevant moments in the aggregated transfer shares.

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

Table 2: Parameter List

Parameter		Value	Source	Moment	Target	Model
Estimation						
Fréchet shape	θ	2.780	NPS			
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	$\bar{c}$	0.086	Annan et al. (2023)			

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 (Annan et al., 2023). Of the countries examined, Tanzania had the largest mobile money cash-out fee, constituting an average of 8.6% of the transaction value. Reflecting this estimate, I set $\bar{c} = 0.086$.

4.1.1 Estimation of θ

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 these shares:

$$\log \widehat{\pi}_{\ell z \ell' z' t} = \theta \log \lambda_{\ell z \ell' z' t} - \theta\delta \log d_{\ell\ell'} + \underbrace{\theta \log p_{\ell t} + \log \Phi_{\ell t} + \log z}_{\ell, z, t \text{ f.e.}} - \underbrace{\log S_{\ell' z' t}}_{\ell', z', t \text{ f.e.}} + \epsilon_{\ell z \ell' z' t}, \tag{18}$$

where $\epsilon_{\ell z \ell' z'}$ is a structural error term and outcome $\widehat{\pi}_{\ell z \ell' z' t}$ is the aggregated transfer share that recipients of type z' in location ℓ' receive from sources of 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 induces a positive correlation between the structural error term $\epsilon_{\ell z \ell' z' t}$ and

realized transfer shares $\log \widehat{\pi}_{\ell z \ell' z' t}$. Therefore, one cannot use Equation (18) to obtain unbiased estimates of parameters θ or δ.

To address this concern, I note that, from Proposition 2, partnership levels $\boldsymbol{\lambda}$ are symmetric and adjust specification (18) by taking the ratio of $\widehat{\pi}_{\ell z \ell' z'}$ to $\widehat{\pi}_{\ell' z' \ell z}$. The adjusted specification is

$$\log\left(\frac{\widehat{\pi}_{\ell z \ell' z' t}}{\widehat{\pi}_{\ell' z' \ell z t}}\right) = \theta \log\left(\frac{p_{\ell t}}{p_{\ell' t}}\right) - \theta\delta \log\left(\frac{d_{\ell\ell'}}{d_{\ell'\ell}}\right) + \gamma_{\ell z t} + \gamma_{\ell' z' t} + \epsilon_{\ell z \ell' z' t}, \tag{19}$$

where $\gamma_{\ell z t}$ and $\gamma_{\ell' z' t}$ are origin-time and destination-time fixed effects. Given credible measures of time-varying, regional prices $\boldsymbol{p}$, one can uncover an unbiased estimate of the Frechét shape parameter θ.[18] This approach yields an estimate of $\theta = 2.78$. The implementation is detailed in Appendix Section C.4.

4.1.2 Estimation of A, Σ, and 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 $\boldsymbol{\Sigma}$, and average household-type productivities $\boldsymbol{z}$.

From Lemma 1, the conditional expectation of real income follows $\mathbb{E}(I_{h\ell}/p_\ell|\boldsymbol{\Phi}) \propto (z_h \Phi_\ell)^{\frac{1}{\theta}}$. Taking logs, I obtain the following regression specification for a household h of productivity z in location ℓ at time t,

$$\log \mathcal{I}_{h\ell z t} = \alpha + \gamma_z + \gamma_{\ell t} + \Gamma' \boldsymbol{\omega}_h + \epsilon_{h\ell z t}, \tag{20}$$

where $\log \mathcal{I}$ is the real income of a household h, γ_z are fixed effects for productivity 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 $\epsilon_{h\ell z t}$ is a normally distributed structural error term. 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 C.4.

The estimated fixed effects $\widehat{\gamma}_z$ and $\widehat{\gamma}_{\ell t}$ map onto $\frac{1}{\theta}\log z_h$ and realizations of stochastic $\frac{1}{\theta}\log \Phi_\ell$, respectively. With this understanding, I estimate entries of the local productivity vector as $\widehat{A}_\ell = \frac{1}{T}\sum_t \exp\left(\theta \widehat{\gamma}_{\ell t}\right)$, where T is the number of interview years represented in the NPS. An entry of the variance-covariance matrix can be estimated as

[18] Note that if transfer frictions $\boldsymbol{\tau}$ are systematically asymmetric—due to, for instance, traffic patterns—one can also use this specification to uncover an unbiased estimate of the distance discount δ.

$\widehat{\sigma}_{\ell\ell'} = \frac{1}{T}\sum_t \left(\exp\left(\theta\widehat{\gamma}_{\ell t}\right) - \widehat{A}_\ell\right)\left(\exp\left(\theta\widehat{\gamma}_{\ell' t}\right) - \widehat{A}_{\ell'}\right)$. Likewise, household productivity can be estimated as $\widehat{z} = \exp\left(\theta\widehat{\gamma}_z\right)$.

4.1.3 Calibration of Other Parameters

I calibrate the distance discount δ, transfer friction convexity γ, capacity parameter $\overline{\lambda}$, 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—referred to as δ_0—during the survey period. I measure the spatial concentration of transfer sources by constructing a Herfindahl index of cross-regional transfer shares. For households in location ℓ of productivity z, the across-region (spatial) transfer source Herfindahl index is $\sum_{\ell'}\left(\sum_{z'}\widehat{\pi}_{\ell' z'\ell z}\right)^2$. 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, where smaller values result in greater cross-regional shares.

Similarly, I measure the local concentration of transfer sources by constructing a Herfindahl index of across-type transfer shares within a region, which pins down transfer friction convexity γ. For a household in location ℓ of productivity z, this measure is $\sum_{z'}\widehat{\pi}^2_{\ell z'\ell z}$. 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 calibrated distance discount δ_0 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 $\overline{\lambda}$ with the average of own-type transfer shares. For a household in location ℓ of productivity z, this is $\pi_{\ell z\ell z} = \left(\overline{\lambda}p_\ell\right)^\theta z\Phi_\ell S_{\ell z}^{-1}$, which arises from adapting Equation (11).

Fourth, I use the across-type average of median transfer amounts as a proportion of income to calibrate the altruism parameter $\underline{\lambda}$. 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 λ realized in equilibrium, which raises transfer inflows.

4.1.4 Multiple Equilibria

The network payment game yields multiple pairwise-stable equilibria, a fundamental characteristic of network formation models with strategic complementarities (Jackson and Zenou, 2015; Herings and Zhan, 2024). However, the equilibrium one ultimately arrives at can be fully characterized by: (i) the initial network, and (ii) the sequence over which pairs best-respond to the existing network, given by Propositions 1 and 2.[19]

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 household pairs. Using these inputs, I calculate the respective pairwise-stable equilibrium. This approach amounts to following different draws of "improving paths" in Jackson and Watts (2001). 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. The algorithm is described in Section B.1.

4.2 Results

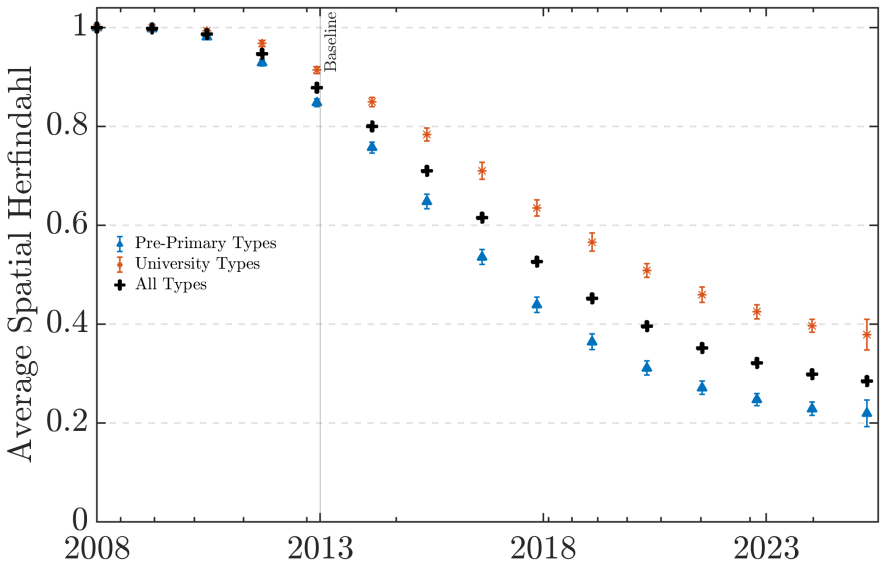
I use the calibration to consider changes in economic outcomes as transfer frictions decline. Figure 5 shows the spatial Herfindahl as δ lowers.[20] The post–mobile-money period in Tanzania coincided with the spatial diversification of transfer sources. By construction, the model quantitatively matches this trend.

I refer to 2008 as the base year, for which the associated δ_{2008} generates an average spatial Herfindahl close to one. The difference between the base δ_{2008} and calibrated δ_0 pins down the five-year rate of decline in transfer frictions. I use the δ rate of decline to project economic outcomes forward over the next few decades as mobile money diffuses.

[19] This observation arises from an examination of techniques to establish the existence of pairwise-stable equilibria, which often hinge on well-behaved characteristics of *improving paths*. Such paths 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.

[20] 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 5: 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. Productivity groups are pre-primary, primary, secondary, and university educated household heads. Pre-primary types on average have more spatially diversified transfer sources than university types. Quantitatively-generated 95% confidence intervals are displayed for the spatial Herfindahl estimates of pre-primary and university types.

4.2.1 Network-Based Consumption Risk

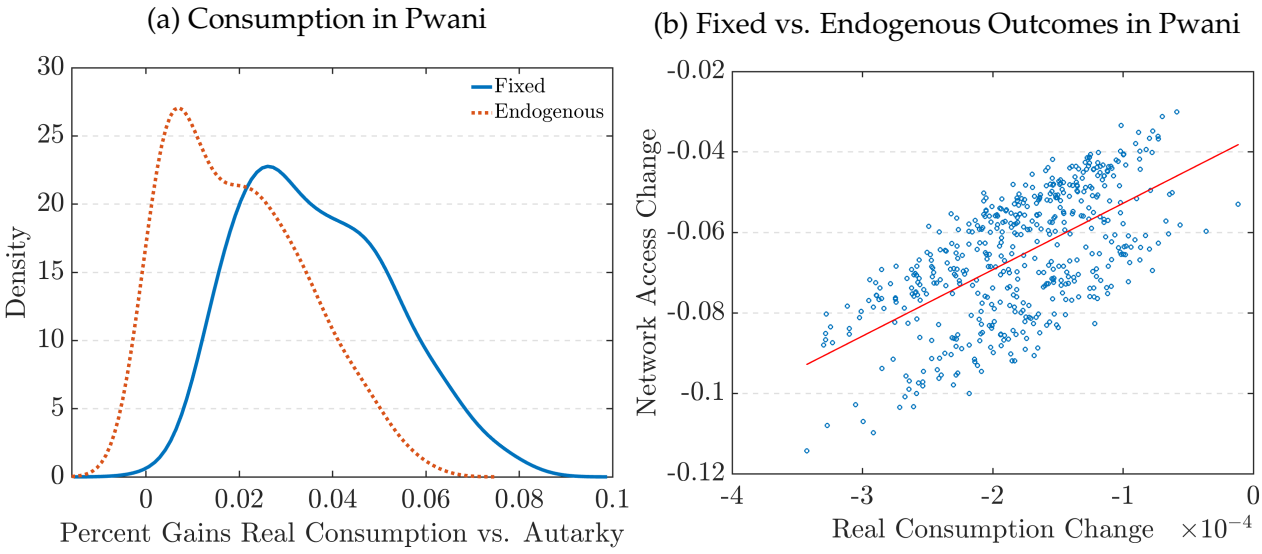
In this section, I examine how transfers flow in response to isolated regional shocks under fixed and endogenous networks. Network reorganization systematically alters the post-shock distribution of consumption and is thus itself a source of consumption risk.

I consider the real consumption of households in location ℓ under local productivity realizations $\mathbf{\Phi}$. Let $\boldsymbol{\lambda}\left(\boldsymbol{A}, \mathbf{\Sigma}\right)$ be the equilibrium network of partnerships formed under the expectations vector $\boldsymbol{A}$ and the variance-covariance matrix $\mathbf{\Sigma}$. When networks are *fixed*, consumption is $\overline{\boldsymbol{C}}\left(\boldsymbol{\lambda}\left(\boldsymbol{A}, \mathbf{\Sigma}\right), \mathbf{\Phi}\right)$. This expression incorporates transfers determined by partnerships $\boldsymbol{\lambda}$ formed under the belief that local shocks realize $\boldsymbol{A}$ in expectation. When networks are *endogenous*, consumption is $\overline{\boldsymbol{C}}\left(\boldsymbol{\lambda}\left(\mathbf{\Phi}, \mathbf{\Sigma}\right), \mathbf{\Phi}\right)$. This expression incorporates equilibrium transfers when households adjust the network to reflect the realized local productivity $\mathbf{\Phi}$.

Net-Receivers After Shocks I estimate Pwani to have the lowest average regional productivity in Tanzania. Suppose Pwani experiences a local productivity Φ_ℓ that is 40% lower than its expectation A_ℓ. In the left panel of Figure 6, I consider the kernel density of post-shock real consumption gains relative to autarky under the network in Pwani.[21] On

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

Figure 6: Outcomes in a Net-Receiver Region After An 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 shock. Under the 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-network post-shock consumption and losses in network access $\overline{S}_\ell = \sum z \Omega_{\ell z} \overline{S}_{\ell z}$ for Pwani households.

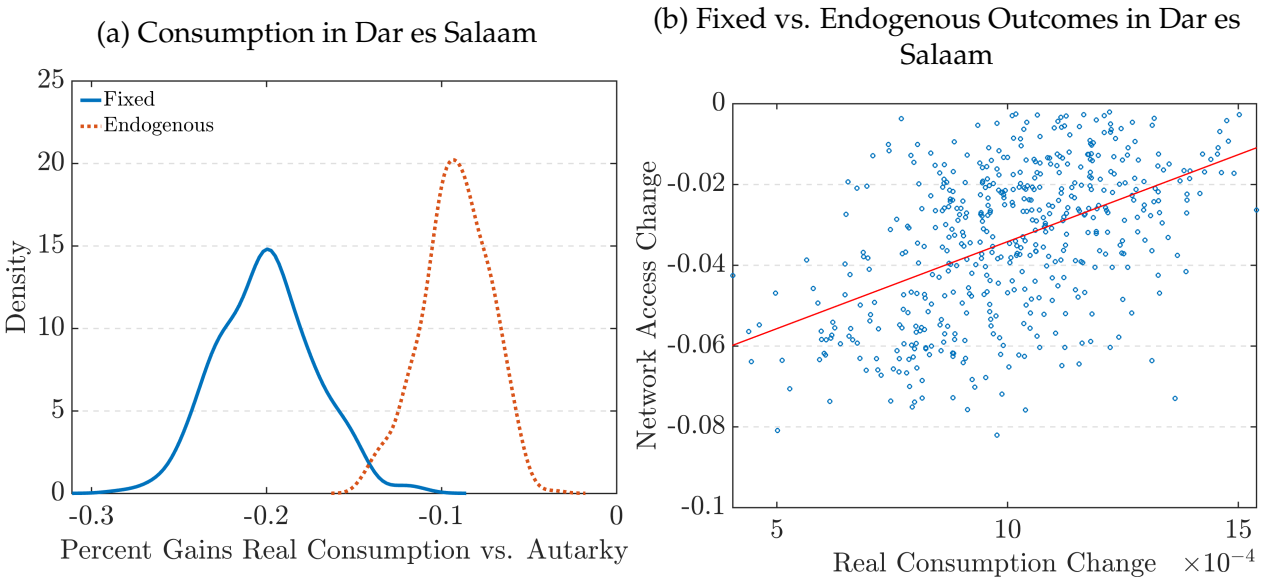
the right panel, I compare the changes in real consumption under endogenous vs. fixed networks against changes in network access.

Figure 6 yields three insights. First, households in Pwani consume more under the network than in autarky, indicating that they receive more transfers than they pay out. Second, the distribution of consumption under the fixed network stochastically dominates that under the endogenous network. This pattern suggests that network reorganization after shocks mitigates the insurance benefits from transfers for net-receivers. Third, losses in network access correlate strongly with real consumption losses. After networks reorganize in response to the shock, households lose access to high-productivity partners, which lowers the transfer amounts they receive.

Net-Givers After Shocks In Figure 7, I consider an isolated shock to Dar Es Salaam, the economic capital of Tanzania. Unlike in Pwani, households in Dar Es Salaam consume less under the network than in autarky, giving out more transfers than they receive. In this case, the distribution of real consumption under the endogenous network stochastically dominates that under the fixed network. The network reorganizes 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 weak. The weakened correlation reflects that households in

Figure 7: Outcomes in a Net-Giver Region After An Isolated Shock



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

Dar es Salaam improve their consumption in part by reducing their obligations to send transfers.

4.2.2 Welfare Under Mobile Money

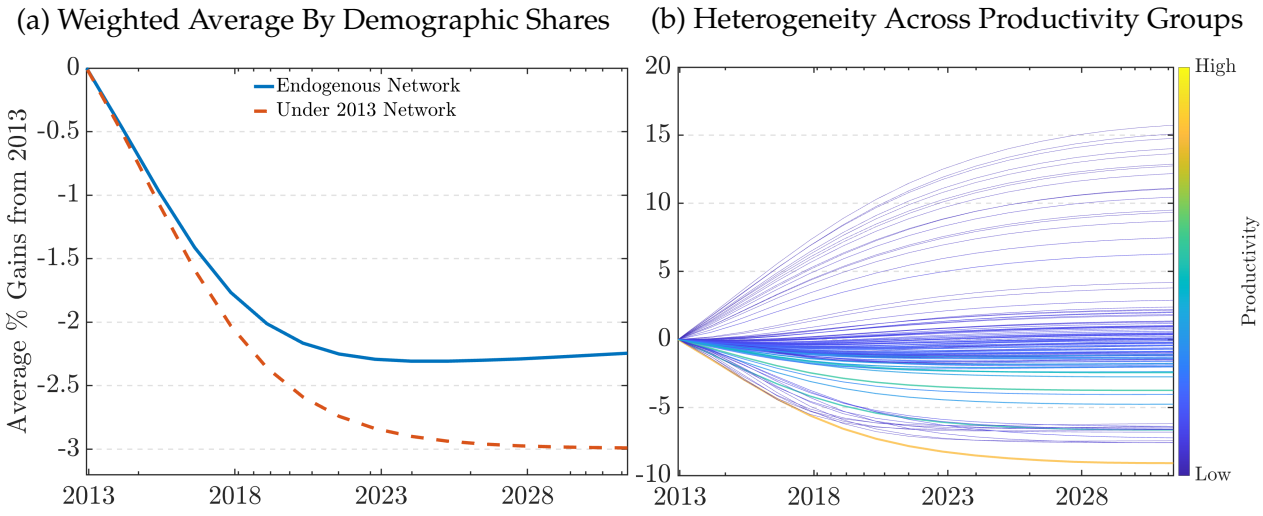
The previous exercise considers real consumption in response to specific spatial shock $\boldsymbol{\Phi}$ realizations. However, the vector $\boldsymbol{\Phi}$ may realize infinitely many possibilities. I consider a household's expected real consumption $\mathbb{E}\left[C_{\ell z}\left(\boldsymbol{\lambda}, \boldsymbol{\Phi}\right)\right]$ as a measure of welfare and quantify its evolution along the diffusion path of mobile money. I aggregate according to demographic shares $\boldsymbol{\Omega}$.

Welfare Over Time I plot the evolution of real consumption in Figure 8 from 2013 to 2028. I decompose the trend at time t relative to the calibrated 2013 "base" period t_0 as

$$\mathbb{E}(\boldsymbol{C}_t) - \mathbb{E}(\boldsymbol{C}_0) = \underbrace{\mathbb{E}\Big(\boldsymbol{C}(\boldsymbol{\lambda}_t, \delta_t)\Big) - \mathbb{E}\Big(\boldsymbol{C}(\boldsymbol{\lambda}_0, \delta_t)\Big)}_{\text{Indirect (Network) Effect}} + \underbrace{\mathbb{E}\Big(\boldsymbol{C}(\boldsymbol{\lambda}_0, \delta_t)\Big) - \mathbb{E}\Big(\boldsymbol{C}(\boldsymbol{\lambda}_0, \delta_0)\Big)}_{\text{Direct Effect}}, \quad (21)$$

where $\boldsymbol{C}_t$ is the equilibrium consumption at time t and $\boldsymbol{\lambda}_t$ is the equilibrium network at time t. The direct effect considers changes in average real consumption when the network

Figure 8: Expected Real Consumption After Mobile Money Relative to 2013 Baseline



Note: The left figure considers average welfare gains, weighted by demographic shares, as the distance discount δ declines. I 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.

is "fixed" at its 2013 level but transfer frictions decline from δ_0 to δ_t. The indirect effect considers the additional impact of endogenous network changes from $\boldsymbol{\lambda}_0$ to $\boldsymbol{\lambda}_t$.

Shown in Figure 8a, mobile money results in average consumption losses when aggregating by the NPS demographic shares $\boldsymbol{\Omega}$, indicating that the average household sends out more transfers than it receives. By 2028, average consumption declines by 2.3% relative to its 2013 level. If networks were fixed to their 2013 level, average losses from mobile money would be 3.0%. Network reorganization therefore reduces this loss by roughly a quarter. Figure A1 shows that the sign and magnitude of this effect are robust to alternative network initializations.

Figure 8b maps consumption gains for each household type along mobile money's diffusion path. The figure offers two insights for interpreting the left panel. First, the average value conceals substantial heterogeneity across households: university-educated households in Dar es Salaam experience consumption losses of 9.3% by 2028 relative to 2013, while non-educated households in Kilimanjaro *gain* 15.6%. Second, the impact of mobile money is progressive, increasing the consumption of lower-productivity households at the expense of higher-productivity counterparts. This progressivity is highlighted in Figure A3. The average losses reported in Figure 8a are entirely attributable to the high demographic weight placed on households in Dar es Salaam.

The counterfactual paths correspond to empirical estimates found in the literature. Jack and Suri (2011) report that M-Pesa users on average sent 4.8% of their consump-

tion while receiving only 2.9%, such that transfer outflows net to 1.9% of consumption. As they aimed to assemble a nationally representative sample, their estimate serves as a close empirical counterpart to Figure 8a. Batista and Vicente (2025) examine the impacts of mobile money in a randomized control trial among rural households in Mozambique. They find that mobile money increases subjective welfare by 5.4% within years after treatment, which corresponds to the upper bound of welfare gains by 2018 in Figure 8b.

Insurance and Redistribution What do such changes in welfare imply for insurance? In this exercise, I consider household consumption under the transfer network relative to autarky, termed *network gains*. By construction, these gains are positive and can be decomposed as

$$\frac{\mathbb{E}\left(C_{\ell z}\left(\mathbf{\Phi}\right)\right)-\mathbb{E}\left(I_{\ell z}\left(\mathbf{\Phi}_{\ell}\right)\right)}{\mathbb{E}\left(I_{\ell z}\left(\mathbf{\Phi}_{\ell}\right)\right)}=\underbrace{\frac{C_{\ell z}\left(\mathbb{E}\left(\mathbf{\Phi}\right)\right)-\mathbb{E}\left(I_{\ell z}\left(\mathbf{\Phi}\right)\right)}{\mathbb{E}\left(I_{\ell z}\left(\mathbf{\Phi}\right)\right)}}_{\text{Redistribution}}+\underbrace{\frac{\mathbb{E}\left(C_{\ell z}\left(\mathbf{\Phi}\right)\right)-C_{\ell z}\left(\mathbb{E}\left(\mathbf{\Phi}\right)\right)}{\mathbb{E}\left(I_{\ell z}\left(\mathbf{\Phi}\right)\right)}}_{\text{Insurance}}. \tag{22}$$

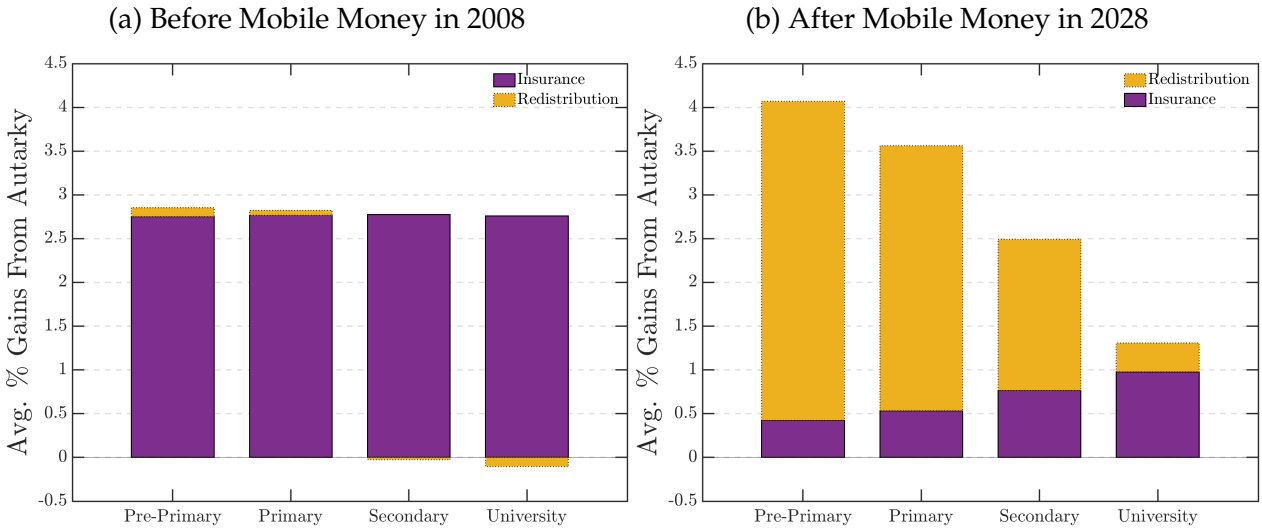
Note that, from the results of Lemma 1, expected consumption is non-linear in the spatial shock realization $\mathbf{\Phi}$. *Insurance* measures the network gains that are attributable to this non-linearity, which shapes the link between households' expected consumption and noise in stochastic network access. By contrast, *redistribution* examines consumption that would occur if spatial shocks realized their expectation.

I examine network gains in 2008 and 2028 in Figure 9. In 2008, these gains stem almost entirely from insurance, and there is no clear progressive pattern across productivity groups. Across groups, average gains hover around 2.8%. "Risk-sharing" is an accurate description of transfer network activities at this time.

By 2028, however, the network serves a qualitatively different function. First, the progressive pattern emerges: non-educated types see average network gains of 4.1%, tripling those of university types. Second, the redistribution component has increased at the expense of insurance. 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. Robustness of these patterns to alternative network initializations is shown in Figure A2.

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. As evidenced by *regressive* insurance benefits in equilibrium, more-productive types enter partnerships primarily for insurance; they weaken

Figure 9: Insurance vs. Redistribution Decomposition of Network Gains



Note: This figure displays expected consumption games under the network over autarky and performs the decomposition of Equation (22) and shows unweighted, across-location results by productivity groups.

connections whose redistributive costs now outweigh the insurance benefit. Meanwhile, less-productive types form partnerships that are now profitable in expectation. While the technology is welfare-improving for poor households, it does not facilitate their ability to smooth against spatially correlated income risk.

5 Conclusion

Since Townsend (1994), a long literature on informal transfer networks in developing countries has centered on one question: is informal insurance enough to shield the most vulnerable households from income risk? In this paper, I argue that endogenous network adjustment is a key feature of informal transfer partnerships and quantify its impacts on household consumption, transfers, and welfare. By introducing strategic network formation into a quantitative spatial model of transfer partnerships, the paper provides two new reasons why informal insurance remains incomplete. First, network reorganization itself is a source of consumption risk for poor households, as their partnerships display particular fragility to persistent, negative shocks. Second, although new digital payment technologies generate progressive welfare gains, they may actually reduce the amount of insurance transfer networks can provide. The effectiveness of informal networks in providing insurance ultimately depends not only on the cost of sending transfers, but also on how households reorganize their relationships when economic conditions change.

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Appendix

A Theoretical Appendix

A.1 Proofs and Derivations

A.1.1 Proof of Lemma 1

Following Eaton and Kortum (2002), from Equation (2) and the definition of $I_{\ell z}(h) = p_\ell \chi_{\ell z}(h)$, income draws have a c.d.f. of

$$\Pr\left(I_{\ell z}(h|\mathbf{\Phi}) \leq \mathcal{I}\right) = \exp\left(-\left(\mathcal{I}/p_\ell\right)^{-\theta} z\Phi_\ell\right).$$

Income $I_{\ell z}(h)$ is also Fréchet-distributed. Next, from the definition in Equation (5), the distribution of transfer inflows is

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

This follows a Fréchet c.d.f. with a shape parameter θ and scale parameter $S_{\ell z}(\boldsymbol{\lambda},\mathbf{\Phi})^{1/\theta}$.

The normalized transfer outflow distribution $\widetilde{R}^-_{\ell z}(h)$ arises from the probability that a source of type (ℓ', z') has the largest income draw among other candidates. From standard calculations,

$$\begin{aligned}\pi_{\ell z \ell' z'}(\boldsymbol{\lambda},\mathbf{\Phi}) &\equiv \Pr\left(h' = \arg\max_{h''\in\mathcal{H}} \lambda_{\ell'' z'' \ell z}\tau_{\ell''\ell} I_{\ell'' z''}(h'')\right) \\ &= \frac{(\lambda_{\ell' z' \ell z}\tau_{\ell'\ell}p_{\ell'})^\theta z\Phi_\ell}{\sum_{\ell'',z''}(\lambda_{\ell'' z'' \ell z}\tau_{\ell''\ell}p_{\ell''})^\theta z''\Phi_{\ell''}}.\end{aligned}$$

A.1.2 Proof of Corollary 1

From the Fréchet distribution and the law of iterated expectations, the expected recipient transfer is

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

A second-order Taylor expansion around $S^{(1)}_{\ell z}(\boldsymbol{\lambda})$ defined in Equation (9) yields

$$\frac{\mathbb{E}\left[S_{\ell z}(\boldsymbol{\lambda}|\boldsymbol{\Phi})^{1/\theta}\right]}{\left(S^{(1)}_{\ell z}(\boldsymbol{\lambda})\right)^{1/\theta}} \approx \underbrace{\left(1-\frac{\theta-1}{2\theta}\frac{S^{(2)}_{\ell z}(\boldsymbol{\lambda})}{\left(S^{(1)}_{\ell z}(\boldsymbol{\lambda})\right)^{2}}\right)}_{\text{Inflow Risk Adjustment} \equiv \varphi^{+}_{\ell z}(\boldsymbol{\lambda})<1},$$

where the volatility $S^{(2)}_{\ell z}(\boldsymbol{\lambda})$ is defined in Equation (10) and $\varphi^{+}_{\ell z}(\boldsymbol{\lambda})$ is a multiplicative risk-adjustment term on transfer inflows that never exceeds one when $\theta > 1$. This implies that

$$\frac{\partial \mathbb{E}\left[R^{+}_{\ell z}(\boldsymbol{\lambda})\right]}{\partial S^{(1)}_{\ell z}(\boldsymbol{\lambda})} > 0, \quad \frac{\partial^2 \mathbb{E}[R^{+}_{\ell z}(\boldsymbol{\lambda})]}{\partial\left(S^{(1)}_{\ell z}(\boldsymbol{\lambda})\right)^{2}} < 0$$

for $\theta > 1$. Therefore, expected inflows are increasing and concave in mean network access $S^{(1)}_{\ell z}(\boldsymbol{\lambda})$, while higher volatility $S^{(2)}_{\ell z}(\boldsymbol{\lambda})$ lowers them.

For transfer outflows, note that, by definition, $R^{-}_{\ell z}(\boldsymbol{\lambda}) = \widetilde{R}^{-}_{\ell z}(\boldsymbol{\lambda}) I_{\ell z}$. The law of iterated expectations implies that

$$\begin{aligned}\mathbb{E}\left[R^{-}_{\ell z}(\boldsymbol{\lambda})\right] &= \mathbb{E}\left(I_{\ell z}(h)\sum_{h'\in\mathcal{H}}\kappa_{\ell z \ell' z'}\lambda_{\ell z \ell' z'}\Pr\left(h = \arg\max_{h'\in\mathcal{H}}\lambda_{\ell'' z'' \ell' z'}\tau_{\ell'' \ell'} I_{\ell'' z''}(h'')|\boldsymbol{\Phi}, I_{\ell z}(h'')\right)\right) \\ &= \Gamma(1-1/\theta)\sum_{\ell', z'}\kappa_{\ell z \ell' z'}\lambda^{\theta}_{\ell z \ell' z'}\tau^{\theta-1}_{\ell \ell'}p^{\theta}_{\ell} z \mathbb{E}\left[\Phi_{\ell} S_{\ell' z'}(\boldsymbol{\lambda}|\boldsymbol{\Phi})^{1/\theta-1}\right],\end{aligned}$$

where the second equality arises from applying the income distribution of Lemma 1. Approximating with a second-order Taylor expansion around $\boldsymbol{A} = \mathbb{E}(\boldsymbol{\Phi})$, one obtains an outflow risk adjustment term

$$\frac{\mathbb{E}\left[\boldsymbol{\Phi}_{\ell} S_{\ell' z'}(\boldsymbol{\lambda}|\boldsymbol{\Phi})^{1/\theta-1}\right]}{A_{\ell}\left(S^{(1)}_{\ell' z'}(\boldsymbol{\lambda})\right)^{1/\theta-1}} \approx \underbrace{1+\frac{(1-\theta)(1-2\theta)}{2\theta^2}\frac{S^{(2)}_{\ell' z'}(\boldsymbol{\lambda})}{\left(S^{(1)}_{\ell' z'}(\boldsymbol{\lambda})\right)^{2}}+\frac{1-\theta}{\theta}\frac{\mathrm{Cov}(S_{\ell' z'}(\boldsymbol{\lambda}), \boldsymbol{\Phi})}{S^{(1)}_{\ell' z'}A_{\ell}}}_{\text{Outflow Risk Adjustment} \equiv \varphi^{-}_{\ell z \ell' z'}(\boldsymbol{\lambda})}.$$

From here, one arrives at the comparative statics that

$$\frac{\partial \mathbb{E}\left(R^{-}_{\ell z}(\boldsymbol{\lambda})\right)}{\partial S^{(1)}_{\ell' z'}(\boldsymbol{\lambda})} < 0, \quad \frac{\partial \mathbb{E}\left(R^{-}_{\ell z}(\boldsymbol{\lambda})\right)}{\partial S^{(2)}_{\ell' z'}(\boldsymbol{\lambda})} > 0, \quad \frac{\partial \mathbb{E}\left(R^{-}_{\ell z}(\boldsymbol{\lambda})\right)}{\partial \mathrm{Cov}\left(S_{\ell' z'}(\boldsymbol{\lambda}), \Phi_{\ell}\right)} < 0.$$

A.1.3 Proof of Proposition 1

Consider the preferred partnership level $\lambda^*_{\ell z \ell' z'}$ of a household of type (ℓ, z) in its relationships with another of type (ℓ', z'). This level solves

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

Assume, for simplicity, that households do not consider how altering $\lambda_{\ell z \ell' z'}$ changes inflow and outflow risk adjustment terms, respectively $\varphi^+_{\ell z}(\boldsymbol{\lambda})$ and $\varphi^-_{\ell z \ell' z'}(\boldsymbol{\lambda})$. The resulting Lagrangian is

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

The first-order condition with respect to $\lambda_{\ell z \ell' z'}$ is

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

The complementary slackness conditions are

$$\Lambda\left(1 - \bar{\lambda} - \sum_{\ell'', z''} \kappa_{\ell z \ell'' z''} \lambda_{\ell z \ell'' z''}\right) = 0, \quad \Xi\left(\sum_{\ell'', z''} \kappa_{\ell z \ell'' z''} \lambda_{\ell z \ell'' z''} - \underline{\lambda}\right) = 0,$$

where $\Lambda = 0$ or $\Xi = 0$ if the feasibility or altruism requirements do not bind, respectively.

I solve for the weight $\lambda_{\ell z \ell' z'}$ for which $\frac{\partial \mathcal{L}}{\partial \lambda_{\ell z \ell' z'}} = 0$, which corresponds to a local maximum if $\mathbb{E}\left[C_{\ell z}(\lambda \cup \boldsymbol{\lambda}_{-\ell z \ell' z'})\right]$ is quasi-concave in λ, shown in Section A.1.4. To do so, note that

$$\frac{\partial \mathbb{E}\left[R^+_{\ell z}(\boldsymbol{\lambda})\right]}{\partial \lambda_{\ell z \ell' z'}} \propto \varphi^+_{\ell z}(\boldsymbol{\lambda})\left(S^{(1)}_{\ell z}(\boldsymbol{\lambda})\right)^{1/\theta - 1} \tau^{\theta}_{\ell' \ell} p^{\theta}_{\ell'} z' A_{\ell'} \lambda^{\theta - 1}_{\ell z \ell' z'}$$

and

$$\frac{\partial \mathbb{E}\left[R^-_{\ell z}(\boldsymbol{\lambda})\right]}{\partial \lambda_{\ell z \ell' z'}} \propto \varphi^-_{\ell z \ell' z'}(\boldsymbol{\lambda})\left(S^{(1)}_{\ell z}(\boldsymbol{\lambda})\right)^{1/\theta - 1} \tau^{\theta - 1}_{\ell \ell'} p^{\theta}_{\ell} z A_{\ell} \lambda^{\theta - 1}_{\ell z \ell' z'} \times \left[\theta + \bar{c}(\theta + \gamma)\lambda^{\gamma}_{\ell z \ell' z'} - (\theta - 1)(1 + \bar{c}\lambda^{\gamma}_{\ell z \ell' z'})\pi_{\ell z \ell' z'}(\boldsymbol{\lambda})\right].$$

Solving for $\lambda_{\ell z \ell' z'}$, one uncovers the expression

$$\lambda^*_{\ell z \ell' z'} = \left(\frac{\Theta_{\ell z \ell' z'} - \theta + (\theta - 1)\pi_{\ell z \ell' z'}(\boldsymbol{\lambda})}{\bar{c}\left(\theta + \gamma - (\theta - 1)\pi_{\ell z \ell' z'}(\boldsymbol{\lambda})\right)}\right)^{1/\gamma}, \tag{A1}$$

where

$$\Theta_{\ell z \ell' z'} \equiv \frac{p_{\ell'}^{\theta} z' A_{\ell'}}{p_{\ell}^{\theta} z A_{\ell}} \left(\frac{S_{\ell' z'}^{(1)}(\boldsymbol{\lambda})}{S_{\ell z}^{(1)}(\boldsymbol{\lambda})} \right)^{1-1/\theta} \tau_{\ell \ell'} \frac{\varphi_{\ell z}^{+}(\boldsymbol{\lambda})}{\varphi_{\ell z \ell' z'}^{-}(\boldsymbol{\lambda})}. \tag{A2}$$

This expression is a fixed point in $\lambda_{\ell z \ell' z'}$. The comparative statics follow.

A.1.4 Proof of Proposition 2

Let $x_{\ell z \ell' z'} = \lambda_{\ell z \ell' z'}^{\theta}$. For a household determining $x_{\ell z \ell' z'}$, which is denoted as x without loss of generality for the rest of this section, expected consumption is the sum of a component un-impacted by the values of x, the benefits of raising x

$$V(x) = \mathbb{E}\left[S_{\ell z}(x)^{1/\theta} - \overline{\lambda}^{\theta} p_{\ell}^{\theta} z \Phi_{\ell} S_{\ell z}(x)^{1/\theta - 1} \right], \tag{A3}$$

minus the costs of raising x

$$D(x) = \mathbb{E}\left[\tau_{\ell \ell'}^{\theta - 1} p_{\ell}^{\theta} z \Phi_{\ell} \left(x + \bar{c} x^{1+\frac{\gamma}{\theta}} \right) S_{\ell' z'}(x)^{1/\theta - 1} \right], \tag{A4}$$

where all components are normalized to a constant and expectations are taken over realizations of $\boldsymbol{\Phi}$.

Continuity The terms $S_{\ell z}(x)$ and $S_{\ell' z'}(x)$ are affine and positive in x, and are thus positive in x. The continuity of payoffs $\mathcal{V}(x) = \mathbb{E}\left[C_{\ell z}(x)\right]$ with respect to x follows from the observation that both Equations (A3) and (A4) are continuous in $S_{\ell z}(x)$ and $S_{\ell' z'}(x)$, and that the equation $\mathbb{E}\left[C_{\ell z}(x)\right] = \chi + V(x) - D(x)$ holds, where χ is independent of x.

Quasiconcavity Let $\Pi(x) \equiv V(x) - D(x)$ and $R(x) \equiv \frac{V'(x)}{D'(x)}$, where $\Pi'(x) = D'(x)[R(x) - 1]$. Note that Π is strictly quasi-concave on the interval $X \equiv [\underline{x}, \overline{x}]$ if and only if there is an $x^* \in X$ such that $R(x) > 1$ on $[\underline{x}, x^*)$ and $R(x) < 1$ on $(x^*, \overline{x}]$, or if $R(x)$ crosses one from above at most once. This condition holds if $R(x)$ strictly decreases in x; in this case, the maximizer x^* is unique. Below is a sufficient condition for the quasi-concavity of payoffs with respect to x.

Consider $V'(x) = \left(\tau_{\ell' \ell} p_{\ell'}\right)^{\theta} z' \Phi_{\ell'} \mathbb{E}\left[\frac{1}{\theta} S_{\ell z}(x)^{1/\theta - 1} + \left(1 - \frac{1}{\theta}\right) \overline{\lambda}^{\theta} p_{\ell}^{\theta} z \Phi_{\ell} S_{\ell z}(x)^{1/\theta - 2} \right] > 0$. Denote as $v_1 = \left(\tau_{\ell' \ell} p_{\ell'}\right)^{\theta} z' \Phi_{\ell'} \frac{1}{\theta} S_{\ell z}(x)^{1/\theta - 1}$ and as $v_2 = \left(1 - \frac{1}{\theta}\right) \theta v_1 \pi_{\ell z \ell z}(x)$. The elasticity of the integrand in $\mathbb{E}[.]$ is $\frac{\partial \log(v_1 + v_2)}{\partial \log x} = \frac{1}{1 + (\theta - 1)\pi_{\ell z \ell z}} \frac{\partial \log v_1}{\partial \log x} + \frac{(\theta - 1)\pi_{\ell z \ell z}}{1 + (\theta - 1)\pi_{\ell z \ell z}} \frac{\partial \log v_2}{\partial \log x}$, which is greater than $\min\left\{ \frac{\partial \log v_1}{\partial \log x}, \frac{\partial \log v_2}{\partial \log x} \right\} = \left(\frac{1}{\theta} - 1\right) \pi_{\ell' z' \ell z}(x) < 0$. Therefore, for all possible realizations $\boldsymbol{\Phi}$, $\frac{\partial (v_1 + v_2)}{\partial x} < \left(\frac{1}{\theta} - 1\right) \inf_{\boldsymbol{\Phi}} \left\{ \left(\tau_{\ell' \ell} p_{\ell'}\right)^{\theta} z' \Phi_{\ell'} \right\} (v_1 + v_2)$, which implies that

$\mathbb{E}\left[\frac{\partial(v_1+v_2)}{\partial x}\right] < \left(\frac{1}{\theta}-1\right)\inf_{\mathbf{\Phi}}\left\{(\tau_{\ell'\ell}p_{\ell'})^{\theta}z'\Phi_{\ell'}\right\}\cdot V'(x)$. By the dominated convergence theorem, $\frac{\partial V'(x)}{\partial x} < 0$, so $V(x)$ is positive and concave.

Next, consider $D'(x) = \tau_{\ell\ell'}^{\theta-1}p_{\ell}^{\theta}z\Phi_{\ell}\mathbb{E}\left[S_{\ell'z'}(x)^{1/\theta-1}N(x)\right] > 0$, where one defines the function $N(x) \equiv 1-\left(1-\frac{1}{\theta}\right)\pi_{\ell z\ell'z'}(x)+\bar{c}x^{\gamma/\theta}\left[1+\frac{\gamma}{\theta}-(1-\frac{1}{\theta})\pi_{\ell z\ell'z'}(x)\right]$. The elasticity $\varepsilon_N(x)$ of the function $N(x)$ to x is

$$\varepsilon_N(x) = \frac{\bar{c}(1+\gamma/\theta)x^{\gamma/\theta}}{N(x)}\left[\gamma/\theta-(1-1/\theta)\,\pi_{\ell z\ell'z'}(x)\right] > 0.$$

Denote the integrand in $\mathbb{E}[.]$ as $d = \tau_{\ell\ell'}^{\theta-1}p_{\ell}^{\theta}z\Phi_{\ell}S_{\ell'z'}(x)^{1/\theta-1}N(x)$. The elasticity of the integrand is $\frac{\partial\log d}{\partial\log x} > \left(\frac{1}{\theta}-1\right)\pi_{\ell z\ell'z'}(x)+\varepsilon_N(x)$. Therefore, for all possible realizations of $\mathbf{\Phi}$, $\frac{\partial d}{\partial x} = \left[\left(\frac{1}{\theta}-1\right)(\tau_{\ell\ell'}p_{\ell})^{\theta}z\Phi_{\ell}+\frac{\varepsilon_N(x)}{x}\right]d > \left(\frac{1}{\theta}-1\right)\inf_{\mathbf{\Phi}}\left\{(\tau_{\ell\ell'}p_{\ell})^{\theta}z\Phi_{\ell}\right\}d$, which implies that $\mathbb{E}\left[\frac{\partial d}{\partial x}\right] > \left(\frac{1}{\theta}-1\right)\inf_{\mathbf{\Phi}}\left\{(\tau_{\ell\ell'}p_{\ell})^{\theta}z\Phi_{\ell}\right\}\cdot D'(x)$. By the dominated convergence theorem, $\frac{\partial D'(x)}{\partial x} > 0$, and is thus positive and convex.

The term in question $R(x)$ is the ratio of the positive and decreasing function $V'(x)$ to the positive and increasing function $D'(x)$. Thus, $R'(x) < 0$. It remains to be shown that $R'(x) > 1$ when $x \to^R \underline{x}$. Point by point, for each $\mathbf{\Phi}$ realization, $R'(\underline{x}) > 1$ if $d(\underline{x}) < v_1(\underline{x})+v_2(\underline{x})$, which simplifies to $\frac{p_{\ell'}^{\theta}z'\Phi_{\ell'}}{p_{\ell}^{\theta}z\Phi_{\ell}}\left(\frac{S_{\ell'z'}(\underline{x})}{S_{\ell z}(\underline{x})}\right)^{1-1/\theta} > \frac{1}{\tau_{\ell\ell'}}\frac{N(\underline{x})}{1+(1-\frac{1}{\theta})\theta\pi_{\ell z\ell z}(\underline{x})}$ when $\boldsymbol{\tau}$ is symmetric. Since $N(x) \to 1$ as $x \to^R \underline{x}$ for $\underline{x}$ arbitrarily small, one household in the pair satisfies this condition at the limit. The other household's payoffs may also satisfy this condition because the decision x is made *prior* to realizations of $\mathbf{\Phi}$, and can be approximated with Corollary 1. If $\varphi^{-}_{\ell z\ell'z'}(\underline{x})$ is sufficiently low or $\varphi^{+}_{\ell z\ell'z'}(\underline{x})$ is sufficiently high, both partners' $R(\underline{x})$ initially exceed one. Therefore, the household (ℓ',z') for which $p_{\ell'}^{\theta}z'\Phi_{\ell'}S_{\ell'z'}(\underline{x})^{1-1/\theta} > p_{\ell}^{\theta}z\Phi_{\ell}S_{\ell z}(\underline{x})^{1-1/\theta}$ has a preferred partnership level with (ℓ,z) above the lowest feasible point if the *ex-ante* risk adjustment terms increase expected payoffs sufficiently from the non-stochastic case; or, in other words, if the household receives a sufficient insurance benefit from the relationship.

Equilibrium Existence Because continuity and quasiconcavity of payoffs are satisfied for the payoffs of both (ℓ,z) and (ℓ',z'), the results of Bich and Morhaim (2020) apply and a pairwise-stable equilibrium exists.

Equilibrium Partnership Levels I show that given two preferred partnership levels $\lambda^{*}_{\ell z\ell'z'}$ and $\lambda^{*}_{\ell'z'\ell z}$ between household pairs (ℓ,z) and (ℓ',z'), the realized partnership in a pairwise-stable equilibrium between the pair is $\lambda_{\ell z\ell'z'} = \lambda_{\ell'z'\ell z} = \min\{\lambda^{*}_{\ell z\ell'z'},\lambda^{*}_{\ell'z'\ell z}\}$.

To do so, I must show that: (i) there is no level $\lambda < \min\left\{\lambda^*_{\ell z \ell' z'}, \lambda^*_{\ell' z' \ell z}\right\}$ such that

$$\mathbb{E}\left(C_{\ell z}\left(\lambda \cup \boldsymbol{\lambda}_{-\ell z \ell' z'}\right)\right) \geq \mathbb{E}\left(C_{\ell z}\left(\boldsymbol{\lambda}\right)\right) \text{ or } \mathbb{E}\left(C_{\ell' z'}\left(\lambda \cup \boldsymbol{\lambda}_{-\ell z \ell' z'}\right)\right) \geq \mathbb{E}\left(C_{\ell' z'}\left(\boldsymbol{\lambda}\right)\right),$$

and (ii) there is no level $\lambda > \min\left\{\lambda^*_{\ell z \ell' z'}, \lambda^*_{\ell' z' \ell z}\right\}$ such that

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

This is a re-statement of Definition 2.

The payoff $\mathbb{E}(C_{\ell z})$ is quasi-concave with respect to $x_{\ell z \ell' z'} = \lambda^{\theta}_{\ell z \ell' z'}$. In particular, the payoff's derivative crosses zero at most once from above, and this point is the payoff's unique maximizer, labeled $\left(x^*_{\ell z \ell' z'}\right)^{1/\theta} = \lambda^*_{\ell z \ell' z'}$. Therefore, when $\lambda < \lambda^*_{\ell z \ell' z'}$, then payoffs are increasing, and when $\lambda > \lambda^*_{\ell z \ell' z'}$, payoffs are decreasing. Through this observation, 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 $\left[0, \min\left\{\lambda^*_{\ell z \ell' z'}, \lambda^*_{\ell' z' \ell z}\right\}\right]$. To show (ii), suppose there is a $\lambda > \min\left\{\lambda^*_{\ell z \ell' z'}, \lambda^*_{\ell' z' \ell z}\right\}$ that is mutually profitable for both households. This would imply that both payoffs $\mathbb{E}\left(C_{\ell z}\right)$ and $\mathbb{E}\left(C_{\ell' z'}\right)$ are increasing in weight $\lambda \in \left[\min\left\{\lambda^*_{\ell z \ell' z'}, \lambda^*_{\ell' z' \ell z}\right\}, 1\right]$. Without loss, suppose $\lambda^*_{\ell z \ell' z'} = \min\left\{\lambda^*_{\ell z \ell' z'}, \lambda^*_{\ell' z' \ell z}\right\}$. This implication would violate the assumption that payoffs are decreasing in λ when $\lambda > \lambda^*_{\ell z \ell' z'}$. So, there is no mutually profitable, upwards deviation in weight λ for household pairs.

A.1.5 Proofs of Testable Implications

Test 1 Consider the preferred partnership level of Equation (A1). Suppose when a household in location ℓ adopts mobile money, a location-specific δ_ℓ declines, such that $\tau_{\ell' \ell}$ for all ℓ' increases while other entries of $\boldsymbol{\tau}$ stay the same, or $\tau_{\ell' \ell} = d^{-\delta_\ell}$. The preferred partnership level $\lambda^*_{\ell z \ell' z'}$ *decreases* in δ_ℓ, or $\frac{\partial \lambda^*_{\ell z \ell' z'}}{\partial \delta_\ell} < 0$, since the asymmetry in $\boldsymbol{\tau}$ results in independence of outflow probabilities $\pi_{\ell z \ell' z'}$ and outflow transfer costs $\tau_{\ell \ell'}$ from the location-specific transfer friction parameter δ_ℓ.

Test 2 Consider the probability that an equilibrium partnership level $\lambda_{\ell z \ell' z'} > \varepsilon$, where ε is an arbitrary threshold that characterizes a "substantial" partnership. From Proposition 2, this implies that $\lambda^*_{\ell z \ell' z'} > \varepsilon$ and $\lambda^*_{\ell' z' \ell z} > \varepsilon$. Rearranging the condition $\lambda^*_{\ell z \ell' z'} > \varepsilon$ yields

$$\frac{p^{\theta}_{\ell'} z' A_{\ell'}}{p^{\theta}_{\ell} z A_{\ell}} > \frac{\varepsilon^{\gamma}\left[\bar{c}\left(\gamma + \theta - (\theta - 1)\pi_{\ell z \ell' z'}(\boldsymbol{\lambda})\right)\right] + \theta - (\theta - 1)\pi_{\ell z \ell' z'}(\boldsymbol{\lambda})}{\tau_{\ell \ell'}\left(\frac{\varphi^{+}_{\ell z}(\boldsymbol{\lambda})}{\varphi^{-}_{\ell z \ell' z'}(\boldsymbol{\lambda})}\right)\left(\frac{S^{(1)}_{\ell' z'}(\boldsymbol{\lambda})}{S^{(1)}_{\ell z}(\boldsymbol{\lambda})}\right)^{1-1/\theta}} \equiv \frac{\chi}{\tau_{\ell \ell'}} \tag{A5}$$

Rearranging the condition $\lambda^*_{\ell' z' \ell z} > \varepsilon$ yields

$$\tau_{\ell'\ell}\overline{\chi} \equiv \frac{\tau_{\ell'\ell}\left(\frac{\varphi^+_{\ell' z'}(\boldsymbol{\lambda})}{\varphi^-_{\ell' z' \ell z}(\boldsymbol{\lambda})}\right)\left(\frac{S^{(1)}_{\ell' z'}(\boldsymbol{\lambda})}{S^{(1)}_{\ell z}(\boldsymbol{\lambda})}\right)^{1/\theta-1}}{\varepsilon^{\gamma}\overline{c}\,(\gamma+\theta-(\theta-1)\pi_{\ell z \ell' z'}(\boldsymbol{\lambda}))+\theta-(\theta-1)\pi_{\ell z \ell' z'}(\boldsymbol{\lambda})} > \frac{p^\theta_{\ell'} z' A_{\ell'}}{p^\theta_\ell z A_\ell}. \tag{A6}$$

Equation (A5) is a lower bound on the idiosyncratic productivity ratio in a "substantial" partnership, and Equation (A6) is an upper bound. Keeping the network $\boldsymbol{\lambda}$ fixed, the lower bound of Equation (A5) increases in $S^{(1)}_{\ell z}(\boldsymbol{\lambda})$, which decreases in the location-specific transfer friction δ_ℓ, reflecting the results of Test 1. Similarly, the upper bound of Equation (A6) increases in $S^{(1)}_{\ell z}(\boldsymbol{\lambda})$. The sustainable range of idiosyncratic productivity ratios in "substantial" partnerships shifts upward as a result of a decline in δ_ℓ.

Test 3 Rearranging Equation (A5) yields $d_{\ell\ell'} < \left(\frac{p^\theta_\ell z A_\ell}{p^\theta_{\ell'} z' A_{\ell'}}\underline{\chi}\right)^{-1/\delta}$, while rearranging Equation (A6) yields $d_{\ell'\ell} < \left(\frac{1}{\overline{\chi}}\frac{p^\theta_{\ell'} z' A_{\ell'}}{p^\theta_\ell z A_\ell}\right)^{-1/\delta}$. Therefore, the distance between pairs in "substantial" partnerships follows

$$d_{\ell\ell'} \leq \min\left\{\left(\frac{p^\theta_\ell z A_\ell}{p^\theta_{\ell'} z' A_{\ell'}}\underline{\chi}\right)^{-1/\delta}, \left(\frac{1}{\overline{\chi}}\frac{p^\theta_{\ell'} z' A'_\ell}{p^\theta_\ell z A_\ell}\right)^{-1/\delta}\right\} \equiv \widetilde{d}_{\ell z \ell' z'}.$$

This distance is sensitive to the idiosyncratic productivity of a household $\widetilde{A}_{\ell z} = p^\theta_\ell z A_\ell$. The comparative statics are as follows: (a) if $\lambda_{\ell z \ell' z'} = \lambda_{\ell' z' \ell z} = \lambda^*_{\ell z \ell' z'}$, then $\frac{\partial \widetilde{d}_{\ell z \ell' z'}}{\partial \widetilde{A}_{\ell z}} > 0$, and (b) if $\lambda_{\ell z \ell' z'} = \lambda_{\ell' z' \ell z} = \lambda^*_{\ell' z' \ell z}$, then $\frac{\partial \widetilde{d}_{\ell z \ell' z'}}{\partial \widetilde{A}_{\ell z}} < 0$.

A.1.6 Derivations for Limited Commitment Extension

Payoffs Under Limited Commitment The definitions of transfer inflows and outflows in Equations (16) and (17) yield tractable expectations. These are defined in Lemma A.1 below.

Lemma A.1. *Consider a household in location ℓ of productivity z facing the limited-commitment network payment game. Given partnership levels $\boldsymbol{\lambda}$ and upper bounds $\overline{\mathbf{I}}$:*

(a) The household's expected recipient transfer is

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

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

(b) The household's expected sender transfer is

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

Proof. Let $t = \mathcal{I}^{-\theta} \frac{S_{\ell z}(\boldsymbol{\lambda})}{\left(\tau_{\ell' \ell} \lambda_{\ell' z' \ell z}\right)^\theta}$ and $dt = -\theta \mathcal{I}^{-\theta-1} \frac{S_{\ell z}(\boldsymbol{\lambda})}{\left(\tau_{\ell' \ell} \lambda_{\ell' z' \ell z}\right)^\theta} d\mathcal{I}$. Then, applying the definition in Equation (16),

$$\mathbb{E}\left(R^+_{\ell z}(\boldsymbol{\lambda})\right) = \sum_{\ell', z'} \tau_{\ell' \ell} \lambda_{\ell' z' \ell z} \left(\int_{\bar{I}^{-\theta}_{\ell' z' \ell z}}^\infty \mathcal{I} \frac{\tau^\theta_{\ell' \ell} \lambda^\theta_{\ell' z' \ell z} p^\theta_{\ell' z'} \Phi_{\ell'}}{S_{\ell z}(\boldsymbol{\lambda})} \exp(-t) dt \right),$$

which simplifies to the expression above. The outflow term uses a similar argument and substitution to the inflow term. □

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

Fixed Point in $\bar{I}$ Lemma A.1 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 results in the following fixed point for $\bar{\boldsymbol{I}}$,

$$\begin{aligned} \bar{I}_{\ell z \ell' z'} = \frac{1-\beta}{\beta} \left(\kappa_{\ell z \ell' z'} \lambda_{\ell z \ell' z'}\right)^{-1} \Bigg[& \tau^\theta_{\ell' \ell} \lambda^\theta_{\ell z \ell' z'} p^\theta_{\ell' z'} A_{\ell'} \left(S^{(1)}_{\ell z}(\boldsymbol{\lambda})\right)^{1/\theta - 1} \varphi^-_{\ell' z' \ell z}(\boldsymbol{\lambda})\, \Gamma\left(1 - 1/\theta; \bar{I}^{-\theta}_{\ell z \ell' z'}\right) \\ & - \kappa_{\ell z \ell' z'} \tau^{\theta-1}_{\ell \ell'} \lambda^\theta_{\ell z \ell' z'} p^\theta_{\ell z} A_\ell \left(S^{(1)}_{\ell' z'}(\boldsymbol{\lambda})\right)^{1/\theta - 1} \varphi^-_{\ell z \ell' z'}(\boldsymbol{\lambda})\, \Gamma\left(1 - 1/\theta; \bar{I}^{-\theta}_{\ell' z' \ell z}\right) + \mathcal{F} \Bigg]. \end{aligned} \tag{A7}$$

This expression arises from applying the definition of $\bar{I}_{\ell z \ell' z'}$ in Equation (15).

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 $\lambda^*_{\ell z \ell' z'}$ a household has in its relationship with another is given by Corollary 2.

Corollary 2. *The desired partnership level $\lambda^*_{\ell z \ell' z'}$ 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*

$$\lambda^*_{\ell z \ell' z'} = \left(\frac{\widetilde{\Theta}_{\ell z \ell' z'}(\boldsymbol{\lambda}) - \theta + (\theta - 1)\, \pi_{\ell z \ell' z'}(\boldsymbol{\lambda})}{\bar{c}\,(\theta + \gamma - (\theta - 1)\, \pi_{\ell z \ell' z'}(\boldsymbol{\lambda}))} \right)^{\frac{1}{\gamma}}, \tag{A8}$$

where the pairwise constant is

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

Proof. The proof follows the same steps as Section A.1.3. □

The desired partnership levels $\boldsymbol{\lambda}$ under limited commitment closely resemble those under full commitment with a few adjustments. The main adjustment is that the desired partnership level increases in the ratio $\frac{\Gamma\left(1-1/\theta;\bar{I}^{-\theta}_{\ell' z' \ell z}\right)}{\Gamma\left(1-1/\theta;\bar{I}^{-\theta}_{\ell z \ell' z'}\right)}$ 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 $\bar{I}_{\ell' z' \ell z}$, and expected sender transfers increase in the household's trustworthiness, as dictated by $\bar{I}_{\ell z \ell' z'}$.

B Quantitative Appendix

B.1 Partial Equilibrium Algorithm

The partial equilibrium algorithm takes as inputs: an $L \times 1$ local productivity vector $\boldsymbol{A}$; an $L \times L$ variance-covariance matrix $\boldsymbol{\Sigma}$; an $L \times 1$ local price vector $\boldsymbol{p}$; a $Z \times 1$ household productivity vector $\boldsymbol{z}$; and 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 $\binom{L \times Z}{2} \times 1$ "queue" vector $\boldsymbol{Q}$.

(b) Calculate $L \times L$ matrix $\boldsymbol{\tau}$ such that the (ℓ, ℓ')th entry is $\tau_{\ell\ell'} = d_{\ell\ell'}^{-\delta}$. Set diagonals $\tau_{\ell\ell} = 1$.

(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 $\overline{\boldsymbol{S}}$ and variance $\boldsymbol{\sigma_S^2}$ of network access terms for each household type. Both are $L \times Z$ matrices. The (ℓ, z) entry of $\overline{\boldsymbol{S}}$ is given by Equation (9) and the (ℓ, z) entry of $\boldsymbol{\sigma_S^2}$ is given by Equation (10).

(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 $\pi_{\ell z \ell' z'} = \lambda_{\ell z \ell' z'}^{\theta} \tau_{\ell'\ell}^{\theta} p_{\ell}^{\theta} z A_\ell \overline{S}_{\ell' z'}^{-1}$.

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

(d) 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 $IPR_{\ell z \ell' z'} = \frac{p_{\ell'}^{\theta} z' A_{\ell'}}{p_{\ell}^{\theta} z A_\ell}$. The matrix $\boldsymbol{NPR}$ of size $L \times Z \times L \times Z$ whose (ℓ, z, ℓ', z') entry is $NPR_{\ell z \ell' z'} = \frac{\overline{S}_{\ell' z'}}{\overline{S}_{\ell z}}$.

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

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

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

$$\overline{\varphi}_{\ell z \ell' z'}^{-} = 1 + \frac{(\theta - 1)(2\theta - 1)}{2\theta^2} \frac{\sigma_{S_{\ell' z'}}^2}{\overline{S}_{\ell' z'}^2} - \frac{\theta - 1}{\theta} \frac{\widetilde{S}_{\ell' z' \ell}}{\overline{S}_{\ell' z'} A_\ell}.$$

(f) Calculate the maximum partnership level that can be 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 ***IntInd*** that equals one if $\boldsymbol{\lambda}^*$ has an interior solution, zero otherwise. The (ℓ, z, ℓ', z') entry of the ***IntInd*** matrix is

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

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

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

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 Algorithm Extensions

B.2.1 General Equilibrium

The general equilibrium algorithm takes as inputs: an $L \times 1$ local productivity vector $\boldsymbol{A}$; an $L \times L$ variance-covariance matrix $\boldsymbol{\Sigma}$; a $Z \times 1$ household productivity vector $\boldsymbol{z}$; an $L \times 1$ spatial shock realization $\boldsymbol{\Phi}$; and 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 $\boldsymbol{p}$ with the goods market clearing condition,

$$p_\ell = \left(\frac{\Phi_\ell \sum_z \Omega_{\ell z} \sum_{\ell',z'} z \kappa_{\ell z \ell' z'} \lambda_{\ell z \ell' z'}^{\theta} \tau_{\ell\ell'}^{\theta-1} \overline{S}_{\ell' z'}^{1/\theta-1}}{\sum_z \Omega_{\ell z} \overline{S}_{\ell z}^{1/\theta}} \right)^{\frac{1}{\theta}}.$$

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

B.2.2 Limited Commitment

The limited commitment, partial equilibrium algorithm takes as inputs: an $L \times 1$ local productivity vector $\boldsymbol{A}$; an $L \times L$ variance-covariance matrix $\boldsymbol{\Sigma}$; an $L \times 1$ local price vector $\boldsymbol{p}$; a $Z \times 1$ household productivity vector $\boldsymbol{z}$; and parameter values θ, δ, $\bar{c}$, γ, $\overline{\lambda}$, $\underline{\lambda}$, and $\max \overline{I}$. The value of $\Gamma\left(1 - 1/\theta; \max \overline{I}^{-\theta}\right) \approx \Gamma\left(1 - 1/\theta\right)$. The algorithm generates as an output the $L \times Z \times L \times Z$ network $\boldsymbol{\lambda}$ and a $L \times Z \times L \times Z$ matrix of upper bounds $\overline{\boldsymbol{I}}$. The steps are as follows:

1. Populate an initial guess for upper bounds $\overline{\boldsymbol{I}}$ as an $L \times Z \times L \times Z$ matrix where all entries are $\max \overline{I}$.
2. Using $\bar{\boldsymbol{I}}$ as an input, run the partial equilibrium algorithm in Section B.1 to find $\boldsymbol{\lambda}$. However, in Step 3(g), replace unconstrained preferred partnership levels with Equation (A8).
3. Store $\overline{\boldsymbol{I}}$ as $\overline{I}^{OLD}$.

Table A1: Summary Statistics Under Alternative Initialization

Initialization	*Unweighted Average Across Types in 2013* Spatial HHI	Self Share	Degree
Baseline	**0.867**	**87.8%**	**0.451**
(1) No University	0.890	90.4%	0.326
(2) No Secondary	0.885	89.9%	0.326
(3) No Primary	0.885	90.1%	0.327
(4) No Pre-Primary	0.885	90.0%	0.327
(5) Less Connected	0.952	96.5%	0.281
(6) Minimally Connected	0.992	99.5%	0.175

4. Using $\boldsymbol{\lambda}$, update $L \times Z \times L \times Z$ matrix $\overline{\boldsymbol{I}}$ with Equation (A7).

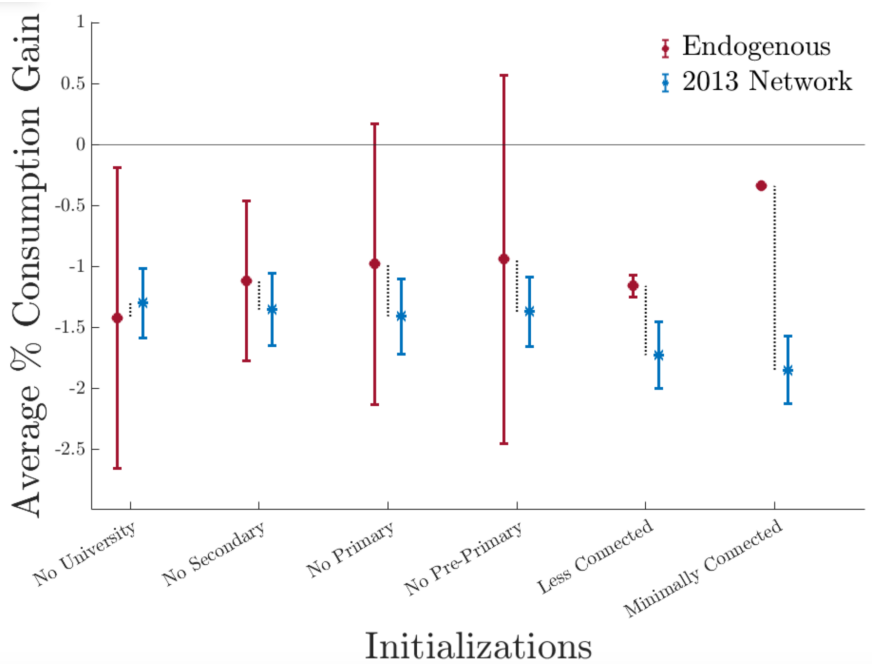
5. Calculate error between $\overline{\boldsymbol{I}}^{OLD}$ and $\overline{\boldsymbol{I}}$, as $\max\left\{|\overline{I}^{OLD}_{\ell z \ell' z'} - \overline{I}_{\ell z \ell' z'}|\right\}$. Update $\overline{\boldsymbol{I}} = 0.25 \cdot \overline{\boldsymbol{I}} + (1 - 0.25) \cdot \overline{\boldsymbol{I}}^{OLD}$. Repeat steps 2 to 5 until convergence.

B.3 Robustness

In this section, I examine robustness of results when there is noise around the initial network $\boldsymbol{\lambda}$ in Section B.1. Herings and Zhan (2024) suggest that the computation of pairwise-stable equilibria is particularly sensitive to decisions around network initializations. I consider six alternatives that adjust the equally weighted, full network in the following ways: (1) a shut-down of university relationships, or $\lambda_{\ell z \ell' z'} \approx 0$ if either z or z' is a university type, (2) a shut-down of secondary-school relationships, (3) a shut-down of primary-school relationships, (4) a shut-down of pre-primary school relationships, (5) a decline in all weights by a multiplicative factor of two (e.g., less connected), and (6) a decline in all weights by a multiplicative factor of five (e.g., minimally connected).

Summary Statistics I consider how the different initializations alter equilibrium network characteristics in Table A1. I randomly generate 100 sequences of pairs and display the average outcome. In general, the distribution of baseline equilibria are the most connected, as evidenced by average degree across types. The less-connected equilibria (i.e., initializations 5 and 6) are associated with higher self-shares and more concentrated transfer sources. Constraining specific productivity types in the initial equilibrium (i.e., initializations 1 to 4) does not substantially change other network characteristics.

Figure A1: Robustness of Average Welfare Gains in 2028 to Alternative Initializations



Note: I examine the robustness of average consumption changes in 2028 relative to 2013 across different network initializations. I aggregate according to NPS demographic shares $\mathbf{\Omega}$. Quantitatively generated 95% confidence intervals are displayed, where variation arises from randomization across the sequence in which pairs best-respond.

Average Consumption Gains I examine the robustness of the average consumption results to network initialization showcased in Figure 8a. These checks are displayed in Figure A1. Across all network initializations, mobile money results in average consumption losses and the indirect network reorganization effect is positive.

Insurance and Redistribution I examine the robustness of the insurance and redistribution results to network initialization of Figure 9. These checks are displayed in Figure A2. Across all network initializations, the progressive pattern of network gains is absent in 2008 but emerges in 2028. Furthermore, in 2028, redistribution rises relative to 2008 at the expense of insurance.

Mobile Money Progressivity In Figure A3, I show the decomposition of Equation (21) across productivity groups. The impacts of mobile money are progressive, as across locations, non-educated households see average consumption gains of 1.4% relative to their 2013 baseline, but university-educated households see an average loss of 0.7%.

Figure A2: Robustness of Network Gain Decomposition to Alternative Initializations

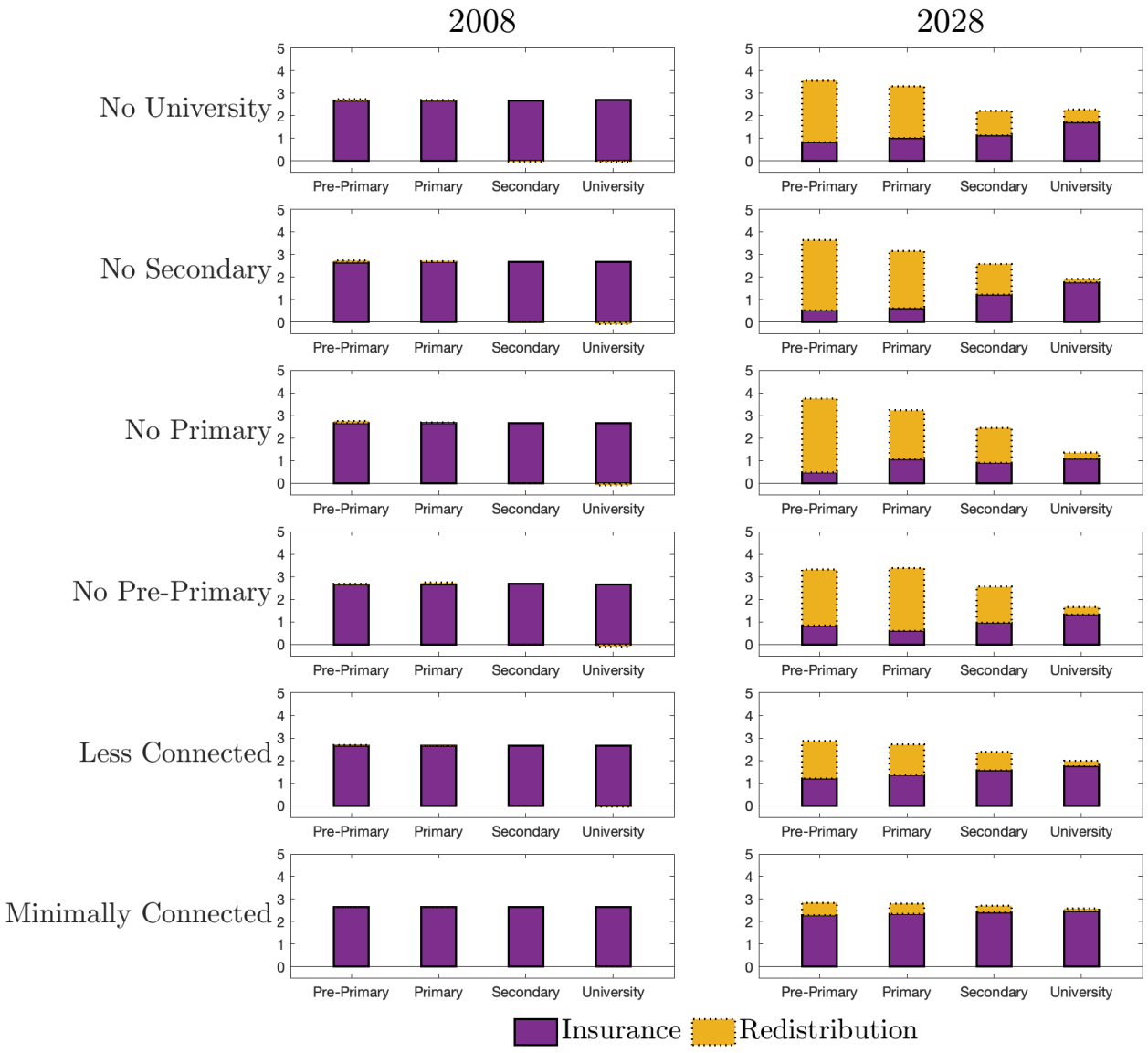
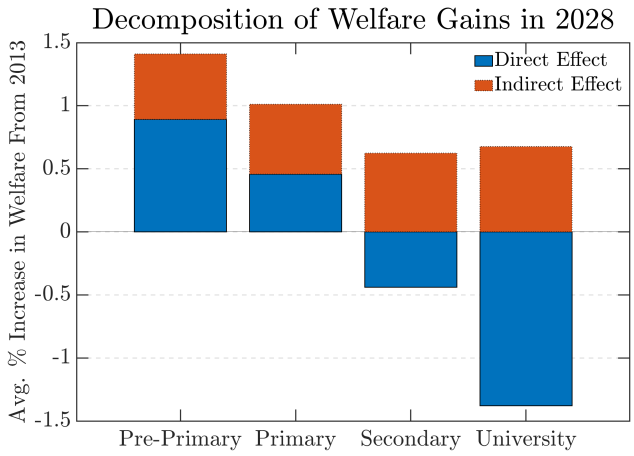


Figure A3: Decomposition of 2028 Mobile Money Consumption Gains Into Direct vs. Indirect Effect



Note: This graph shows the across-location unweighted averages of consumption gains in 2028 relative to the calibrated 2013 baseline by productivity groups, proxied for by education level of the household head. The direct effect keeps the network λ fixed at its 2013 level, while the indirect effect considers additional gains arising from the adjustment of λ.

B.4 Quantitative Exercise of Limited Commitment Extension

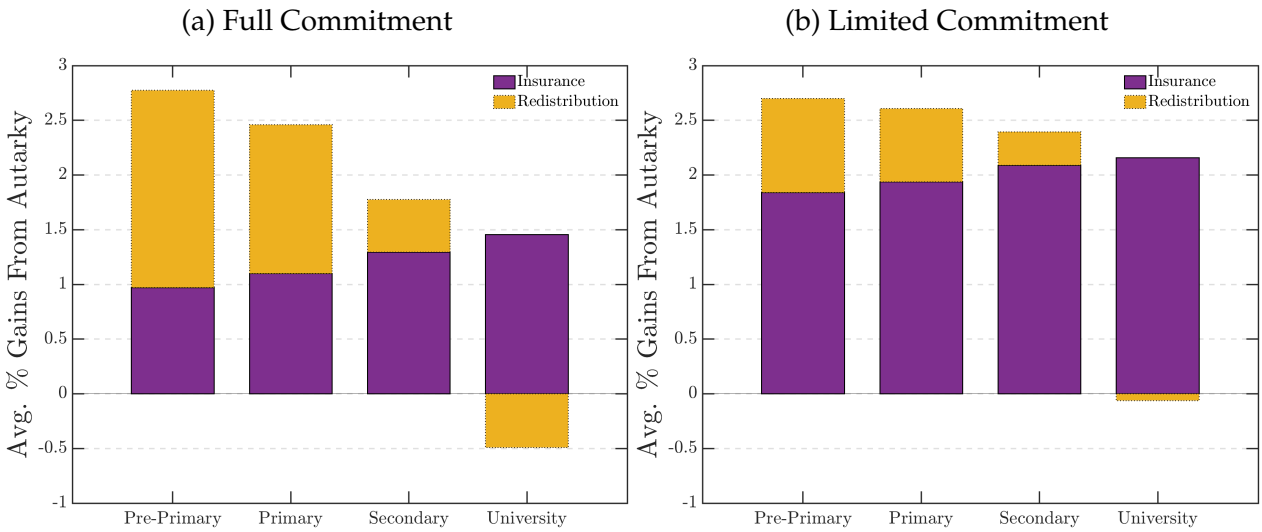
I quantify the model using the same parameter values in Table 2 but set the distance discount to $\log \delta = -2.5$. Additional to these model inputs, I consider a "high" ($\mathcal{F} = 1$) and a "low" ($\mathcal{F} = .5$) cost of deviation. These punishments amount to approximately 30% and 15% of a university-educated household's expected income in Dar es Salaam.

Summary Statistics How do networks change under limited commitment relative to full commitment? Table A2 documents these changes across four summary statistics. The

Table A2: 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 λ	0.451	0.354	0.176
Average Spatial Herfindahl	0.130	0.144	0.175
Average Change in Network Volatility	—	–0.174	–0.531

Figure A4: Network Gains 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.

first is the percentage of household type pairings whose transfers are constrained by limited commitment.[A1] As the costs of deviation decrease, the proportion of constrained pairs increases. The second statistic is the unweighted average of the sum of partnership levels $\sum_{\ell',z'} \lambda_{\ell z \ell' z'}$ across household types, corresponding to a node's degree in a weighted network. Households maintain fewer connections as the costs of deviation decrease. The third statistic is an adjusted spatial Herfindahl of transfer inflow shares, in which self-shares are excluded.[A2] Transfer networks concentrate spatially as concerns of limited commitment become more binding. 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 $\mathcal{V}$ are lower for more distant than proximate partners.

I also examine changes in size-adjusted network access volatility.[A3] As the costs of deviation decline, this volatility reduces in equilibrium, indicating that transfers—and therefore, consumption—become more stable despite the contraction in network size.

[A1] This statistic is given by the number of pairs (ℓ, z) and (ℓ', z') for which $\min\left\{\Gamma\left(1-1/\theta; \bar{I}^{-\theta}_{\ell z \ell' z'}\right), \Gamma\left(1-1/\theta; \bar{I}^{-\theta}_{\ell' z' \ell z}\right)\right\} < \Gamma(1-1/\theta)$ over the total number of pairs in the network.

[A2] For a household in location ℓ of productivity z, this measure is $\sum_{\ell'} \left(\sum_z \pi_{\ell z \ell' z'}(\boldsymbol{\lambda})\right)^2$, where I set exogenously $\pi_{\ell z \ell z} = 0$.

[A3] This statistic is given by $\log\left(\sigma_S^{LC}/\bar{S}^{LC}\right) - \log\left(\sigma_S^{FC}/\bar{S}^{FC}\right)$.

Insurance and Redistribution In Figure A4, 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 insurance 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 transfer networks are fixed, limited commitment typically acts as a friction that prevents perfect risk-sharing (Ligon et al., 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.

Table A3: Geographic Frictions in the Transfer Network

	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 (A9). 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 Empirical Appendix

C.1 Additional Stylized Facts

In this section, I present additional stylized facts about the transfer network.

C.1.1 Geographic transfer frictions 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 yields a gravity-like pattern in transfer flows, where households receive transfers 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',

$$Y_{h\ell\ell' t} = \exp\left[\alpha + \beta \cdot d_{\ell\ell'} + \gamma_h + \gamma_t + \gamma_{\ell'}\right] \epsilon_{h\ell\ell' t}, \tag{A9}$$

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, $d_{\ell\ell'}$ is the distance between region ℓ and source region ℓ' in hundreds of kilometers, γ_h are household fixed effects, γ_t are interview quarter 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 A3 reports estimates from Equation (A9) 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, while column (3) restricts the sample to non-users. Geographic frictions are lower for mobile money users but remain nontrivial: among mobile money users, a 100-kilometer increase in distance corresponds to a 31.6% reduction in transfer amounts, relative to a 59.1% reduction for non-users. Columns (4) and (5) redefine the outcome as transfers from friends and from children, respectively.[A4] 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% confidence level.

C.1.2 Transfer distance 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,

$$Y_{ht} = \exp\left[\alpha + \beta \cdot Shock_{ht} + \delta \cdot Span_{ht} + \xi \cdot (Shock_{ht} \times Span_{ht}) + \gamma_h + \gamma_t\right] \epsilon_{ht}, \quad \text{(A10)}$$

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 acts as a form of insurance.

[A4] 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 A4: Transfer Distance 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 (A10). 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.

I focus on two types of shocks when running the specification of Equation (A10). 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 Section 2.2, climate shocks display spatial correlation: geographically proximate households are likely to report experiencing droughts or floods 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. Figure 3 shows that this shock is not spatial because responses display no salient geographic patterns.

Results are displayed in Table A4. For both specifications, the coefficient in front of transfer span is positive and statistically significant at the 1% confidence level, indicating that households accessing geographically distant sources receive more transfers. A few within-household, across-time mechanisms can explain this relationship. For example, facing geographic transfer frictions, households may only activate particularly profitable transfer opportunities, which induces 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% confidence 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% confidence 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% confidence level. A household's transfer distance determines the level of received transfers after shocks, suggesting that span itself may act as a form of insurance when shocks are spatially correlated. 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.2 Robustness of Fact 3

In this section, I consider the robustness of Fact 3 in Section 2.2 to a variety of specifications. Across specifications, the only source type for which households receive statistically significantly more transfers is less-educated sources.

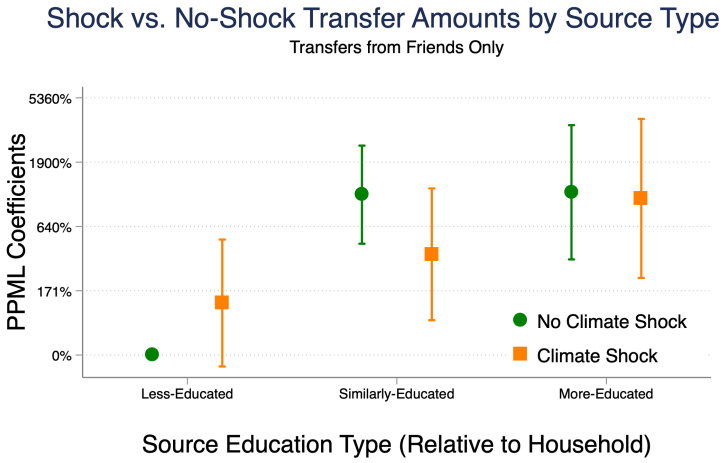
In Tables A5 and A6, I restrict the outcome to only transfers from friends and children respectively; the fact is robust to keeping fixed source relationships. In Table A7, the fact still holds when considering the non-spatial household death shock of Figure 3, suggesting the pattern is *not* driven by the co-location patterns of households. If anything, the pattern is even more pronounced, as the transfers households receive from less-educated sources when shocked nearly matches the amount they receive from other source types. I additionally examine results with respect to non-spatial household death shocks when keeping fixed source relationships to friends and children, respectively Tables A8 and A9, and find that the pattern is robust. I truncate the sample to only primary- and secondary-school educated households in Table A10 to eliminate households for which there are no more- or less-educated sources. Results also hold when restricting the sample to only mobile money adopters or only non-adopter, respectively Tables A11 and A12.

C.3 Testing Micro-Level Implications with the NPS

Table A5: Transfer 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

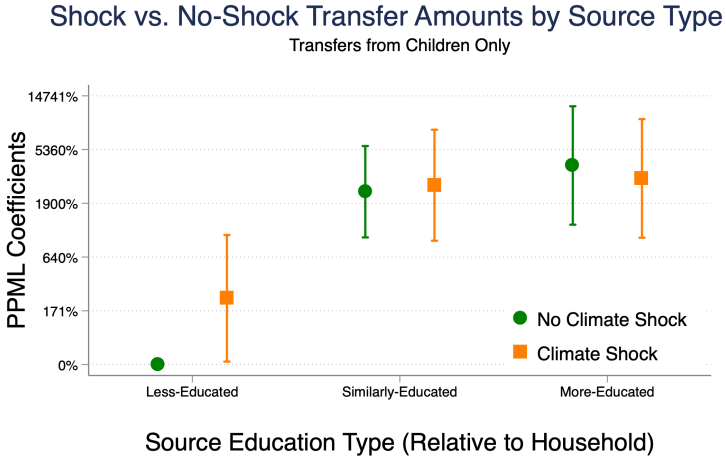


Note: The outcome variable is transfer amounts arising from friends. A household that experiences a shock reports being "severely impacted" by a "drought or flood" in the past year. I include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard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

Table A6: Transfer Amounts (TZS) From Children After Climate Shocks

	From Children (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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

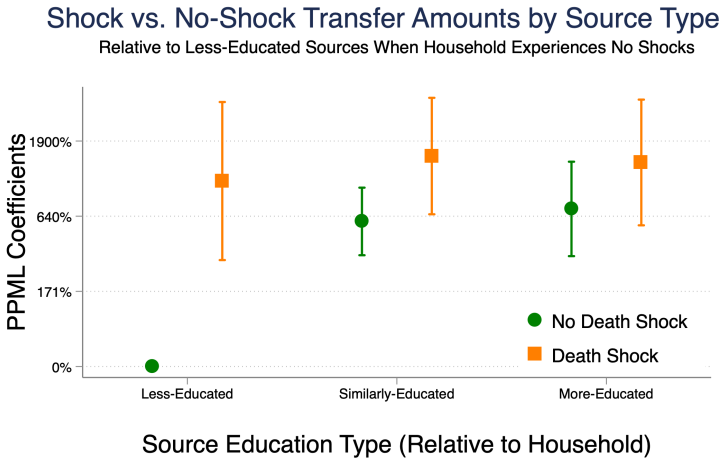


Note: The outcome variable is transfer amounts arising from children. A household that experiences a shock reports being "severely impacted" by a "drought or flood" in the past year. I include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard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

Table A7: All Transfer Amounts (TZS) After Household Death Shocks

	Transfer Amount (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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

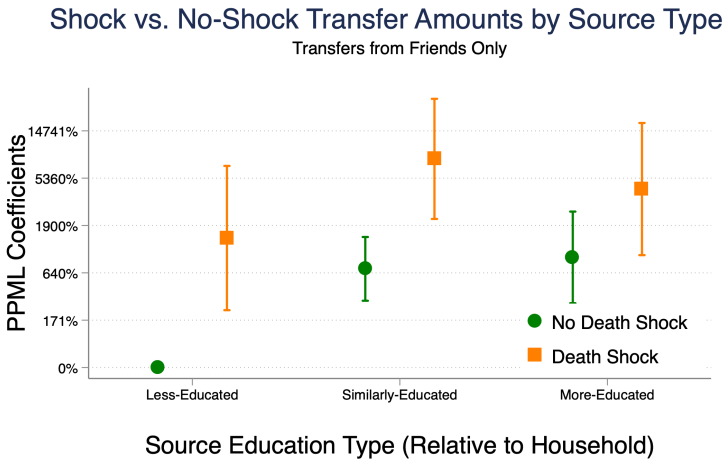


Note: The outcome variable is total transfer amounts. A household that experiences a shock reports being "severely impacted" by a "death of a household member" in the past year. I include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White standard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

Table A8: Transfer 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

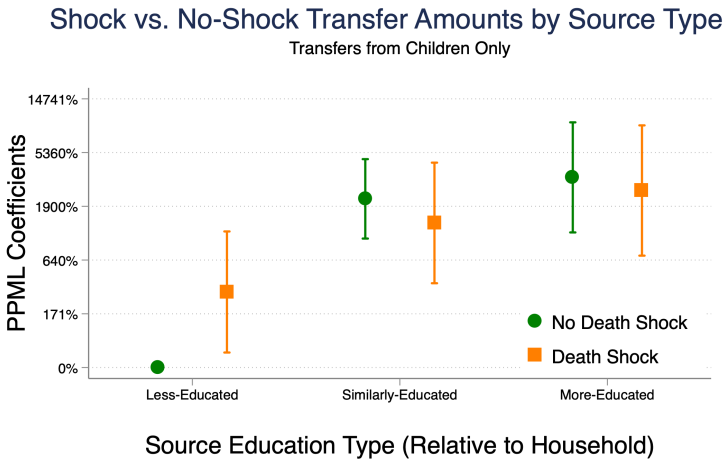


Note: The outcome variable is transfer amounts arising from friends. A household that experiences a shock reports being "severely impacted" by a "death of a household member" in the past year. I include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White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

Table A9: Transfer 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

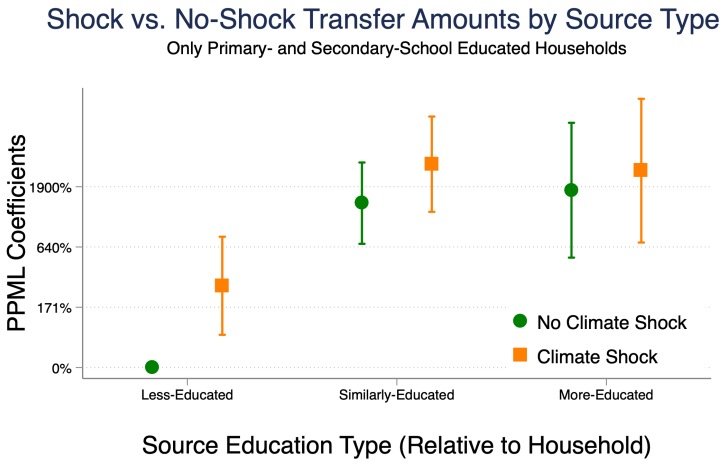


Note: The outcome variable is transfer amounts arising from children. A household that experiences a shock reports being "severely impacted" by a "death of a household member" in the past year. I include household fixed effects, interview quarter fixed effects, and source education fixed effects. Huber-White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

Table A10: All Transfer 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

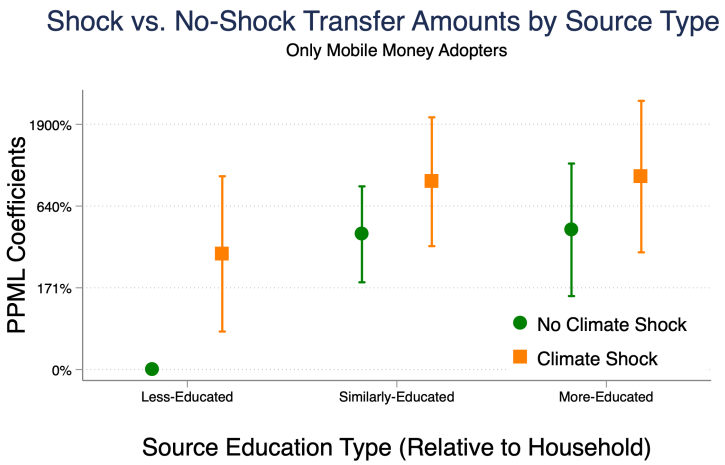


Note: The outcome variable is total transfer amounts. I restrict the sample to only primary- and secondary-school educated households. A household that experiences a shock reports being "severely impacted" by a "drought or flood" in the past year. I include household fixed effects, interview quarter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

Table A11: Transfer 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

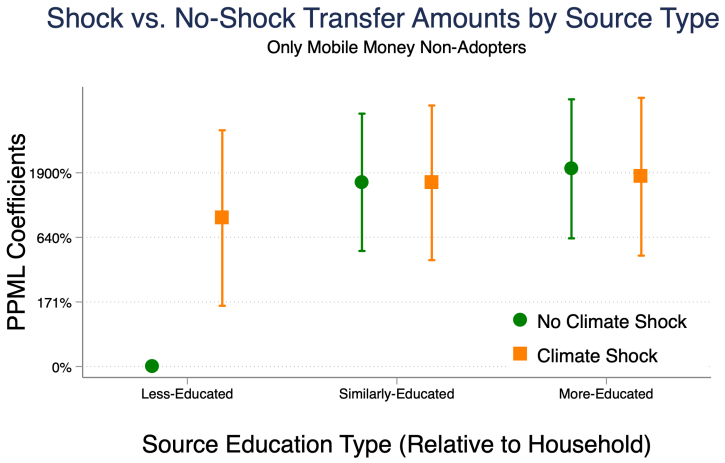


Note: The outcome variable is total transfer amounts. I restrict the sample to only mobile money adopters. A household that experiences a shock reports being "severely impacted" by a "drought or flood" in the past year. I include household fixed effects, interview quarter fixed effects, and source education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

Table A12: Transfer 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. I restrict the sample to only non-adopters. A household that experiences a shock reports being "severely impacted" by a "drought or flood" in the past year. I 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.

C.3.1 Shift-Share Instrument

The implication described on page 28 of Section 3.4 can be tested with the following regression specification. Consider the following for a household h at interview time t:

$$Y_{ht} = \alpha + \beta \cdot MM_{ht} + \mathbf{\Gamma'}\boldsymbol{\omega}_{ht} + \varepsilon_{ht} \tag{A11}$$

where Y_{ht} is the household h's reported number of transfer sources at time t, MM_{ht} is an indicator variable for whether a household h reports using mobile money at time t, $\boldsymbol{\omega}_{ht}$ is a vector of household- 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_{ht} 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.

When transfer networks are exogenous, as in Jack and Suri (2014), mobile money increases network density and $\beta > 0$. In Section 3.4, I demonstrate that this statement does not necessarily hold when networks are endogenous.

Relevance 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 adopt 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 (Aker and Mbiti, 2010; Jack and Suri, 2014; Hamdan et al., 2022). 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).[A5]

Consider the instrument Z_{ht} for a household h in village v at interview time t

$$Z_{ht} = \sum_{k=1}^{K} \Omega_{vk0,-h} \Delta \overline{MM_{kt}}, \tag{A12}$$

where $\Omega_{vk0,-h}$ is the leave-one-out, size-weighted share of demographic group k in vil-

[A5] In the 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 57 years and older), (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 96 demographic groups that feed into the "shares". There are 246 different villages in the dataset.

lage v during 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.[A6] Intuition for the instrument's relevance goes as follows: "I am more likely to adopt when my neighbors are more likely to adopt."

Exclusion Restriction From Goldsmith-Pinkham et al. (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 (A11) 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 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 simultaneous changes in the transfer network constant, I incorporate time fixed effects for all IV specifications.

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

$$MM_{ht} = \alpha + \beta \cdot Z_{ht} + \Gamma'\boldsymbol{\omega_{ht}} + \gamma_h + \gamma_t + \epsilon_{ht}, \tag{A13}$$

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 A13. The instrument Z_{ht} statistically significantly predicts mobile money use. Keeping household characteristics and other time trends constant, a 10.0 percentage point increase in the imputed village-level adoption rate from Equation (A13) increases the average probability a household uses

[A6] 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 A13: 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.

mobile money by 7.3 percentage points. This relationship is statistically significant at the 1% confidence 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.3.2 Test 1 Results

Using the empirical strategy discussed in Section C.3.1, I examine whether mobile money increases the number of distinct transfer sources reported by a household in a year. A household adopts mobile money if it reports using M-Pesa, ezyPesa, Airtel Money, Tigo

Table A14: 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. The Kleibergen-Paap rk Wald F-statistic is reported in IV specifications.

Pesa, Z-Pesa, or Zap to transfer money over the past twelve months. The OLS and IV results are shown in Table A14.

C.3.3 Test 2 Results

I use the following source-level regression specification to test the implication described on page 29 in Section 3.4. For a source s of household h at interview time t, consider

$$Y_{hst} = \alpha + \beta \cdot MM_{ht} + \Gamma' \boldsymbol{\omega}_{hst} + \varepsilon_{hst}, \tag{A14}$$

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, $\boldsymbol{\omega}_{hst}$ is a vector of source- and time-level controls, and ε_{hst} is a normally distributed structural error term. The OLS and IV results are shown in Table A15.

C.3.4 Test 3 Results

I test whether the predicted responses of transfer distance to shocks hold in the data. I run the following regression specification for a household h at interview time t:

$$Y_{ht} = \alpha + \beta \cdot Shock_{ht} + \zeta \cdot HighProd_{ht} + \delta \cdot (Shock_{ht} \times HighProd_{ht}) + \Gamma' \boldsymbol{\omega_{ht}} + \gamma_h + \gamma_t + \epsilon_{ht}, \tag{A15}$$

Table A15: 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 the 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. The Kleibergen-Paap rk Wald *F*-statistic is reported in IV specifications.

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, idiosyncratic shock at time t.

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

Empirical Results The results of this exercise are found in Table A16. Including the entire vector of controls, less-productive 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 A16. After a persistent, idiosyncratic shock, high-productivity households experience a near two-fold

Table A16: The Impact of Shocks on Transfer Distance and Transfer Amounts

	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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

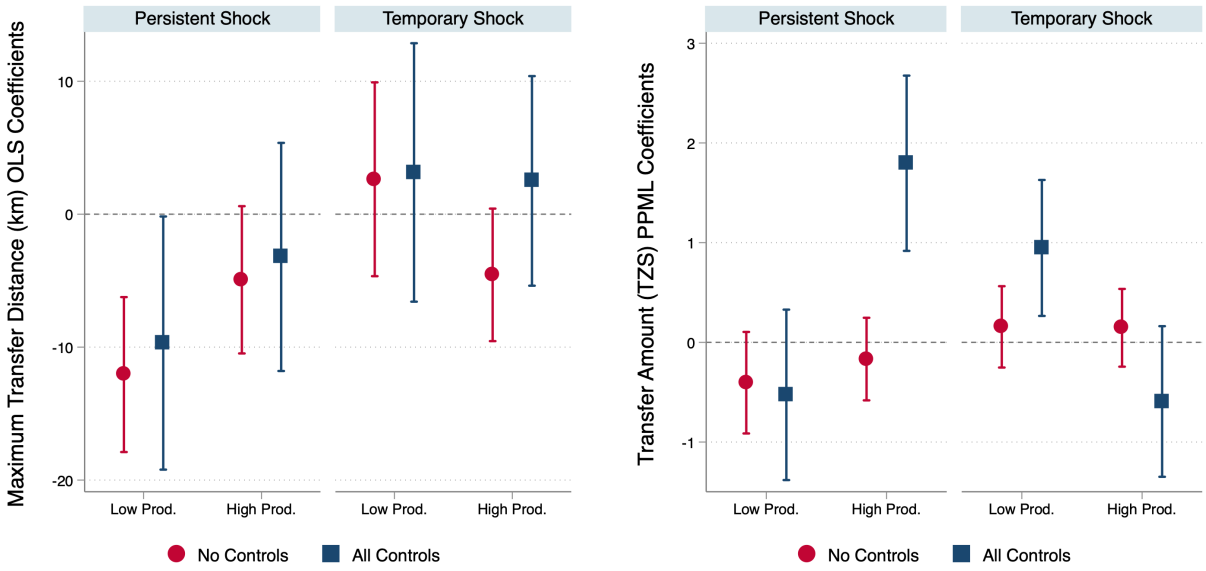
Note: Huber-White standard errors clustered at the household level are in parentheses. Village characteristics include leave-one-out averages of log income, number of transfer sources, and transfer distance. The outcome is maximum reported transfer distance and total transfer amounts a household receives.

increase in transfer amount. Less-productive 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 A5, I plot 95% confidence intervals around the post-shock response of low and high-productivity households.[A7] In these plots, it is easy to see that less-productive households contract transfer distance after persistent, but not temporary, shocks. Furthermore, less-productive households increase recipient transfer amounts after temporary, but not persistent, shocks. By contrast, more-productive households do not alter their transfer distance, but see a substantial increase in recipient transfer amounts after persistent, but not temporary, shocks. In the model, this pattern is only generated if more-productive households strengthen partnership levels after persistent shocks.

[A7] These are estimates of β and $\beta + \delta$ in regression specification (A15), respectively.

Figure A5: Coefficient Plots of Households Shock Response of Transfer Distance and Amount



Note: The figure displays coefficient plots for regression results of Equation (A15). 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.

C.4 Details on Estimating θ

I detail the estimation of θ below.

Construction of Price Indices 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. 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. I remove categories from which fewer 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 I include observations for which both shares $\widehat{\pi}_{\ell z \ell' z' t}$ and $\widehat{\pi}_{\ell' z' \ell z t}$ are non-zero. As the matrix of aggregate transfer flows is sparse due to data limitations, this exercise results in around 100 pairs. Results are shown in Table A17.

Without fixed effects, regional price differences account for 58.0% of the observed variation in transfer inflow matrix asymmetries. With fixed effects, the specification (19)

Table A17: 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		✓

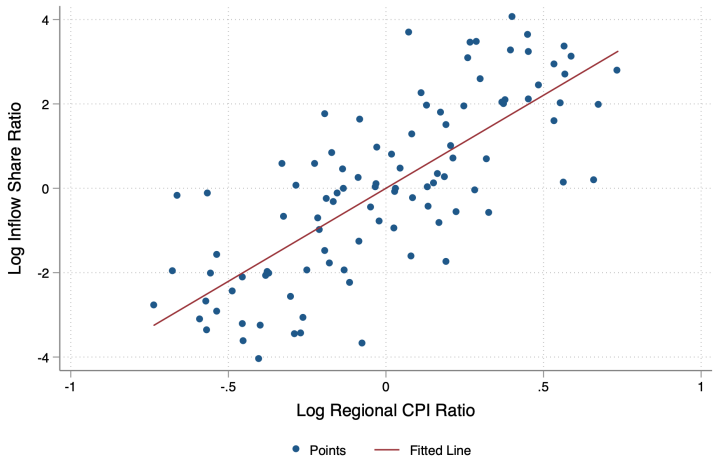
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows results of Equation (19). 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 Section C.4.

yields an estimate of $\theta = 2.78$ that is statistically significant at the 5% level. A scatterplot is shown in Figure A6, which reveals that the two ratios have a log-linear relationship.

C.5 Additional Figures

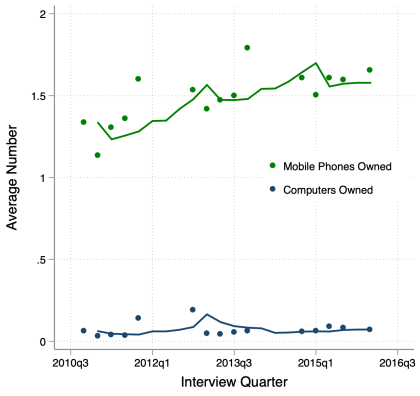
Figure A6: Scatterplot of log $\frac{\widehat{\pi}_{\ell z \ell' z'}}{\widehat{\pi}_{\ell' z' \ell z}}$ vs. log $\frac{p_\ell}{p'_\ell}$



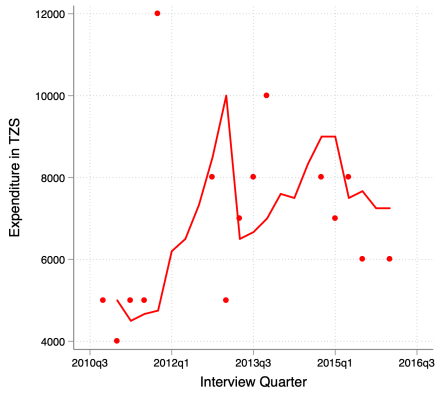
Note: This figure shows the raw scatterplot of the ratio of inflow shares against differences in regional prices using Equation (19) as an OLS specification. This exactly corresponds to the results displayed in Table A17. The slope corresponds to the estimate for θ.

Figure A7: Technology Ownership and Expenditure in NPS Over Time

(a) Computer and Mobile Phone Ownership

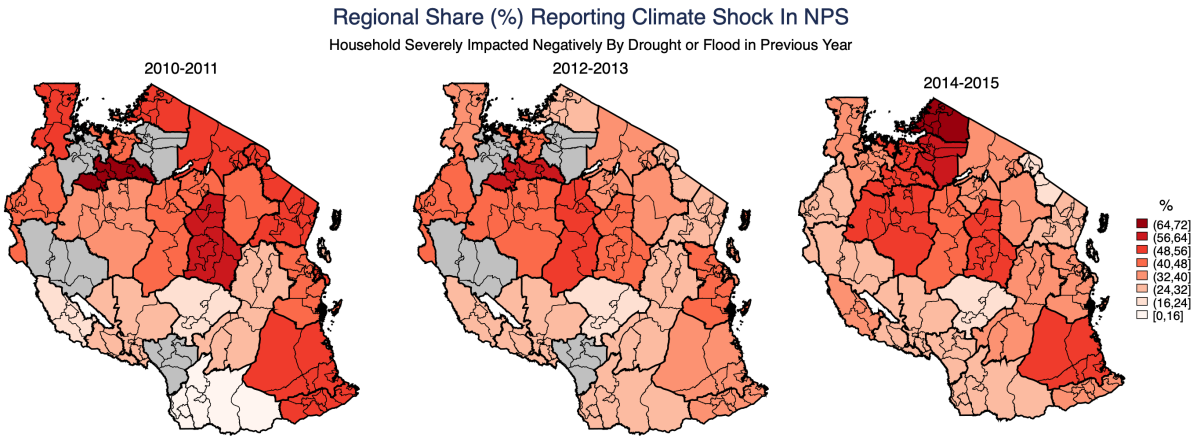


(b) Median Technology Expenditure in TZS



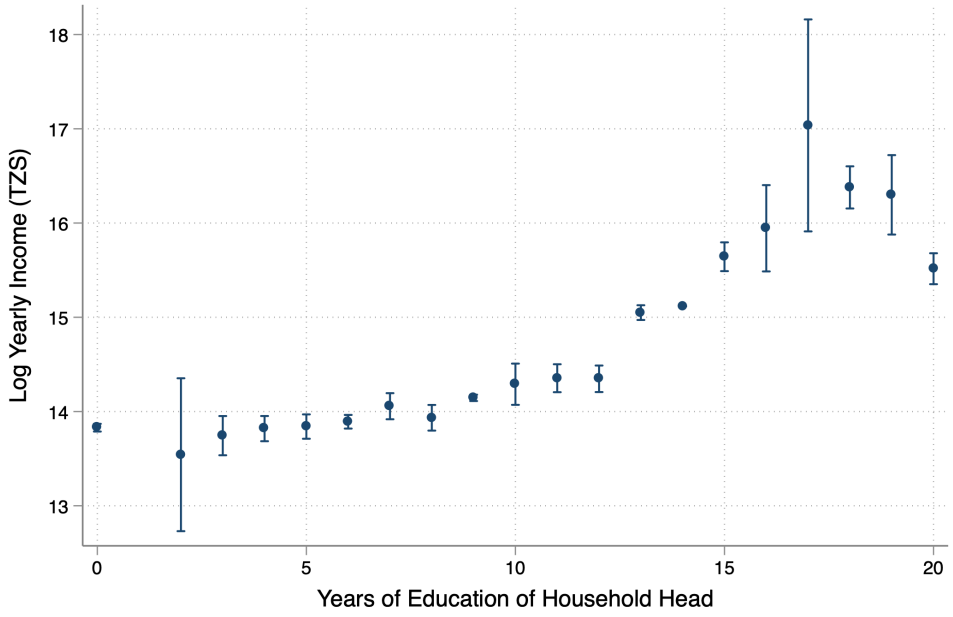
Note: Quarters with fewer than ten respondents are dropped. Smoothed time series, indicated with lines, have a window of five. The left panel records the average number of mobile phones and computers owned by households in each each interview quarter. Technology expenditure is the cash amount in TZS spent on "cell phone vouchers" or "phone, internet, postage stamps, or other postal fees" by a household.

Figure A8: 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 correspond to greater respondent proportions. I exclude regions with fewer than ten respondents in a round.

Figure A9: The Relationship Between Income and Education



Note: This binned scatterplot shows the relationship between a household's yearly income and its head's years of education. The bars indicate 95% confidence intervals. Yearly income is calculated as the sum of wage income, business profits, and fifty times the value of household's self-produced consumption.