Social networks and factor misallocation in agriculture*

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Abstract

When active, agricultural factor markets in developing countries should reduce misallocation, but do not; factor trade must be between the "wrong" farmers. We use a novel transaction-level panel dataset to examine who trades with whom in Rwandan villages. Within villages, physical distance and social connections are more important than productivity in predicting factor trade. We develop and estimate a model of factor trade in networks to characterize the frictions resolved by physical and social distance. We find social connections increase the elasticity of land rentals by reducing the cost of sustaining productive trades. In all we estimate that 56% of the gains from trade are from trade between connections, 69% of which are generated by this mechanism. Evidence from an RCT suggests the land market frictions alleviated by social connections are not easily resolved through policy.

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1 Introduction

Large scale misallocation should be surprising in the presence of active factor markets. Agriculture in developing countries is a particularly salient context, as a substantial body of work characterizes the stark productivity implications of the severe misallocation of land and labor (Adamopoulos and Restuccia, 2014; Restuccia and Rogerson, 2017; Adamopoulos et al., 2022). However, agricultural land and labor markets are quite active in a wide variety of lower income countries, including sub-Saharan Africa (Dillon and Barrett, 2017). These stylized facts present a fundamental puzzle: why don't active land and labor markets more meaningfully reduce misallocation?[1]

A nascent literature studies the effect of land transactions on misallocation directly. Chari et al. (2021) demonstrate that more productive farmers are more likely to rent in land following property rights reform in China that legalized rentals. Yet the reform eliminated only a small fraction of measured misallocation. Acampora et al. (2025) induce new transactions through a land rental subsidy and characterize both sides of these induced transactions. They find that these marginal transactions most commonly occur with friends and relatives, suggesting an important role for social networks to resolve issues related to incomplete contracting. Once again, these new transactions have only a modest impact on misallocation.

In this paper, we examine equilibrium trade in rural factor markets to determine how and why misallocation coexists with frequent trade. We collect bilateral transaction-level data on land and labor trade in Rwanda to provide some of the first direct evidence on the nature of trading frictions in factor markets. We link our transaction database to a 4 year plot-level panel on farm production and physical and social network maps of 110 Rwandan villages.

[1] We follow a large literature (e.g., Hsieh and Klenow, 2009) and describe productively inefficient factor allocations as "misallocation". If some sources of misallocation are "technological", such as travel costs, misallocation as defined may exist at the efficient factor allocation (Bergquist et al., 2026). Starting in Section 4, we present a model and analysis in which we clarify what sources of productive inefficiency we interpret as distortions, and which we allow may be technological.

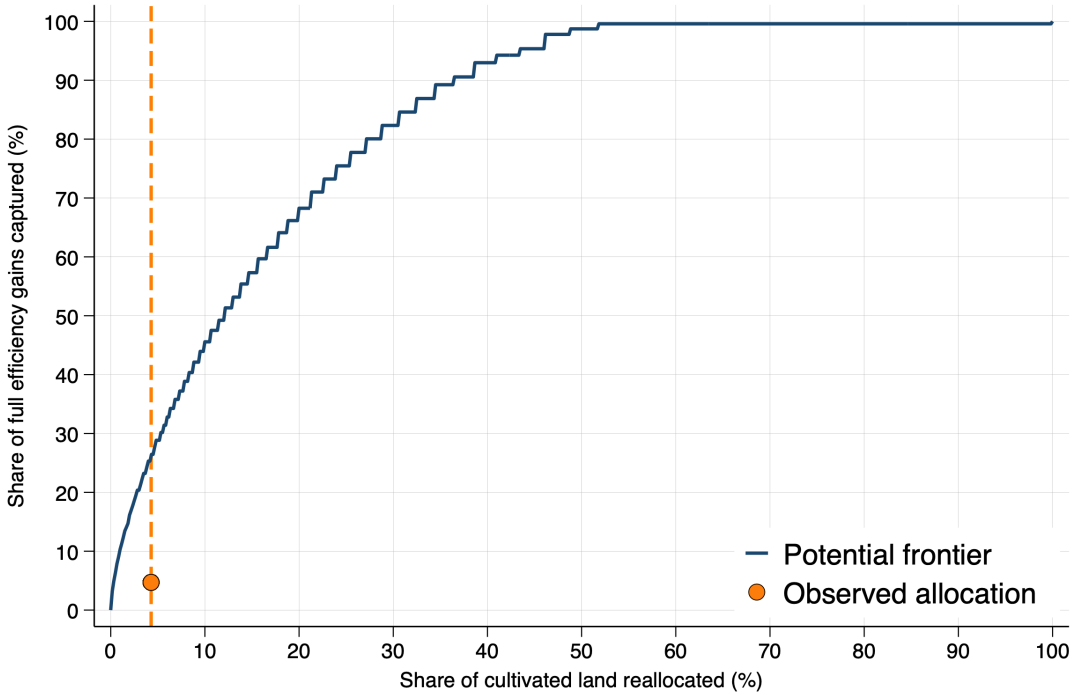
We characterize several aspects of rural factor trade and misallocation. As in Dillon and Barrett (2017), we find that land and labor markets are active: over 4 years, 80% of farmers participate in land markets and 94% of farmers participate in labor markets. Despite frequent trade, we also find that factors of production in Rwanda are misallocated to a similar degree as in other contexts. Observed factor trade is far from the productively efficient frontier: in Figure 1, we calculate the potential productivity gains that could be realized if different fractions of land were traded optimally. We find that observed land rentals eliminate 5% of misallocation, but that the maximally productive allocation of the 4% of land we observe traded through rentals would eliminate 26% of misallocation[2]. The extent of this misallocation is perhaps particularly surprising due to Rwanda's strong property rights over land: all plots are explicitly demarcated and titled, and farmers have rights to use, improve, rent, and buy or sell landholdings (Goldstein et al., 2018). We note that the development of exactly these property rights is the most common prescription for land misallocation in the literature.

Our bilateral transaction data provide clear evidence of factor market frictions in these active factor markets. More productive farmers rent in more land and hire more labor, as we would expect from theory. However, social and physical geography more strongly predict rentals and hiring than productivity. Both rentals and hiring occur much more frequently among farmers who live very near each other, and between a small set of social connections within these villages. For instance, half of rentals in these active factor markets occur within the 5% of household dyads that are socially connected. In principle, trade costs that lead to a dominant share of networked trade could either increase or decrease misallocation. Yet a preference for trading within the network alone is unlikely to explain the substantial distance of observed factor trade from the productively efficient frontier (Figure 1), unless there are other sources of inefficiency in the choice of trading partners[3].

[2]The frequency and efficiency of rentals in Rwanda are very similar to the effects of the provision of land rental rights in China studied by Chari et al. (2021), where rental rights led to a 7% increase in land rented and a 10% increase in efficiency.

[3]In the context of our data, networks are only modestly homophilous in TFP. Thus, if farmers were

Figure 1: Realized and potential productive allocative efficiency gains from land trade



Notes: The realized and potential productive efficiency gains from land trade are plotted in this figure. Let Z_i and Z_{ii} denote the area cultivated and non-rented area cultivated for household i at baseline, A_i denote total factor productivity, and L_i denote labor used. Autarkic area cultivated is $Z_i^a \equiv \frac{Z_{ii}}{\sum_j Z_{jj}} \sum_j Z_j$, and autarkic production is $Y^a \equiv \sum_i A_i \left(Z_i^a\right)^{\alpha_Z} L_i^{\alpha_L}$. Realized gains are $\left(\sum_i A_i Z_i^{\alpha_Z} L_i^{\alpha_L}\right) - Y^a$, and traded land is $\sum_i (Z_i - Z_i^a)\mathbf{1}\{Z_i > Z_i^a\}$. Potential productive efficiency gains solve $\max_z \left(\sum_i A_i z_i^{\alpha_Z} L_i^{\alpha_L}\right) - Y^a$, subject to the constraints $\sum_i z_i \leq \sum_i Z_i$ and $\sum_i (z_i - Z_i^a)\mathbf{1}\{z_i > Z_i^a\} \leq p \sum_i Z_i^a$ for some fraction p. Details on implementation are in Section C.1.

Inefficient factor trade is not typically identified as a mechanism to generate misallocation, which leaves us with little guidance in the literature as to how to understand the patterns we observe. We develop a model of trade frictions beyond proportional trade costs to help resolve our puzzle.[4] We consider a model of factor supply in networks that features two distinct frictions. Iceberg frictions reduce the factor's utility from being hired by a given

able to seek out the highest surplus match, they would be able to realize most of the potential gains from reallocation, even if they were willing to accept a less productive match to rent within their network.

[4]An alternate interpretation of Figure 1 is that factor trade is productively efficient, and observed dispersion in marginal factor products is driven by mismeasurement (Gollin and Udry, 2021). Our primary test that bilateral ties increase the productive efficiency of factor trade is robust to conventional forms of measurement error in TFP.

farm, which may include travel costs or distaste working for others (Agness et al., 2025). Potential factor trading partners may also differ in reliability (Macchiavello and Morjaria, 2015); low reliability increases the cost of sustaining efficient trades through increased match destruction, perhaps generated by contractual breakdowns or distrust (Acampora et al., 2025). Our model delivers distinct predictions for each friction: while iceberg frictions reduce the probability of trade, low reliability reduces the factor trade elasticity and in turn reduce the efficiency of realized factor trade.

We apply these predictions to our data. First, through the lens of our model, the concentration of land and labor trade between social connections and over short distances is consistent with either reduced iceberg frictions or greater reliability in the network. Second, we find that social connections, but not physical proximity, decrease the rate of match destruction for land rentals, but not hires. The model attributes this change to low reliability as a barrier to land trade outside of the network. Our model predicts this should translate into an increased land trade elasticity. Third, and as predicted, we find that land rentals among social connections are more elastic to farm TFP.[5] These results highlight an advantage to use of the network for land trade: because transactions are more reliable, farmers can anticipate identifying more productive and persistent matches when they rent within the network.

Fourth, we apply a model-inspired decomposition of productive allocative efficiency gains from factor trade to these results. 56% of efficiency gains from land trade are from trade along social connections, and 69% of these gains are from the effect of social connections on the land trade elasticity.

Finally, we test whether the land market frictions that social connections reduce could also be overcome with policy. Given that property rights are already strong in this context, we focus our interventions on policy that might boost the efficiency of trade among anonymous trading partners. We conduct an RCT with two interventions to reduce information

[5] Also consistent with model predictions, we do not find robust evidence that labor hires are more elastic to farm TFP among connections, or that physical proximity leads to more elastic transactions in either factor market.

and contracting frictions in land markets: an information intervention, that works with local extension workers to match pairs of potential renters-in and renters-out, and a contracting intervention, which offers a more formal contracting template with room for official signatures. While implementation fidelity was high in both cases, neither intervention led to an increase in land transactions. In a complementary descriptive analysis, we similarly observe that social connections through common organized groups do not increase land transactions. Overall, we conclude that lower reliability of transacting outside the social networks is important to misallocation, but that policy needs more creative solutions to reduce the need for personal trust in contracting when property rights are strong.

Contributions This paper principally contributes to a deep literature in development economics studying inefficiencies in agricultural factor markets. Social ties have been asserted to distort agricultural factor markets since at least Lewis (1954), who hypothesized that "code[s] of ethical behaviour" or "social prestige" motivate farms to post wages above the marginal product of labor. Subsequent work observed that Lewis's hypothesis predicts distortions across household-farms (Singh et al., 1986), derived tests for across-farms distortions, and implemented them in newly available microdata (Rosenzweig, 1980; Benjamin, 1992). More recent work has experimentally identified mechanisms responsible for distortions: social norms constrain agricultural workers from accepting low wage offers in India (Breza et al., 2021, 2025), and search costs generate distortions in spot labor markets in Tanzania (Jeong, 2021). Social ties are at the core of these mechanisms: in agrarian economies, social networks mediate social pressure (Chandrasekhar et al., 2019) and information sharing (Beaman et al., 2021; Kondylis et al., 2025). Yet, to our knowledge, this is the first paper to directly test the association between bilateral social ties and trade in agricultural factor markets.[6] We build on this analysis to produce new evidence on the impact of social ties on

[6]A few related papers have analyzed bilateral social ties among trading pairs in agricultural factor markets. Acampora et al. (2025) find that rentals in Kenya are frequently between friends and family. Swanson (2025) finds that farm managers often use a temporary subsidy to hire family, but managers are less likely to do so when they can plausibly deny that they chose who to hire. Cefala et al. (2025) find that nearly-landless laborers in Burundi are rarely socially connected to their employers. In a complementary

the efficiency of factor markets.

A complementary literature studies the productive consequences of inefficiencies in factor markets. A growing set of papers have built on Hsieh and Klenow (2009), which finds that factor misallocation reduces manufacturing productivity, and documented that misallocation of land and labor across farms has stark consequences for agricultural technology adoption (Jones et al., 2022) and productivity (e.g., Adamopoulos and Restuccia, 2014). Recent work has shown that land rental market thickness is associated with reduced misallocation in Malawi (Chen et al., 2023) and India (Bolhuis et al., 2026). Complementary work has directly estimated the impacts of land market liberalization, and finds that it increases agricultural productivity by enabling relatively more productive farms to scale up (Ravallion and Van De Walle, 2006; Chari et al., 2021). We bring to this literature theory and evidence on the role of networks and space in factor markets and consequences for misallocation.

In studying bilateral trades in agricultural factor markets, we build on an empirical literature on the economic geography of factor markets. In early quantitative work, McFadden (1974) found that bilateral commuting choices are responsive to distance and cost. More recent work has embedded these choices into gravity (Anderson, 2011) models of commuting (Ahlfeldt et al., 2015; Manning and Petrongolo, 2017; Monte et al., 2018). We apply tools from this literature to the study of intravillage land and labor markets, leveraging our bilateral data on land and labor trade over physical and social distance. In addition, we extend the gravity model, introducing low reliability as a cost that generates heterogeneous bilateral trade elasticities which we link to factor market efficiency.

Roadmap We proceed as follows. Section 2 describes our study context and data. Section 3 presents descriptive statistics on factor trade and misallocation in networks. Section 4 develops a model of factor trade with iceberg frictions and heterogeneous contract reliability,

approach, Macours et al. (2010) find rentals in the Dominican Republic are assortatively matched within economic class, suggesting a role of social ties. A much larger literature has studied the association between social ties and trade in non-agricultural labor markets, reviewed in Beaman (2016). This literature often emphasizes altruism, whether strategic or unstrategic, and information on unobserved worker productivity, as key mechanisms (e.g., Beaman and Magruder, 2012).

and Section 5 applies the model to our data. Section 6 presents our experimental results. Section 7 concludes.

2 Context and data

2.1 Context

Our study takes place in the newly constructed Muyanza hillside irrigation scheme in Rwanda, a 1,100-hectare command area serving over 100 villages in and around the scheme. Cultivation is seasonal, with three growing seasons (2 rainy, 1 dry). Farmers cultivate mainly maize, beans, bananas, and horticultural crops, the latter being especially reliant on the existence of irrigation infrastructure in the dry season. The institutional environment is one of relatively strong formal property rights: Rwanda completed a national land titling campaign from 2009–2012, mapping and titling 10.8 million parcels; title holders can improve, use, sell, and rent land, subject to some restrictions (e.g., emphyteutic leases, a flat fee for registering land sales until 2023, subdivision limits for plots below one hectare) (Ali et al., 2014).

We study misallocative frictions in a context where misallocation has direct policy relevance, despite stronger property rights than in the majority of sub-Saharan Africa. Previous work in this context demonstrates the presence of frictions in land and labor markets, and highlights a consequence of these frictions: much of the land with access to irrigation is in the hands of farmers who do not have sufficient household labor to make use of the system without paying high (market) labor costs. This misallocation leads to a low utilization rate of the infrastructure, at levels where long run sustainability is in doubt (Jones et al., 2022).

2.2 Data

The empirical analysis is based on a 5-year data collection effort. We first sampled all 110 villages that intersected the command area and catchments of the Muyanza hillside irrigation scheme. These villages also served as the complete experimental sample for the

randomized control trial described in Section 6. To identify households, our starting point was the national *Ubudehe* social registry ("census"), which enumerates all households in each village (14,344 households in total). We randomly selected 50% of households in each village for a detailed household listing, which gathered basic demographic information and coarse information on agricultural production, factor market participation, and household GPS coordinates. The 7,200 households that responded to this listing comprise our "listing sample". From this listing, we randomly sampled 28 households in command area villages and 10 households in non-command area villages for a baseline survey conducted in early 2019. The 2,362 households that responded to our baseline survey comprise our "survey sample". We approached our survey sample for four rounds of household surveys total, with three follow-up surveys in late 2019, 2021, and 2023. The detailed survey includes a plot-level panel on two primary plots per household, with GPS mapping at baseline and seasonal data on cultivation choices, input use, production, and revenues. We present household-level summary statistics from these data in Table A1.

We match all bilateral data—land and labor transactions, and social connections—to our census in two steps. First, during surveys, we had enumerators match all names to the within-village census. Because any analysis using distance requires dropping households outside our listing sample for whom we do not observe GPS, our primary bilateral analysis sample is dyads (i, j) where household i is in our survey sample and household j is in our listing sample. Second, to produce selected descriptive statistics, we also fuzzy matched all names to the census in all 110 villages.

2.2.1 Factor trade

What is novel in our household survey data are bilateral transaction information in land and labor markets.

For land, we comprehensively track all rentals in, rentals out, purchases or acquisitions, and sales or losses of agricultural land across all four surveys. At baseline, we recorded detailed characteristics of households' 4 most important agricultural plots (either owned and

cultivated, owned and rented out, or rented in). In addition, we collected data on each additional plot that was either rented in or out. In each follow up survey, we recorded all plots that were sold or lost, and all plots that were newly rented out or no longer rented in. For each recorded plot, we identify the counterparty to the rental or transfer of ownership.

For labor, we ask households the identities of the two most frequently hired laborers in each survey. In our agricultural modules, we record labor-days from the two most frequently hired laborers and in total; conditional on hiring labor, 77-81% of the average household's hired labor is from the two most frequently hired laborers during the main agricultural seasons.

For all bilateral analysis of factor trade, we aggregate to the household dyad-by-survey round. Our primary analysis uses binary indicators for any rental in or any hire in.

2.2.2 Networks

We complement our factor trade data with three types of measures of social and physical geography: social connections, common group membership, and physical distance.

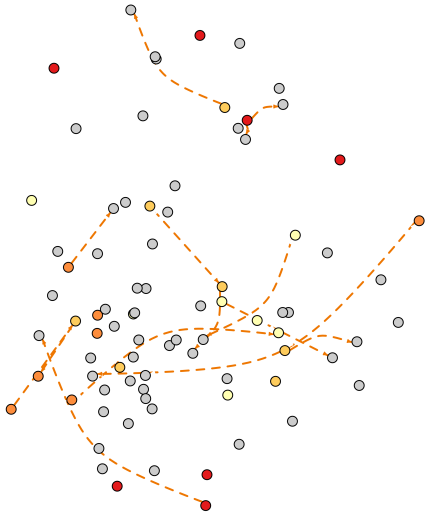
Our baseline survey included a social network elicitation that enumerated all connections in eight categories: people with whom the respondent discusses agricultural decisions, crop choice, problems with agriculture, or agricultural marketing and land, borrows from or lends to, is close family with, is close friends with, or spends time with. Our primary analysis uses a dyad-level indicator that household i reported any social connection to household j.

Prior to our listing survey, we conducted a community survey that enumerated all churches, farmer groups, and ROSCAs. For each household in our listing survey, we recorded all memberships. Our primary analysis uses dyad-level indicators that households i and j share common membership in a ROSCA, in a farmer group, or in a church. Lastly, our listing survey recorded GPS coordinates, and our primary analysis uses dyad-level bilateral distance between the dwellings of households i and j.

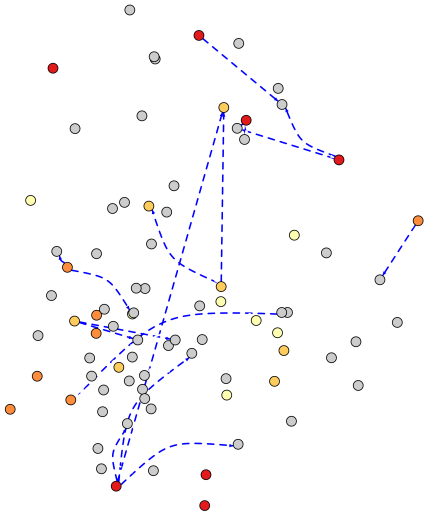
Much of our analysis relies on overlaying our bilateral factor trade data on physical geography and social networks. We present an example of this overlay in Figure 2. Node

color indicates TFP quartiles for the households in our sample, where TFP is calculated as discussed in Section 2.2.3. Curved edges indicate trade relationships where a transaction takes place among a pair that share a social tie. To our knowledge, our data are novel both in the mapping of bilateral rentals and hiring between household-farms and in our ability to relate productivity and trade in those markets to both social and physical geography.

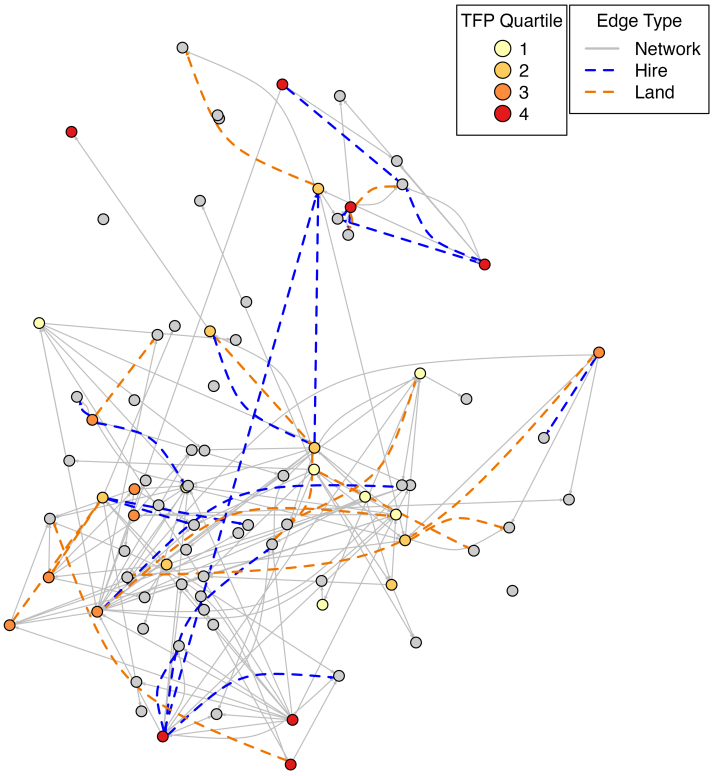
Figure 2: Factor trade in networks



(a) Land rentals



(b) Labor hires



(c) Factor trade in the social network

Households in Rwandan villages are situated closely together, a consequence of the 1996 *Imidugudu* (villagization) policy (Kondylis, 2008). In our sample, the average pair of households in a village are located 560 meters apart (Table A1). Despite this geographic proximity, social networks within villages are sparse. Using the union of all reported ties, density is just 0.05, meaning that only 5% of all potential directed dyads in a village are linked (Table 1). The mean out-degree is 9.01 (SD 4.73), indicating that on average a household names about seven other households in the union network. These low levels of connection are similar to those obtained from network elicitations in other contexts (e.g., Beaman et al., 2021). We also present summary statistics from the factor trade networks, and from geographic networks, where we have defined connected by geography to be a distance which would yield similar density to our observed social networks. Trade networks are much sparser than social networks, with trade occurring along about 1/1000 (1/2000) dyads for land (labor). We also report the reciprocity of different networks, which shows the share of ties that are reciprocated. Geographic ties, by definition, are perfectly reciprocal while social ties are quite likely to be reciprocated, with 39% of named connections also naming a connection to the counterparty. In contrast, trade is essentially never reciprocated, with 0% of renters out ever renting in from their renters, and 0.7% of employers ever working for their workers. This trend highlights that factor markets in the Rwandan context are not characterized by exchanges of land or labor.

Table 1: Network statistics

Network:	Social Link	Distance (km) ≤ 0.14	Rent In	Hire
	(1)	(2)	(3)	(4)
Panel A: Households				
Out-degree	9.01	5.233	0.099	0.227
	(4.73)	(3.782)	(0.330)	(0.530)
Panel B: Villages				
Density	0.05	0.089	0.001	0.002
	(0.044)	(0.049)	(0.001)	(0.003)
Edgewise reciprocity	0.390	1.000	0.000	0.007
	(0.190)	(0.000)	(0.000)	(0.052)

Notes: Standard deviations in parentheses. Using directed graphs. Link represents the union of all social network sub-graphs. Distance network is defined by households living within 0.14 km of one another, chosen to match average link density. Rent In and Hire are the networks of dyadically linked transactions. Out-degree is the total reported number of social connections in the baseline-village sample. Density is the share of observed links out of the number of potential links in the baseline-baseline sample. Edgewise reciprocity is XXX in the baseline-baseline sample. Measurements in Panel A are at the household level while measurement in Panel B represent village-level averages.

2.2.3 Productivity and misallocation

For our analysis of agricultural productivity and misallocation, we begin by leveraging our plot-level panel to construct measures of production and factor use in each survey round. We calculate output value as total value of production, labor use as total household and hired labor-days, and land use as area cultivated. For all three measures, we sum across all three agricultural seasons in each survey round.

We then closely follow Aragón et al. (2022) in measuring farm-level TFP. First, we assume farms have Cobb-Douglas production functions for output value with labor and land as inputs, with factor loadings α_L and α_Z, respectively. That is, we specify

$$\log Y_{ivt} = \alpha_L \log L_{ivt} + \alpha_Z \log Z_{ivt} + \log \text{TFP}_i + \psi_{vt} + \nu_{ivt} \tag{1}$$

where Y_{ivt}, L_{ivt}, and Z_{ivt} are the output value, labor use, and land cultivated by farm i in village v in survey round t, ψ_{vt} are village-round productivity shocks and ν_{ivt} are idiosyncratic household productivity shocks. Second, we assume that within-farm changes in land and labor are uncorrelated with changes in farm-productivity; Shenoy (2021) and Aragón et al. (2022) argue that this is a reasonable identifying assumption for constrained household farms. Formally, we assume

$$\mathbf{E}[(\log L_{ivt}, \log Z_{ivt}, \log \text{TFP}_i, \psi_{vt})' \nu_{ivt}] = \mathbf{0}$$

Under this assumption, we estimate Equation 1 using OLS. While household TFP is estimated with error, Aragón et al. (2022) argue that the inclusion of multiple years of data significantly reduces measurement error. We conduct substantial robustness analysis in Appendix B, including estimating TFP using spatial fixed effects, following the approach of Chari et al. (2021), and demonstrating robustness of our primary specifications to different TFP estimates derived from a grid spanning all possible pairs of factor loadings. Our primary conclusions are robust to a variety of alternative sensable measurements of TFP.

We report estimates of the factor loadings in Equation 1 in Table A2. We estimate factor loadings on labor and land of $\alpha_L = 0.49$ and $\alpha_Z = 0.36$. For comparison, Aragón et al. (2022) estimate $\alpha_L = 0.34$ and $\alpha_Z = 0.37$ in Uganda, while Gollin and Udry (2021) estimate α_L between 0.22 and 0.43 and α_Z between 0.53 and 0.73 in Uganda and Tanzania. We therefore estimate a slightly higher labor loading and slightly lower land loading than in other contexts, consistent with a relatively high labor intensity of agriculture in Rwanda (Jones et al., 2022). All subsequent analysis uses the household fixed effects in Table A2 as our measure of log TFP.

3 Factor trade and misallocation in networks

We begin our analysis in four steps. First and second, we replicate well know descriptive statistics on factor trade (Section 3.1) and misallocation (Section 3.2) in agriculture in our context. Third, we relate factor trade and misallocation (Section 3.3). Fourth, we relate social connections and physical distance to factor trade in Section 3.4.

3.1 Factor markets are highly active

We first present descriptive statistics on the activity of factor markets in Table 2. We aggregate rentals and hiring across all four survey rounds. 80% of households participate in at least one land rental or transfer: 55% of households rent in land, 33% rent out, 20% purchase land, and 25% report land lost or sold (Table 2). Labor markets appear even more active: 94% of households report hiring labor or working for others, with 64% hiring in and 59% hiring out. These participation rates are somewhat higher than in other African countries: Dillon and Barrett (2017) report annual rates of hiring in labor that range from 30% to 49% and renting in land that range from 20% to 39% across five African countries.

3.2 Factors are misallocated

Despite highly active factor markets, our context exhibits standard patterns of misallocation. We present two widely used measures of misallocation derived from the Cobb-Douglas production function (e.g., Gollin and Udry, 2021; Adamopoulos et al., 2022; Chen et al., 2023; Aragón et al., 2024). First, under efficient allocations, marginal products of labor and land are constant across farms. We present the densities of log output per worker ($1/\alpha_L$ times the log marginal product of labor) and log output per hectare ($1/\alpha_Z$ times the log marginal product of land) in Figure 3. We estimate a standard deviation of the log marginal products of labor and land of 0.37 and 0.38, respectively. We also plot the densities of residual measures of these outcomes after villageXsurvey round fixed effects are included,

Table 2: Factor markets are highly active

	Mean (1)	SD (2)	Obs (3)
A. Land			
Ever Transact	0.80	0.40	2362
Ever Rent In	0.55	0.50	2362
Ever Rent Out	0.33	0.47	2362
Ever Purchase	0.20	0.40	2362
Ever Lost/Sold	0.25	0.43	2362
B. Labor			
Ever Transact	0.94	0.24	2362
Ever Hire In	0.64	0.48	2362
Ever Hire Out	0.59	0.49	2362

Notes: The table reports household-level means, standard deviations, and numbers of nonmissing observations. All outcomes are binary indicators equal to one if the household engaged in the indicated transaction in any of the four survey rounds (baseline and three follow-ups). Rental indicators include arrangements active since the previous survey that ended before the current interview. "Hire In" denotes hiring labor, while "Hire Out" denotes supplying household labor outside the household. Transaction categories are not mutually exclusive.

to remove any spatial or time trends. Only a modest amount of this variation is explicable by these spatial and time trends. Second, under efficient allocations, a 1% increase in TFP should be associated with an $\frac{1}{1-\alpha_L-\alpha_Z}\%$ (which we estimate to be 6.67%) increase in land and labor allocations. To recover empirical elasticities, we estimate

$$y_{ivt} = \beta \log \text{TFP}_i + X_i'\gamma + \psi_{vt} + \nu_{ivt} \tag{2}$$

for outcome y_{ivt}, either land cultivated or labor use, for farm i in village v in survey round t. We include the number of social network connections in X_i as a control. For this and all other analysis in the paper, we report robust standard errors clustered at the village level. We estimate elasticities of land and labor to TFP in Table 3 of -0.33 and 0.19, respectively,

far from the efficient benchmark.

3.3 Factor markets partially reduce misallocation

While we observe that misallocation persists despite active factor markets, this says little about the effect of factor markets on misallocation. We take two approaches to qualitatively and quantitatively assess the effects of factor markets on misallocation.

First, in Table 3, we estimate Equation 2 and report the relationship between log TFP and the number of plots rented in and the number of workers hired. A 1% increase in TFP is associated with a 0.17% increase in the number of plots rented in (0.1 additional plots) and a 0.36% increase in the number of workers hired (0.45 additional workers).

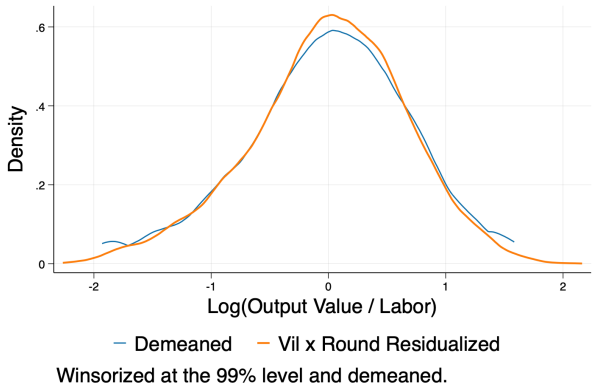
[7] These coefficients are still far from the efficient elasticity of land and labor allocations to TFP. However, they are meaningfully larger than the observed elasticity of land and labor allocations to TFP, implying factor markets relatively increase land and labor use by higher TFP farms.

Second, we test the effect of factor markets on land and labor allocations by estimating the elasticity of land use relative to household-owned land use, and labor use relative to household-labor use, to TFP. The resulting coefficients are the differences between the elasticities of observed land or labor use and elasticities of autarkic (i.e., household-owned) land and labor use to TFP, and therefore reflect the impact of factor markets on efficiency. We find that rentals and hires increase the elasticity of land use to TFP by 0.03 (from -0.35) and labor use to TFP by 0.06 (from 0.13). While these magnitudes are small relative to the efficient benchmark, they are large relative to the elasticities of owner cultivated land and household labor to TFP.

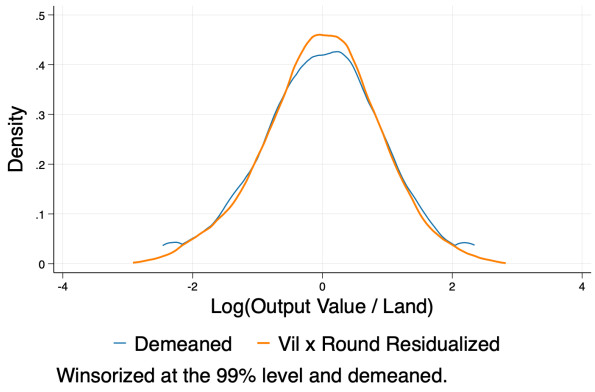
[7] Throughout the paper, we focus our analysis on rentals in, rather than rentals out, as they are typically reported more accurately in agricultural household surveys (Abate et al., 2025).

Figure 3: Marginal factor products exhibit substantial dispersion

(a) Density of log output value per worker



(b) Density of log output value per hectare



Notes: The densities of log output per worker (Figure 3a) and per hectare (Figure 3b) are presented in this figure. When production is Cobb-Douglas (Equation 1), these are equal to the log marginal product of labor divided by the labor factor loading (0.49), and the log marginal production of land divided by the land factor loading (0.36).

Table 3: Factor elasticities to TFP are far from efficient benchmark, but factor trade partially reduces misallocation

	Land			**Labor**		
	Log(Land)	Plots Rented In	$\text{Log}\left(\frac{\text{Land}}{\text{Own Land}}\right)$	Log(Labor)	Total Hires	$\text{Log}\left(\frac{\text{Labor}}{\text{HH Labor}}\right)$
	(1)	(2)	(3)	(4)	(5)	(6)
log TFP	-0.593***	0.098***	0.017**	0.067***	0.450***	0.036***
	(0.034)	(0.018)	(0.007)	(0.022)	(0.073)	(0.008)
Degree	0.053***	0.007**	-0.000	0.036***	0.065***	0.006***
	(0.005)	(0.003)	(0.001)	(0.003)	(0.008)	(0.001)
N	9075	9161	8866	9072	9161	9050
Mean of Dep Var	-0.977	0.369	0.054	4.168	0.984	0.135
Vil x Rnd FE	X	X	X	X	X	X

Notes: Each observation is a household–survey round; the sample covers 2,362 panel households in 110 villages over the baseline and three follow-up survey rounds. Land is the area the household cultivated in the round, and Own Land is the area cultivated on plots the household owns. Labor is total person-days of labor used (household plus hired), and HH Labor is person-days supplied by household members. Plots Rented In is the number of plots the household rents in at the time of the survey, and Total Hires is the number of workers on the household's hired-labor roster for the round. Land and labor quantities are winsorized at the 99th percentile before taking logs. Log(TFP) is the household fixed effect from Equation 1, and Degree is the household's out-degree in the union of all elicited networks. All columns include village × round fixed effects. Standard errors clustered at the village level are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level.

3.4 Factor trade is concentrated locally and within social networks

The findings above imply that factor trade only partially reduces misallocation, but do not shed light on why. We now use our social network and geographic mapping to formally test whether social and geographic proximity, and not just productivity, can explain observed factor trade. To do so, we estimate using OLS

$$y_{ijvt} = \beta_1 \text{Link}_{ij} + \beta_2 \text{Distance}_{ij} + X'_{ij}\gamma + \psi_{vt} + \nu_{ijvt} \tag{3}$$

for outcome y_{ijvt}, either an indicator for rental in or hire in, in village v and survey round t by farm j from household i. Our primary coefficients of interest are those on the indicator Link_{ij} that j is connected to i, and on the distance Distance_{ij} between farm j and household i. In addition, we include bilateral controls for common membership in churches, farmer groups or ROSCAs, along with farm j controls for number of social connections and log TFP, in X_{ij}. We include village-round fixed effects ψ_{vt} in all models, and we estimate robustness that include household i fixed effects and farm j fixed effects. We report estimates of Equation 3 in Table 4.[8]

Across specifications, we robustly find that social connections and distance between households have large impacts on the probability of factor trade. A social connection increases the probability of a bilateral rental in by 0.6pp and of a bilateral hire in by 1.1pp. These effects are roughly 12 and 8 times larger than the average bilateral rental and hiring probability. While just 5% of bilateral links are social connections, these effects imply that slightly more than half of rentals, and slightly less than half of hires, are between social connections. We also find that a one kilometer increase in distance decreases the probability of a bilateral rental in by 0.1pp and of a bilateral hire in by 0.4pp. Comparing magnitudes, the relative importance of social connections is several times larger than the effect of distance for most household-pairs, and twice as large in land markets as in labor markets[9].

[8] In Table A3, we instead estimate a Poisson model. The qualitative patterns of coefficients, their statistical significance, and their relative magnitudes, are all unaffected.

[9] The effect of a social connection is approximately equivalent to the effect of 7 km of distance in land

Table 4: Intravillage factor trade is concentrated in networks

	Rent In			**Hire**		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Link)	0.0058***	0.0058***	0.0059***	0.0110***	0.0121***	0.0120***
	(0.0006)	(0.0006)	(0.0006)	(0.0010)	(0.0011)	(0.0011)
Distance (km)	-0.0009***	-0.0011***	-0.0010***	-0.0045***	-0.0050***	-0.0061***
	(0.0001)	(0.0002)	(0.0002)	(0.0004)	(0.0005)	(0.0006)
1(Same ROSCA)	-0.0001	-0.0004	-0.0005	0.0001	0.0002	0.0001
	(0.0003)	(0.0005)	(0.0005)	(0.0007)	(0.0008)	(0.0009)
1(Same Coop)	-0.0009*	-0.0009	-0.0011*	-0.0018	-0.0003	-0.0016
	(0.0005)	(0.0006)	(0.0007)	(0.0013)	(0.0013)	(0.0015)
1(Same Church)	0.0001	0.0000	0.0001	0.0005**	0.0009***	0.0009**
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
TFP X	0.0005***	0.0005***		0.0009***	0.0008***	
	(0.0001)	(0.0001)		(0.0002)	(0.0002)	
Degree	-0.0000	-0.0000		0.0001***	0.0001***	
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	
Constant	0.0011***	0.0013***	0.0010***	0.0033***	0.0034***	0.0050***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0004)
N	496152	496152	496152	496152	496152	496152
Mean of Dep Var	0.0004	0.0004	0.0004	0.0019	0.0019	0.0019
Vil x Round FE	X	X	X	X	X	X
X Node FE			X			X
Y Node FE		X	X		X	X

While these results strongly suggest that social connections increase rentals and hiring, an alternative explanation is reverse causality: rentals and hiring could be responsible for social connections. To test this hypothesis, we replicate Table 4 but restricting to our three post-baseline survey rounds, and using *new* rentals and hires in as our outcome. In Table A5, we find qualitatively similar impacts of social connections on bilateral rentals and hires that were not present at baseline. While coefficients mechanically fall as new rentals and hires are a subset of rentals and hires, coefficients remain unaffected relative to average new rental and hire probabilities.

markets (0.0056/0.0008) and 2.1 km of distance in labor markets (0.0116/0.0055); the mean pair of households in a given village is 560m apart (sd 200m)(Table A1).

The impacts we estimate of social connections and distance on factor trade are large relative to the impact of TFP. Our estimates imply a one standard deviation increase in the social connection indicator (0.22) is associated with a 0.13pp increase in bilateral land rentals and a 0.24pp increase in bilateral hires in, while a one standard deviation increase in TFP (0.50) is associated with a 0.02pp increase in land rentals and a 0.05pp increase in hires in.

That is, variation in social connections explains 4-to-6 times more variation in factor trade than TFP.

That farmers frequently transact among their social ties is a symptom of important trade costs in these markets. However, this result says little about why farmers transact among their social ties, or even whether the use of the network for land and labor market transactions contributes positively or negatively towards misallocation. In principle, an altruistic preference for trading within the network might increase misallocation, as farmers accept lower rents from lower productivity farmers to realize that preference (as suggested by Lewis (1954)). In contrast, the availability of networks with lower trade costs could increase efficiency: by avoiding distortionary trade costs, transacting within the network could lead to significant efficiency gains. Separating these mechanisms requires a model which distinguishes between trade costs which reduce all trade, and those which reduce the efficiency of trade.

Explaining the efficiency of factor trade, and not just its probability, will therefore be necessary to explain misallocation.

4 A model to separate trade costs

The descriptive findings in Section 3 suggest that observed factor trade is inefficient, and frictions may shape both the thickness and efficiency of factor markets. In Section 4.1, we develop of a model of intravillage factor trade that incorporates both iceberg frictions, which reduce gains from trade, and low reliability, which we model as a search cost that increases

the costs of directing trade to where there are gains. In Section 4.2, we show that while both iceberg and low reliability reduce trade, only low reliability reduces the factor trade elasticity, a testable prediction. In Section 4.3, we show low reliability decreases the efficiency of trade, and decompose productive gains from changes in factor trade into intensity and efficiency margins. In Section 4.4, we discuss applying these predictions to the effects of social and physical proximity on factor trade and its efficiency.

4.1 Environment

4.1.1 Factor search

Factor endowments and factor trade Household $i \in \mathcal{I}$ hosts a continuum of land, or labor, $\overline{Z}_i$. Each atomistic unit of land from household i maximizes expected utility, net of search costs, with respect to its probability of being hired by farm $j \in \mathcal{I}$, P_{ij}. As a consequence, $Z_{ij} \equiv P_{ij}\overline{Z}_i$ units of land from household i are hired by farm j, and farm j cultivates $Z_j \equiv \sum_i Z_{ij}$ total units of land.

The factor problem and its first order condition Household i's land solves

$$(P_{ij})_{j\in\mathcal{I}} = \arg\max_{\sum_j p_{ij}=1} \underbrace{\sum_{j\in\mathcal{I}} p_{ij}u_{ij}}_{\text{expected utility}} - \underbrace{\sum_{j\in\mathcal{I}} \mu_{ij}c(p_{ij})}_{\text{search costs}} \tag{4}$$

We assume $c'' > 0$ (increasing marginal search costs) and $\mu_{ij} > 0$. Let λ_i denote the multiplier on the constraint $\sum_j p_{ij} = 1$, which we refer to as the shadow value of land. The household's first order condition is

$$c'(P_{ij}) = \frac{1}{\mu_{ij}}(u_{ij} - \lambda_i) \tag{5}$$

The marginal cost of increasing the probability of being hired by farm j, $c'(P_{ij})$, is equal to normalized utility, $u_{ij} - \lambda_i$, divided by μ_{ij}.

Reliability $1/\mu_{ij}$ μ_{ij} is modeled as an entropy cost of matching (Fudenberg et al., 2015), similar to an utility cost which can microfound the logit discrete choice model. In the static model, μ_{ij} increases the cost of directed search towards high utilities u_{ij}. Note that when μ_{ij} doubles, the household must pay the same search costs twice to match with the same probability. We therefore interpret inverse reliability μ_{ij} as proportional to the rate of match destruction, such as might follow a contractual breakdown, after which the household must repeat the search process for that unit of land. We formalize this interpretation in a dynamic model in Appendix C.4[10].

Prediction 1. *Lower reliability increases the probability of match destruction.*

Bilateral factor utilities and iceberg frictions τ_{ij} We canonically decompose $u_{ij} \equiv \eta \log(R_j/\tau_{ij})$. That is, the utility from being hired by j is proportional to the log of the posted rent, R_j, scaled down by iceberg costs τ_{ij}.[11] Importantly, many potential sources of iceberg frictions are "technological" and may therefore generate heterogeneity in marginal products of land and labor even at efficient allocations (Bergquist et al., 2026). Households' workers may face travel costs to reach the farms that hire them, while farmers may face travel costs to farm rented plots. Workers may prefer to work for their own household's farm even absent differences in the nature of or renumeration from the work.

As choices described by Equation 5 are homogeneous of degree 0 in u_{ij}, they are homo-

[10]Reliability frictions have several links in incomplete contracting literatures, where reliability is more typically modeled as the outcome of a dynamic game. By increasing the probability of match destruction and creating heterogeneity in the desirability of different trade partners, this specification of reliability recalls the asymmetric information problem solved through relational contracts in Macchiavello and Morjaria (2015). Similarly, there is a clear link to maintenance costs in the literature on network formation (Jackson and Wolinsky, 1996), where random mutations in gains from costly connections determine link destruction (Jackson and Watts, 2002). Our formulation is attractive for our context due to its ability to generate a gravity model as we discuss below

[11]In principle, farm j could negotiate rents bilaterally with each household, that is post rents R_{ji}. In practice, household (i.e., factor owner) characteristics and bilateral ties do not predict wages or rents within hiring farm (Table A6, Table A7), and we therefore model each hiring farm as posting a single wage or rent.

thetic (homogeneous of degree 1) in R_j. Substituting into Equation 5 yields

$$c'(P_{ij}) = \frac{1}{\mu_{ij}}(\eta \log R_j - \eta \log \tau_{ij} - \lambda_i) \tag{6}$$

Gravity with heterogeneous bilateral trade elasticities Below we derive statics in a particularly tractable specification of marginal search costs; we present statics for general specifications of marginal search costs in Section C.5. Our preferred tractable specification yields a generalization of the "gravity" model of trade (Anderson, 2011), in which heterogeneous bilateral trade elasticities ϵ_{ij} are derived from heterogeneous bilateral matching frictions μ_{ij}.

Proposition 1. *Suppose Equation 6 holds, and* $c'(q) = a \log q + b$. *Then*

$$P_{ij} = \left(\frac{R_j}{\Lambda_i \delta_{ij}}\right)^{\epsilon_{ij}} \tag{7}$$

where $\epsilon_{ij} \equiv \eta/(a\mu_{ij})$, $\delta_{ij} \equiv \tau_{ij} \exp(b/(a\epsilon_{ij}))$, *and* $\Lambda_i \equiv \exp(\lambda_i/\eta)$.

Links to gravity and models of consumer demand Fudenberg et al. (2015) study choices that can be represented as solutions to Equation 5 under constant μ_{ij}, which they refer to as "Additive Perturbed Utility". They show that for additive perturbed utility, multinomial logit choice is equivalent to either independence of irrelevant alternatives or $c'(q) = a \log q + b$ (as we assume in Proposition 1). Fudenberg et al. (2015) interpret c as reflecting "implementation costs" associated with directed search, such as contracting, while Denti (2022) notes that the strict concavity of c makes it is an inappropriate representation of costs of information acquisition.

The choices described by Equation 6 are a special case of "homothetic single aggregator" demand (Matsuyama and Ushchev, 2017; Fally, 2022). Equation 7 is equivalent to "separable translog" demand (Matsuyama and Ushchev, 2017), with demand elasticities ϵ_{ij}

In modeling trade and migration, recent work uses rational inattention (reviewed in

Maćkowiak et al., 2023) to generate heterogeneous trade elasticities across either destinations ($\epsilon_{ij} = \epsilon_j$ in Dasgupta and Mondria, 2018) or origins ($\epsilon_{ij} = \epsilon_i$ in Bertoli et al., 2020; Porcher, 2025). Alternatively, Lenoir et al. (2023) show that matching frictions between origin firms and destination buyers can generate elasticities of demand across exporting firms that vary by origin-destination pair while aggregating to a homogeneous trade elasticity across origins.

4.1.2 Existence and uniqueness of an equilbrium

Our theoretical results in Section 4.2 and Section 4.3 are derived entirely from the factor's problem in Section 4.1.1, and abstract from the farm's problem. The interpretation of our results may be less clear if there is not a unique equilibrium for a reasonable specification of the farm's problem. We apply a result from Allen et al. (2024) to provide sufficient conditions for equilibrium uniqueness.

Theorem 1. *Suppose Equation 7 holds, each farm j posts rent $R_j = A_j Z_j^{-(1-\alpha)}$ for $\alpha \in (0,1)$, and land markets clear. If $\max_{i,j} \epsilon_{ij} - \min_{i,j} \epsilon_{ij} < \frac{1}{1-\alpha}$, then there is a unique equilibrium.*

Proof. See Section C.2. □

Theorem 1 states that when Cobb-Douglas farms post rent equal to the marginal product of land, there is a unique equilibrium as long as there is not too much heterogeneity in bilateral trade elasticities relative to the elasticity of land demand.[12]

4.2 Iceberg frictions, reliability, and trade

Iceberg frictions τ_{ij} and inverse reliability μ_{ij} enter the factor's first order condition in very different ways in Equation 6. The implications are clear in Equation 7: decreases in reliability μ_{ij} decrease the factor trade elasticity ϵ_{ij}, but may increase or decrease trade. Iceberg

[12] Alternatively, farms may take the market rent R as given. Suppose farms may apply costly effort to increasing hiring conditional on posted rent, such as offering amenities or advertising intent-to-hire. One would then interpret R_j as the unit cost gross of rent for farm j, with more marginally productive farms posting a higher amenity and therefore offering higher R_j.

frictions τ_{ij} reduce rent received R_j/τ_{ij}, shifting trade away from j, but do not affect the factor trade elasticity.

Prediction 2. *Hold fixed the shadow value of land λ_i. Iceberg frictions decrease bilateral trade. Decreases in reliability have an indeterminate effect on bilateral trade.*

$$\left.\frac{d\log P_{ij}}{d\log \tau_{ij}}\right|_{\lambda_i} = -\epsilon_{ij} < 0 \qquad \left.\frac{d\log P_{ij}}{d\log \mu_{ij}}\right|_{\lambda_i} = -\log P_{ij} - \frac{b}{a}$$

Prediction 3. *Hold fixed the shadow value of land λ_i. Iceberg frictions have no impact on the factor trade elasticity. Reductions in reliability decreases the factor trade elasticity.*

$$\left.\frac{d}{d\log \tau_{ij}}\frac{d\log P_{ij}}{d\log R_j}\right|_{\lambda_i} = 0 \qquad \left.\frac{d}{d\log \mu_{ij}}\frac{d\log P_{ij}}{d\log R_j}\right|_{\lambda_i} = -\epsilon_{ij} < 0$$

4.3 Iceberg frictions, reliability, and misallocation

Increasing the factor trade elasticity increases the relative share of factor trade towards high utility farms, such as those offering higher rents. This intuition suggests that decreasing matching frictions increases productive efficiency, which we confirm below.

Prediction 4. *A uniform proportional reduction in reliability decreases average rent if and only if the factor trade elasticity-weighted covariance of rent and utilities is positive.*

$$\sum_j \frac{d}{d\log \mu_{ij}} \sum_k P_{ik}R_k < 0 \Leftrightarrow \sum_j \epsilon_{ij}P_{ij}\left(R_j - \frac{\sum_k \epsilon_{ik}P_{ik}R_k}{\sum_k \epsilon_{ik}P_{ik}}\right)\left(u_{ij} - \frac{\sum_k \epsilon_{ik}P_{ik}u_{ik}}{\sum_k \epsilon_{ik}P_{ik}}\right) > 0$$

Proof. Totally differentiating Equation 5 yields

$$\frac{dP_{ik}}{d\log \mu_{ij}} = -\frac{\mathbf{1}\{j=k\}}{c''(P_{ij})\mu_{ij}}(u_{ij} - \lambda_i) - \frac{1}{c''(P_{ik})\mu_{ik}}\frac{d\lambda_i}{d\log \mu_{ij}}$$

Applying the constraint $\sum_k \frac{dP_{ik}}{d\log \mu_{ij}} = 0$ yields

$$\frac{d\lambda_i}{d\log \mu_{ij}} = -(u_{ij} - \lambda_i)\frac{1/(c''(P_{ij})\mu_{ij})}{\sum_k 1/(c''(P_{ik})\mu_{ik})}$$

We now derive

$$\sum_j \frac{d}{d\log\mu_{ij}} \sum_k P_{ik}x_k = \sum_j \sum_k \frac{dP_{ik}}{d\log\mu_{ij}} x_k$$
$$= -\sum_j \frac{1}{c''(P_{ij})\mu_{ij}} (u_{ij} - \lambda_i) \left(x_k - \frac{\sum_k x_k/(c''(P_{ik})\mu_{ik})}{\sum_k 1/(c''(P_{ik})\mu_{ik})} \right)$$

This expression is just the negative of the $1/(P_{ij}c''(P_{ij})\mu_{ij})$ weighted covariance of u_{ik} and x_k. Prediction A.2 in Appendix C.5 shows that these weights are proportional to the factor trade elasticity $\left.\frac{d\log P_{ij}}{d\log R_j}\right|_{\lambda_i}$, which is equal to ϵ_{ij}. □

Prediction 4 underscores that that the impact of a change in reliability on productive efficiency is an empirical question; if utilities and rent are strongly correlated, as would be the case if iceberg frictions are small, then improving reliability would strongly increase average rents. In contrast, if variation in utilities is largely driven by iceberg frictions, increasing reliability may have a limited effect on productive efficiency. The effect of a change in iceberg frictions on productive efficiency is similarly an empirical question: reductions in iceberg frictions increase relative trade, and therefore will improve productive efficiency if they decrease relatively more towards higher rent farms.

We therefore take an empirical approach to evaluate the role of bilateral ties, through reliability and iceberg frictions, in shaping allocative efficiency through factor markets.

Prediction 5. *Let C_{ij} denote a binary bilateral tie between i and j, and suppose C_{ij} is independent of marginal products without rentals MPZ_i and landholdings $\overline{Z}_j$. The fraction of productive efficiency gains from rentals in that are from rentals in conditional on $C_{ij} = 1$*

is approximately

$$\frac{\sum_i (MPZ_i - \overline{MPZ}) \sum_{j \neq i} C_{ij} P_{ji} \overline{Z}_j}{\sum_i (MPZ_i - \overline{MPZ}) \sum_{j \neq i} P_{ji} \overline{Z}_j}$$
$$\approx \left(1 + \underbrace{\frac{\sum_{j \neq i} (1 - C_{ij}) P_{ji} \overline{Z}_j}{\sum_{j \neq i} C_{ij} P_{ji} \overline{Z}_j}}_{\textit{relative rental probability}} \underbrace{\frac{\boldsymbol{Cov}[\log P_{ji}, \log MPZ_i | C_{ij} = 0]_{j \neq i} / \boldsymbol{Var}[\log MPZ_i | C_{ij} = 0]_{j \neq i}}{\boldsymbol{Cov}[\log P_{ji}, \log MPZ_i | C_{ij} = 1]_{j \neq i} / \boldsymbol{Var}[\log MPZ_i | C_{ij} = 1]_{j \neq i}}}_{\textit{relative productive efficiency}} \right)^{-1} \tag{8}$$

Proof. See Appendix C.6. □

Prediction 5 decomposes the role of bilateral ties in the productive efficiency of rentals into two terms.[13] The first term is the relative frequency of rentals along that bilateral tie; for instance, rentals in social networks contribute a larger fraction of productive efficiency gains when a larger fraction of rentals are within social networks. The second term is the relative productive efficiency of rentals along that bilateral tie; for instance, rentals in social networks contribute a larger fraction of productive efficiency gains when they disproportionately flow to more marginally productive farmers.

4.4 From theory to data

Our results in Section 3 do not allow us to distinguish between iceberg frictions and differences in reliability. Both social and physical proximity increase land and labor trade (Table 4), but this could be attributable to reduced iceberg frictions, improved reliability, or both (Prediction 2). We apply our model predictions, which we synthesize in Table 5, to formally test the hypotheses that social and physical proximity reduce matching frictions in land and labor markets.

[13] In practice, our data is not well equipped for studying the productive efficiency of rentals out, and we therefore focus on rentals in.

Table 5: Model predictions

		Effect of a decrease in...	
		Iceberg frictions	Inverse reliability
		(1)	(2)
Match destruction rate	(Prediction 1)	0	−
Bilateral trade	(Prediction 2)	+	?
Factor trade elasticity	(Prediction 3)	0*	+

Notes: Testable predictions of our model are synthesized in this table. * is used to indicate predictions that impose Equation 6.

Persistence and testing for increased reliability Prediction 1 implies a simple approach to test whether bilateral ties, such as social or physical proximity, increase reliability in either land or labor markets. If bilateral ties increase reliability in a given market, they should decrease the probability that a given bilateral trade ends. In Section 5, we test this leveraging our panel data on bilateral factor trade.

Factor trade elasticity and testing for increased reliability Prediction 3 implies that bilateral ties that increase reliability should also increase the factor trade elasticity, while bilateral ties that reduce iceberg frictions should not.[14] Bilateral ties that increase match persistence should therefore also increase the factor trade elasticity.

Addressing sparsity of trade and endogeneity of factor prices In practice, networks of land and labor trade are sparse, land and labor trade is discrete, and many households do not hire any land or labor. This has two significant implications for estimation of the factor trade elasticity. First, bilateral rental probabilities P_{ij} are not directly observed. We instead use an indicator that j hires from i (as in Table 4). Second, posted factor prices are both

[14] In Appendix C.5, we show that iceberg frictions may also affect the factor trade elasticity under a more general specification of marginal search costs, due to departures from log linearity in the effect of factor prices on trade. However, this pattern should not be robust to alternative specifications of the link function in the estimating equation, such as linear rather than log. We discuss evidence of robustness in Section 5.2.

endogenously measured and are also endogenous to realized factor trade.[15] We therefore instead use log TFP ($\log A_j$) instead of posted factor prices ($\log R_j$), as conditional on the factor allocation Z_j the marginal product of the factor is proportional to TFP.

Bilateral ties and misallocation Prediction 4 suggests that bilateral ties that reduce matching frictions should generate larger increases in allocative efficiency, while Prediction 5 presents an approach to calibrating the effects of bilateral ties on allocative efficiency using their effects on the probability of factor trade and its elasticity to TFP. After estimating the impacts of bilateral ties on the probability of factor trade and its elasticity to TFP in Section 5.2, we substitute these estimates into Prediction 5 to compare the effects of more or less socially or physically proximate factor trade on allocative efficiency.

5 Results

The theory in Section 4 provides tests of whether bilateral ties increase the efficiency of factor trade by reducing the costs of sustaining efficient trades, a first step in unpacking the inefficiency of observed factor trade. In Section 5.1, we test Prediction 1 on reliability differences, by testing whether social connections and physical distance increase the persistence of rentals and hires. In Section 5.2, we test Prediction 3 on reliability differences, by testing whether the bilateral ties that increase persistence also increase the factor trade elasticity.

[15] This discreteness, and the determinants of decisions to participate in factor trade, are likely to have important consequences for factor misallocation in agriculture but are beyond the scope of this paper.

5.1 Social connections increase the persistence of land rentals

We begin by testing whether bilateral ties increase the persistence of factor trade, leveraging our dyadic transaction panel. Specifically, we regress

$$y_{ijvt} = \beta_1 \text{Link}_{ij} + \beta_2 \text{Distance}_{ij} + \beta_3 y_{ijvt-1} + \beta_4 \text{Link}_{ij} \times y_{ijvt-1} + \beta_5 \text{Dist}_{ij} \times y_{ijvt-1} + X'_{ij}\delta + \psi_{vt} + \nu_{ijvt} \quad (9)$$

where y_{ijvt} is an indicator for farm j renting in or hiring from household i in village v in year t. Our coefficients of interest are β_4 and β_5, the differential persistence of rentals or hires when they are between social connections or over longer distances. A positive coefficient on β_4, for instance, indicates that rentals or hires between social connections are less likely to terminate. In all specifications, we include controls for common group membership, along with farm j controls for number of social connections, and village-round fixed effects. We also estimate an extended specification that controls for fixed effects for each member of the dyad[16]. This holds constant how likely farm j is to rent or hire, as well as how likely household i is to rent out or sell labor. This isolates variation, for example, in whether farm j is differentially likely to rent from household i if they had rented in the previous year, if they are socially connected or physically close.

[16] We note that this specification, which features individual fixed effects and a lagged dependent variable, is a classic violation of strict exogeneity in a fixed effects specification. In this case, we are confident that bias should be small, both because in the dyadic data there are a large number of ijt observations per i and j fixed effect, and also because (empirically) point estimates are very stable with and without fixed effects.

Table 6: Transaction Persistence

	Rent In		**Hire**	
	(1)	(2)	(3)	(4)
1(Link)=1	0.002***	0.002***	0.007***	0.008***
	(0.000)	(0.000)	(0.001)	(0.001)
1L.Outcome	0.244***	0.226***	0.291***	0.262***
	(0.063)	(0.064)	(0.034)	(0.033)
1(Link)=1 × 1L.Outcome	0.175***	0.178***	0.051	0.056
	(0.061)	(0.062)	(0.039)	(0.039)
Distance (km)	-0.001***	-0.001***	-0.004***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.001)
1L.Outcome × Distance (km)	0.150	0.147	-0.020	-0.017
	(0.106)	(0.107)	(0.058)	(0.057)
Degree	-0.000		0.000***	
	(0.000)		(0.000)	
Constant	0.001***	0.001***	0.003***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
N	445002	445002	445002	445002
Unlinked Mean	0.0004	0.0004	0.0021	0.0021
Vil x Rnd FEs	X	X	X	X
Dyadic Controls				
X Node FE		X		X
Y Node FE		X		X

Estimates from this regression are presented in Table 6. First, and perhaps unsurprisingly, farmer pairs repeatedly contract. $\hat{\beta}_3$, the estimated coefficient on lagged rentals and hires, is positive, statistically significant, and quite stable across specifications. Both land and labor markets are highly fluid: both rentals and hired are renewed about 25% of the time. Relatedly, holding constant lagged contracting, social and physical closeness remain associated with new transactions. Second, we observe differences in the effects of bilateral ties on persistence in land and labor markets. In land markets, we observe that transactions are more likely to persist for the socially connected. The point estimate suggests a large effect: land rentals persist year-on-year 18 percentage points more frequently for the socially

connected, or a 78% increase above the estimated persistence rate for the unconnected. In contrast, we do not see evidence that physical proximity impacts persistence in either land or labor markets, nor that social connections increase persistence in labor markets. Based on Prediction 1, we interpret these findings as evidence that social connections increase reliability in land markets by reducing the costs of sustaining trade.

5.2 Social connections reduce land misallocation

In Section 5.1 above, we presented evidence that social connections reduce matching frictions in land markets. Prediction 3 of our model therefore predicts that social connections should increase the elasticity of land rentals. In contrast, based on the results of Section 5.1 and Prediction 3, we should not observe effects of social connections on the elasticity of hires, nor effects of physical distance on either elasticity as these were not associated with persistent hires.

We test Prediction 3 by estimating a modified version of Equation 7 directly building on Section 4.4.[17] Formally, we estimate

$$\log \mathbf{E}[y_{ijvt}] = \underbrace{\beta_1 \text{Link}_{ij} + \beta_2 \text{Distance}_{ij}}_{\text{“iceberg frictions” } \delta_{ij}} + \underbrace{(\beta_3 + \beta_4 \text{Link}_{ij} + \beta_5 \text{Distance}_{ij})}_{\text{“factor trade elasticity” } \epsilon_{ij}} \times \underbrace{\log \text{TFP}_j}_{\log R_j \text{ proxy}} + X'_{ij}\gamma + \underbrace{\eta_i}_{\epsilon_{ij} \log \Lambda_i} + \psi_{vt} \quad (10)$$

where y_{ijvt} is an indicator for farm j renting in or hiring from household i in village v in year t. Our primary coefficients of interest are β_4 and β_5, the effects of social connections and

[17] There are a few departures from Equation 7. First, as discussed in Section 4.4, we account for the discreteness of factor trade by treated observed bilateral rentals and hires as if they are observed with probability P_{ij}, in which case Equation 7 yields a Poisson estimating equation very similar to Equation 10. Second, also discussed in Section 4.4, we proxy posted factor prices $\log R_j$ with $\log \text{TFP}_j$. Third, we use household i fixed effects instead of the infeasible $\epsilon_{ij} \log \Lambda_i$. This approach is valid under the null hypothesis of no heterogeneity in matching frictions, that is $\epsilon_{ij} = \epsilon$. In results not reported, we interacted household fixed effects with Link_{ij}, rationalized by the assumption $\epsilon_{ij} = \epsilon_0 + \epsilon_1 \text{Link}_{ij}$, and find this does not qualitatively affect our results. Fourth, we parametrize δ_{ij} and ϵ_{ij} to make estimation feasible. And fifth, we explore robustness to additional controls $X'_{ij}\gamma$ and ψ_{vt}.

distance on the factor trade elasticity. Following the discussion in Section 4.4, we estimate Equation 10 using Poisson PML. For robustness, we also report estimates using OLS.[18]

Table 7: Factor Trade Elasticity

	Farm ... from Household			
	Rents In		**Hires**	
	(1)	(2)	(3)	(4)
1(Link)=1	0.0058***	2.0057***	0.0132***	1.5863***
	(0.0006)	(0.1885)	(0.0011)	(0.1089)
TFP X	0.0003	0.3257	0.0019***	0.3405**
	(0.0002)	(0.3689)	(0.0004)	(0.1409)
Distance (km)	-0.0011***	-2.1533***	-0.0051***	-3.1293***
	(0.0001)	(0.3005)	(0.0004)	(0.2166)
1(Link)=1 × TFP X	0.0038***	0.6882**	-0.0007	-0.2861*
	(0.0011)	(0.3064)	(0.0019)	(0.1730)
TFP X × Distance (km)	-0.0004	-0.2909	-0.0017***	0.4031
	(0.0002)	(0.6588)	(0.0004)	(0.3238)
Degree	-0.0000	-0.0115	0.0001***	0.0471***
	(0.0000)	(0.0172)	(0.0000)	(0.0082)
Constant	0.0012***	-3.1471***	0.0039***	-3.2478***
	(0.0001)	(0.2082)	(0.0004)	(0.1170)
N	586996	21209	586996	88571
Unlinked Mean	0.0004	0.0116	0.0019	0.0125
Model	OLS	Poisson	OLS	Poisson
Vil x Rnd FE	X	X	X	X
Y Node FE	X	X	X	X

First, and consistent with Table 4, in both land and labor markets we observe that social connections and physical distance predict trade across specifications.

Second, we find robust impacts on the factor trade elasticity only for social connections in land markets, consistent with our findings in Section 5.1 and our model. For land rentals

[18] Table 5 notes that the prediction that iceberg frictions do not affect the factor trade elasticity is sensitive to functional form assumptions. Prediction 6 demonstrates that iceberg frictions do not robustly affect the factor trade elasticity across alternative link functions for generalized linear models (e.g., log for Poisson, linear for OLS).

the coefficient on the interaction between social connections and log TFP is positive and statistically significant in both specifications. Interpreted from the farm's perspective, these estimates imply that high-TFP farms disproportionately use social links to rent in land: the elasticity of trade to TFP is higher among linked pairs. These results are consistent with the finding in Section 5.1, that social connections increase persistence in land markets through reduced matching frictions, that is reduced costs of sustaining efficient trades. Similar to the results in Section 5.1, we do not observe evidence that physical distance affects the elasticity of land rentals to TFP, nor that social connections affect the elasticity of labor hiring to TFP. More surpisingly, we observe that the elasticity of labor hiring to TFP is different for the physically close, though the sign flips across specifications: the association between log TFP and hiring is decreasing with distance in the OLS specification, and increasing with distance in the Poisson specification.[19] This lack of functional form robustness, especially combined with the lack of evidence that physical distance predicts match destruction in Section 5.1, leads us to conclude that there is not robust evidence that reliability in labor markets is affected by social or physical distance.

We make two notes about this test. First, our model provided sharper predictions on the presentation of reliability differences than on iceberg frictions. While we emphasize the identification of reliability differences in land markets, the results presented in this section remain consistent with additional but important iceberg frictions, that are resolved by social connections and physical distance as well in both land and labor markets.

Second, the test for reliabiliy differences relies on estimating a precise correlation between measured TFP and rentals. In that sense, classical measurement error in TFP would reduce our ability to detect the presence of matching frictions resolved by social networks. Similarly, this test is also robust to alternative mechanisms for increased transactions within network unless they are correlated with the renting-in farm's TFP, and differentially so within and outside of social networks.

[19] This sign flip is consistent with the functional form of marginal effects under Poisson regression. Taking the second derivative $\partial^2 \mathbf{E}[y]/\partial \log \text{TFP} \partial \text{Distance}$ in Equation 10, at Distance $= \log \text{TFP} = \text{Link} = 0$, yields $\mathbf{E}[y] * (\beta_5 + \beta_2\beta_3) = \mathbf{E}[y] * (0.403 + -3.13 * 0.34) < 0$.

We conclude this section by applying Prediction 5 to calculate the efficiency gains from rentals and hires in through social networks, and decompose those gains into the roles of the relative intensity and relative efficiency of rentals and hires within network. First, 5% of dyads are social connections; absent any effects of social connections on the probability of rentals or hires, or their allocative efficiency, we would expect rentals and hires in through social networks to account for 5% of efficiency gains. Second, our Poisson estimates in Table 7 imply that rentals in and hires in are 652% and 389% more likely by social connections. These estimates imply that, absent any effect of social connections on the efficiency of trade, rentals in and hires in through social networks would account for 28% and 20% of efficiency gains. Third, our Poisson estimates in Table 7 imply that rentals by social connections are 224% more efficient. Incorporating this estimate, rentals in through social networks account for 56% of efficiency gains. A similar calculation implies that 39% of the efficiency gains from rentals are attributable to the increased efficiency of rentals by social connections. Common empirical approaches that focus on the impact of trade frictions on the probability or intensity, rather than the efficiency, of trade would fully miss these gains.

6 Experimental evidence and mechanisms

Motivated by evidence on important frictions in land markets, we ran an RCT on two common interventions that could in principle resolve either search or iceberg costs. Our experiment worked within local institutions to try and support contracting in two different ways: through improved contract documentation and through resolving information frictions. First, at baseline, most land rentals are conducted under incomplete verbal contracts, where disagreements are adjudicated by village leaders; this leads to plausible uncertainty both on a number of the terms of rental agreements (e.g. contract end dates, any restricted activities, tenant obligations) as well as the punishments for breaching the contract. Second, while the Rwandan government employs lead farmers in each village to assist with extension provision, there are no real estate agents or other intermediaries charged with resolving information

frictions in land markets. In the experiment, the first step of randomization allocated all 110 sampled villages into one of three treatment states and a control condition.

T1 Information: lead farmers were tasked with collecting information on the households in the village interested in either renting in or renting out additional land. Brokers then aggregated this information into "rental in" and "rental out" lists, sharing these lists with other farmers in the village. Finally, the lead farmers helped to broker rental transactions.

T2 Contracts: written contract templates were designed, after extensive piloting, that could be used in land rental transactions. These contracts were delivered by lead farmers to all farmers in the village.

T3 Information × Contracts: villages were given both T1 and T2.

For T1 and T3—the information treatments—households were further randomized into a priority list. Farmer brokers were told to visit these households first, ensuring that they had an opportunity to be placed on the lists.

We find strong evidence of implementation fidelity. Table A8 documents that an additional approximately 40% of farmers in T2 and T3 villages have seen a written contract, and nearly as many currently possess one. It also highlights, however, that the contracting intervention is unlikely to be effective: there is a precise zero on whether being assigned to T2 or T3 led to farmers being more likely to use a written contract.

The primary results of our experiment are presented in Table 8. In Columns 1 and 2, we report difference-in-difference estimates from the specification

$$y_{ijvt} = \beta_1 \text{T1}_v \times \text{Post}_t + \beta_2 \text{T2}_v \times \text{Post}_t + \beta_3 \text{T3}_v \times \text{Post}_t + X'_{ij}\gamma + \eta_i + \psi_t + \nu_{ijvt}$$

where y_{ijvt} is an indicator for farm j renting in or hiring from household i in village v in year t.

Columns 1 and 2 reveal that neither the contracting intervention, nor the information intervention, increased rentals. Apparently, the trade costs that are alleviated by networks and proximity persist in the presence of more complete contracts and an improved information environment.

However, in Columns 3 and 4 of Table 8, we exploit non-experimental variation across dyads in who was "matched" by the farmer brokers. That is, we augment our dyadic specification with List Match, an indicator that household i was listed as interested in renting out and household j was listed as interested in renting in. To partially address endogeneity, we estimate a difference-in-difference design, interacting List Match with a post-intervention indicator. Results are presented in Columns 3 and 4 of Table 8. After the intervention, list matched households are 0.2pp more likely to transact than they were before the intervention. However, even in this comparison of linked farmers, this effect is only 1/3 as large as the effect associated with social connections; we can reject equality of the coefficients. These results indicate that the constraints resolved by networks go beyond formal contracting and information barriers and may require some creative policy design to address.

Table 8: RCT Treatment Effects

	Rent In			
	(1)	(2)	(3)	(4)
T1-Info × Post=1	-0.0001	-0.0001		
	(0.0002)	(0.0002)		
T2-Contracts × Post=1	0.0002	0.0002		
	(0.0002)	(0.0002)		
T3-Info x Contracts × Post=1	0.0001	0.0001		
	(0.0002)	(0.0002)		
1(Link)=1			0.0056***	0.0056***
			(0.0006)	(0.0006)
Distance (km)			-0.0007***	-0.0008***
			(0.0001)	(0.0002)
1(List Match - RI)=1			0.0013	0.0000
			(0.0024)	(0.0034)
1(List Match - RI)=1 × Post=1			0.0022*	0.0022*
			(0.0012)	(0.0012)
Constant	0.0006***	0.0006***	0.0007***	0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
N	564864	564864	564864	564864
Control/Unlinked Mean	0.0007	0.0007	0.0003	0.0003
Rnd FE	X	X	X	X
Dyadic Controls	X	X	X	X
X Node FE	X	X	X	X
Y Node Strata	X		X	
Y Node FE		X		X

Outcomes vary at the household-by-season level. Standard errors are clustered at the village level. ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors in parentheses.

6.1 Organized Groups

If networks are providing a role which is hard for policy to duplicate, can policy produce bigger networks? Organized groups exist as a common mechanism to expand networks; in our context three frequent organized groups are ROSCAs, farmer cooperatives, and churches. During our census, we identified the names of any ROSCAs, cooperatives, or churches oper-

ating in each of the villages and asked respondents which they were members of. In Table 4 we presented non-experimental evidence on whether farmers were more likely to rent in or hire other farmers that belonged to the same group. Examining the coefficients on common membership in a ROSCA, farmer cooperative, or church, we again find that land and labor markets are different. We find no impact of common group membership on rentals in, suggesting that organized groups cannot fulfill the same role as networks in facilitating land trade. In contrast, we find that common membership in churches, and less robustly agricultural cooperatives, predicts hires in. One interpretation, which is consistent with the model results in Section 5 is that measured networks consist of "strong" ties, which can support trust in land contracts (and which allows farmers to find contracts within network that persist, increasing the elasticity of trade). Under this interpretation, organized groups forge only "weaker" ties, which were unsuccessful in generating new transactions in land markets. On the other hand, these new "weak" ties may be useful in spreading information (e.g. Granovetter (1973)), reducing the costs of transacting in labor markets.

7 Conclusion

In Rwanda, property rights are strong, and factor markets are characterized by frequent trade. We provide some of the first transaction-level data in these markets, which reveal a puzzle: frequent trade does not resolve substantial misallocation. Instead, factor markets operate through sparse social networks and are subject to steep distance-related trade costs. Ultimately, this means that trade is failing to allocate factors to the most productive farmers. This specific problem has received little attention in either the trade or misallocation literatures, yet in our context it appears to have important implications for rural productivity gaps.

We develop a trade model where iceberg frictions coexist with reliability costs, and both are heterogeneous across dyads of farmers. The model yields several predictions about the shape of trade implied by matching versus iceberg costs. Our analysis suggests that both

networks and distance may be related to iceberg costs, but that networks in particular are improve contract reliability in land markets. These frictions ultimately lead to match destruction among the unconnected and prevent trade from allocating land to the most productive farmers. In labor markets, by contrast, we do not find robust evidence on reliability costs that are alleviated by social connections or physical distance.

In a complementary RCT, we tested whether formal institutions could resolve these frictions in land markets as well. Here, the evidence is not positive: neither introducing formal contracts nor through improving information environments were successful in inducing additional trade. Nor do weak ties seem to resolve frictions in land markets, despite increasing labor hiring.

We conclude that, even in an environment with strong formal property rights and dense physical settlement, substantial misallocation remains. Transaction-level evidence shows that factor trade is frequent and modestly reallocative, but much of the potential for efficiency gains is left on the table. Land and labor markets are governed by different frictions: labor is relatively constrained by physical distance, while land is more constrained by search and trust frictions that operate along social ties. Standard titling and contract-formalization policies may therefore be insufficient to fully unlock the productivity gains from factor reallocation. Instead, interventions that substitute for the role of trust in contracting under strong property rights are needed.

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A Appendix Figures and Tables

Figure A1: Misallocation in Networks - Labor

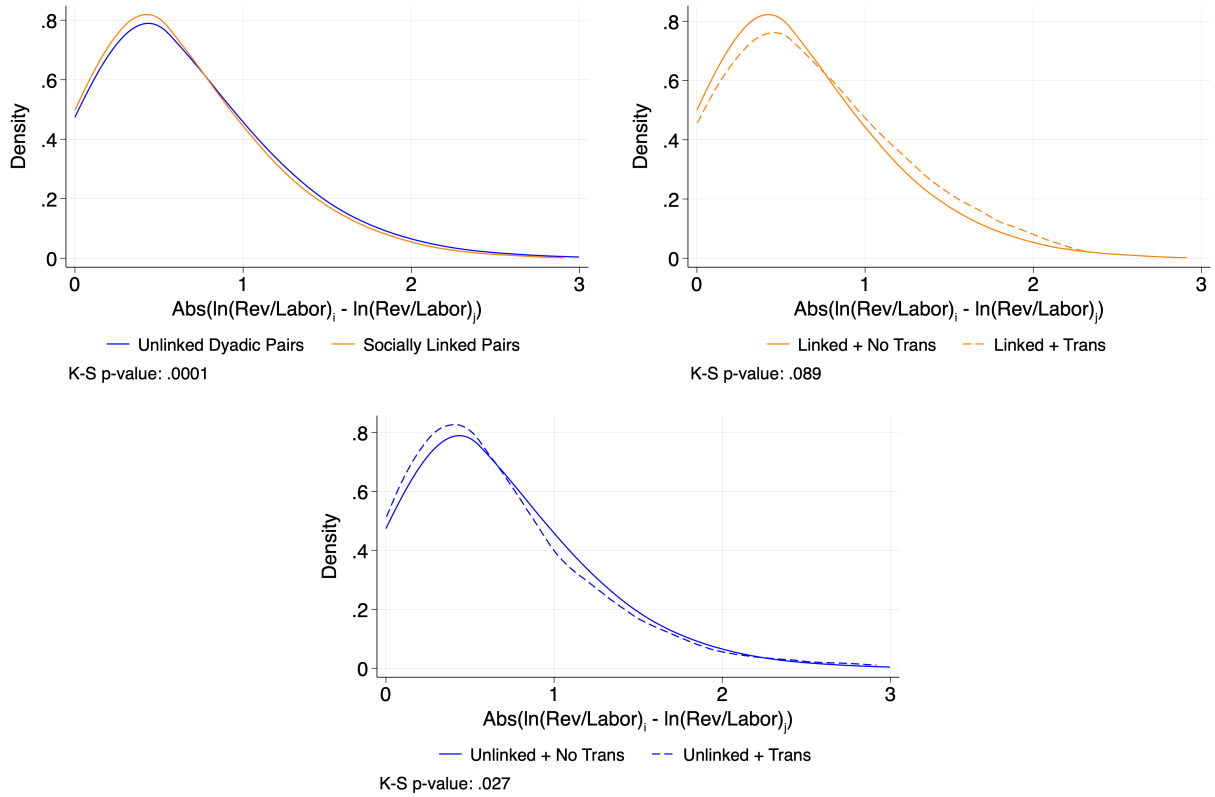


Table A1: Household Summary Statistics

	Mean	SD	Obs
	(1)	(2)	(3)
HH Members	4.59	1.91	2362
HHH - Female	0.29	0.45	2362
HHH - Primary +	0.37	0.48	2353
Num. Plots	3.60	1.24	2362
Plot Area (ha)	0.33	0.26	2362
Dry Season Cultivate	0.63	0.48	2358
Grow Maize	0.55	0.50	2362
Grow Beans	0.77	0.42	2362
Grow Banana	0.44	0.50	2362
Horticulture	0.24	0.42	2362
Irrigate	0.10	0.31	2362
Avg dist to vil member (km)	0.56	0.20	2358

Notes: The table reports household-level means, standard deviations, and numbers of nonmissing observations for the baseline survey in 110 villages. HHH denotes the household head, and "Primary +" indicates primary schooling or higher. Unless otherwise noted, variables are indicators equal to one if the household reported the indicated activity on at least one plot. The number of plots and total plot area exclude plots reported as rented out or lost/sold. Plot counts and areas cover the household's up-to-four main plots and any additional transacted plots; plot areas beyond the main-plot roster were not measured at baseline. Average distance to a village member is the mean straight-line GPS distance from the household to all other listed households in its village; pairwise distances and plot areas are winsorized at the 99th percentile before averaging.

Table A2: TFP Estimation

	Ln(Output Value)	
	(1)	(2)
Ln(Labor)	0.715***	0.464***
	(0.015)	(0.017)
Ln(Land)	0.220***	0.489***
	(0.012)	(0.028)
Constant	8.404***	9.713***
	(0.070)	(0.083)
N	9076	9050
Mean of Dep Var	11.171	11.172
Vil x Rnd FEs	X	X
HH FEs		X

Table A3: Transaction Prediction - Poisson

	Rent In			**Hire**		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Link)	2.3813***	2.1322***	4.0948***	1.2183***	1.4888***	1.9275***
	(0.1887)	(0.1931)	(0.8971)	(0.0973)	(0.1222)	(0.1841)
Distance (km)	-1.6689***	-2.1630***	-3.5920***	-2.9917***	-3.0843***	-4.7053***
	(0.3447)	(0.3440)	(1.1882)	(0.2264)	(0.2308)	(0.3878)
1(Same ROSCA)	-0.1123	-0.5586	-1.8991*	0.0035	-0.0616	0.0648
	(0.2802)	(0.4595)	(0.9856)	(0.1960)	(0.2295)	(0.3472)
1(Same Coop)	-0.8377	-0.7065	1.7337	-0.4916	0.1154	0.1346
	(0.7216)	(0.7663)	(1.4977)	(0.3621)	(0.4954)	(0.5471)
1(Same Church)	0.1013	-0.0854	0.4219	0.1929**	0.3608***	0.4897***
	(0.1505)	(0.2068)	(0.5855)	(0.0833)	(0.1022)	(0.1556)
TFP X	0.5826***	0.6198***		0.3361***	0.3571***	
	(0.1674)	(0.1767)		(0.0809)	(0.0797)	
Degree	-0.0202	-0.0226		0.0441***	0.0453***	
	(0.0186)	(0.0192)		(0.0088)	(0.0091)	
Constant	-6.2728***	-2.8905***	-2.1202***	-5.2088***	-3.3276***	-1.4797***
	(0.2146)	(0.2424)	(0.6141)	(0.1227)	(0.1357)	(0.1663)
N	309682	15794	2238	461494	67307	23042
Mean of Dep Var	0.0006	0.0128	0.0952	0.0020	0.0139	0.0417
Vil x Round FE	X	X	X	X	X	X
X Node FE			X			X
Y Node FE		X	X		X	X

Table A4: Baseline links predict new transactions

	New Rent In			**New Hire**		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Network Link)	0.0056***	0.0047***	0.0046***	0.0210***	0.0181***	0.0178***
	(0.0007)	(0.0010)	(0.0010)	(0.0016)	(0.0020)	(0.0019)
Distance (km)		-0.0018***	-0.0020***		-0.0119***	-0.0144***
		(0.0003)	(0.0005)		(0.0010)	(0.0013)
1(Same Rosca)		-0.0000	0.0003		0.0020	0.0022
		(0.0008)	(0.0009)		(0.0020)	(0.0022)
1(Same Coop)		0.0011	0.0005		0.0005	-0.0033
		(0.0019)	(0.0021)		(0.0028)	(0.0028)
1(Same Church)		-0.0000	-0.0000		0.0013**	0.0014**
		(0.0002)	(0.0002)		(0.0006)	(0.0007)
Degree	0.0000	-0.0000		0.0002***	0.0002***	
	(0.0000)	(0.0000)		(0.0000)	(0.0001)	
Constant	0.0006***	0.0020***	0.0019***	0.0020***	0.0090***	0.0122***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0008)	(0.0008)
N	298348	125469	125469	298348	125469	125469
Mean of Dep Var	0.0008	0.0007	0.0007	0.0040	0.0045	0.0045
Vil FE	X	X	X	X	X	X
X Node FE			X			X
Y Node FE		X	X		X	X

Table A5: Family links predict new transactions

	New Rent In			**New Hire**		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Family Link)	0.0079***	0.0061***	0.0060***	0.0333***	0.0232***	0.0228***
	(0.0016)	(0.0021)	(0.0021)	(0.0031)	(0.0038)	(0.0038)
Distance (km)		-0.0022***	-0.0025***		-0.0136***	-0.0164***
		(0.0004)	(0.0005)		(0.0011)	(0.0014)
1(Same Rosca)		0.0001	0.0004		0.0023	0.0026
		(0.0008)	(0.0009)		(0.0020)	(0.0022)
1(Same Coop)		0.0013	0.0007		0.0011	-0.0027
		(0.0020)	(0.0022)		(0.0027)	(0.0028)
1(Same Church)		-0.0000	0.0001		0.0014**	0.0017**
		(0.0002)	(0.0002)		(0.0006)	(0.0007)
Degree	0.0000**	0.0000		0.0003***	0.0003***	
	(0.0000)	(0.0000)		(0.0000)	(0.0001)	
Constant	0.0006***	0.0022***	0.0024***	0.0020***	0.0099***	0.0141***
	(0.0002)	(0.0004)	(0.0003)	(0.0003)	(0.0008)	(0.0009)
N	298348	125469	125469	298348	125469	125469
Mean of Dep Var	0.0010	0.0010	0.0010	0.0047	0.0054	0.0054
Vil FE	X	X	X	X	X	X
X Node FE			X			X
Y Node FE		X	X		X	X

Table A6: Wages, TFP, and bilateral ties

	Ln(Wage Paid)					
	(1)	(2)	(3)	(4)	(5)	(6)
TFP X	0.0213**	0.0181**	0.0180**		-0.0035	
	(0.0098)	(0.0089)	(0.0089)		(0.0146)	
1(Link)			-0.0101	0.0002	-0.0034	0.0073
			(0.0095)	(0.0087)	(0.0140)	(0.0211)
Distance (km)					0.0984**	0.0306
					(0.0400)	(0.0521)
Constant	6.5706***	6.5713***	6.5726***	6.5753***	6.5422***	6.5636***
	(0.0090)	(0.0019)	(0.0020)	(0.0011)	(0.0132)	(0.0199)
N	4268	4258	4258	4055	943	635
Mean of Dep Var	6.575	6.575	6.575	6.575	6.568	6.575
Vil x Rnd FEs		X	X	X	X	X
X Node FE				X		X

Table A7: Rent, TFP, and bilateral ties

	Ln(Annual Rental Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
TFP X	0.2206***	0.1790***	0.1834***		0.2820	
	(0.0500)	(0.0565)	(0.0567)		(0.2433)	
1(Link)			-0.0958	0.1225	0.2424	0.2139
			(0.0738)	(0.1228)	(0.1605)	(0.2591)
Distance (km)					0.8651**	-0.2473
					(0.3286)	(0.6565)
Constant	9.0227***	9.0286***	9.0375***	9.0515***	8.5204***	8.8280***
	(0.0318)	(0.0065)	(0.0089)	(0.0125)	(0.1337)	(0.2780)
N	2411	2363	2363	2061	163	96
Mean of Dep Var	9.048	9.049	9.049	9.064	8.961	8.881
Vil x Rnd FEs		X	X	X	X	X
X Node FE				X		X

Table A8: Contract Take-up

	Seen Written Contract		Has Written Contract		Used Written Contract	
	(1)	(2)	(3)	(4)	(5)	(6)
T1-Info	0.021	0.026*	0.002	0.004	-0.004	0.001
	(0.014)	(0.014)	(0.006)	(0.007)	(0.011)	(0.011)
T2-Contracts	0.430***	0.428***	0.372***	0.371***	0.002	0.001
	(0.023)	(0.024)	(0.021)	(0.021)	(0.011)	(0.010)
T3-Info x Contracts	0.399***	0.412***	0.329***	0.339***	-0.002	0.002
	(0.024)	(0.023)	(0.018)	(0.018)	(0.012)	(0.011)
N	6852	6814	6852	6814	9247	9161
Control Mean	0.105	0.105	0.033	0.033	0.060	0.060
Round FEs	X	X	X	X	X	X
Vil Strata	X	X	X	X	X	X
HH Strata		X		X		X
HH Controls		X		X		X

Outcomes vary at the household-by-season level. Standard errors are clustered at the village level. ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors in parentheses.

B Appendix Productivity Estimation

Our preferred estimate of TFP closely follows the construction in Aragón et al. (2022). However, we recognize that there are a variety of of alternative approaches to farm TFP estimation. Our data, which include crop- and plot-specific production allow for a number of alternative specifications. We outline these below, first showing how they change factor loadings before showing robustness of our primary primary results to the use of these alternative measures.

B.1 Alternative TFP Specifications

We consider five sets of robustness checks for our TFP estimation: (1) adding household controls; (2) estimating at the household-plot level; (3) including spatial FEs; (4) at the household-plot-crop

level as in Chari et al. (2021); (5) using constrained production functions. We explain each below and present their corresponding production function estimates.

B.2 Main Elasticity Robustness

Having re-estimated TFP, we now show robustness of our main estimates to these alternative measures. Specifically, we re-estimate Equation 10 substituting in each new TFP measure measure.

In Appendix Table A9 we show how the alternative TFP measures impact our elasticity estimate for Rentals In while in Appendix Table A10 we show the same for Hires.

Table A9: Elasticity Robustness - Rent In

	Rent In								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1(Link)=1	0.0054***	0.0054***	0.0047***	0.0041***	0.0055***	0.0057***	0.0047***	0.0057***	0.0057***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
TFP X	0.0002	0.0003	0.0001	0.0001	0.0003	0.0005	0.0003	0.0004	0.0004
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
1(Link)=1 × TFP X	0.0036***	0.0033***	0.0023***	0.0017**	0.0039***	0.0043***	0.0035***	0.0041**	0.0040***
	(0.0010)	(0.0011)	(0.0008)	(0.0008)	(0.0011)	(0.0016)	(0.0013)	(0.0016)	(0.0015)
Distance (km)	-0.0010***	-0.0010***	-0.0010***	-0.0008***	-0.0010***	-0.0011***	-0.0010***	-0.0011***	-0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
TFP X × Distance (km)	-0.0003	-0.0003	-0.0002	-0.0001	-0.0002	-0.0004	-0.0002	-0.0003	-0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Constant	0.0010***	0.0010***	0.0010***	0.0009***	0.0010***	0.0011***	0.0010***	0.0011***	0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
N	558560	558560	546080	488928	534840	367464	341768	366124	366124
TFP Type	tfp_hr_1	tfp_hr_2	tfp_hr_3	tfp_hp_3	tfp_hp_4	tfp_hps_4	tfp_hps_5	tfp_hps_6	tfp_hps_7
Unlinked Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sample	BL-Listing	BL-Listing	BL-Listing	BL-Listing	BL-Listing	BL-Listing	BL-Listing	BL-Listing	BL-Listing
Link Type	Directed	Directed	Directed	Directed	Directed	Directed	Directed	Directed	Directed
Vil x Rnd FE	X	X	X	X	X	X	X	X	X
Dyadic Controls	X	X	X	X	X	X	X	X	X
Y Node FE	X	X	X	X	X	X	X	X	X

XXX

Table A10: Elasticity Robustness - Hire

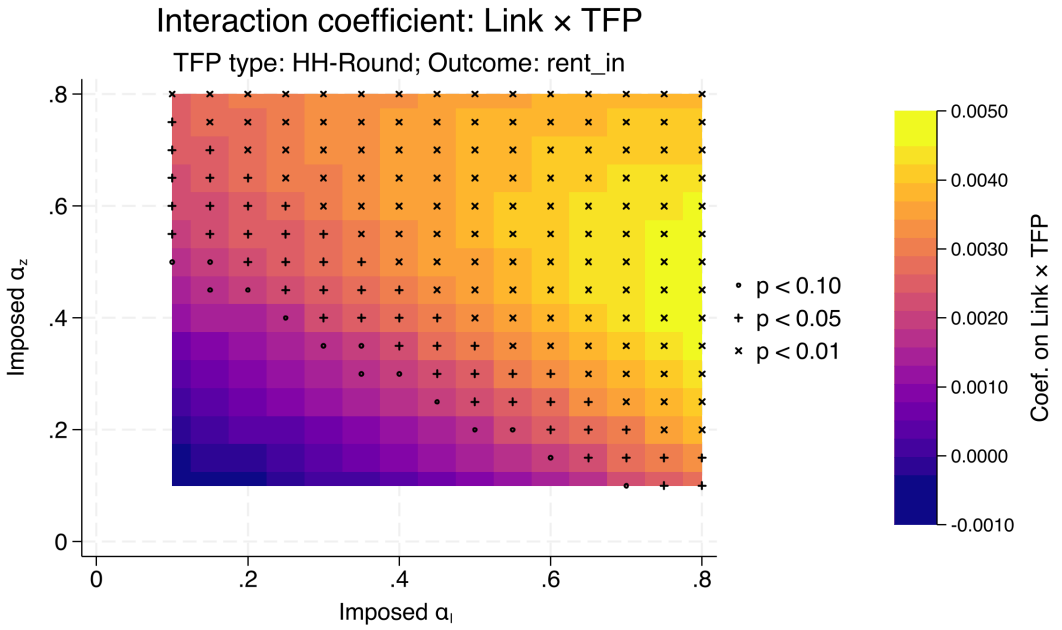
	Hire								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1(Link)=1	0.0119***	0.0119***	0.0116***	0.0118***	0.0122***	0.0117***	0.0117***	0.0115***	0.0115***
	(0.0011)	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0013)	(0.0014)	(0.0012)	(0.0012)
TFP X	0.0020***	0.0020***	0.0020***	0.0028***	0.0010***	0.0019***	0.0018***	0.0017***	0.0017***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0005)	(0.0006)	(0.0005)	(0.0005)
1(Link)=1 × TFP X	0.0010	0.0006	0.0014	0.0008	-0.0012	0.0017	0.0022	0.0016	0.0017
	(0.0017)	(0.0018)	(0.0015)	(0.0016)	(0.0018)	(0.0022)	(0.0020)	(0.0022)	(0.0022)
Distance (km)	-0.0045***	-0.0045***	-0.0045***	-0.0047***	-0.0045***	-0.0045***	-0.0046***	-0.0044***	-0.0044***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
TFP X × Distance (km)	-0.0018***	-0.0017***	-0.0018***	-0.0023***	-0.0007*	-0.0017***	-0.0017***	-0.0014***	-0.0015***
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0005)	(0.0005)
Constant	0.0037***	0.0037***	0.0037***	0.0038***	0.0036***	0.0037***	0.0038***	0.0036***	0.0036***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
N	558560	558560	546080	488928	534840	367464	341768	366124	366124
TFP Type	tfp_hr_1	tfp_hr_2	tfp_hr_3	tfp_hp_3	tfp_hp_4	tfp_hps_4	tfp_hps_5	tfp_hps_6	tfp_hps_7
Unlinked Mean	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Sample	BL-Listing	BL-Listing	BL-Listing	BL-Listing	BL-Listing	BL-Listing	BL-Listing	BL-Listing	BL-Listing
Link Type	Directed	Directed	Directed	Directed	Directed	Directed	Directed	Directed	Directed
Vil x Rnd FE	X	X	X	X	X	X	X	X	X
Dyadic Controls	X	X	X	X	X	X	X	X	X
Y Node FE	X	X	X	X	X	X	X	X	X

XXX

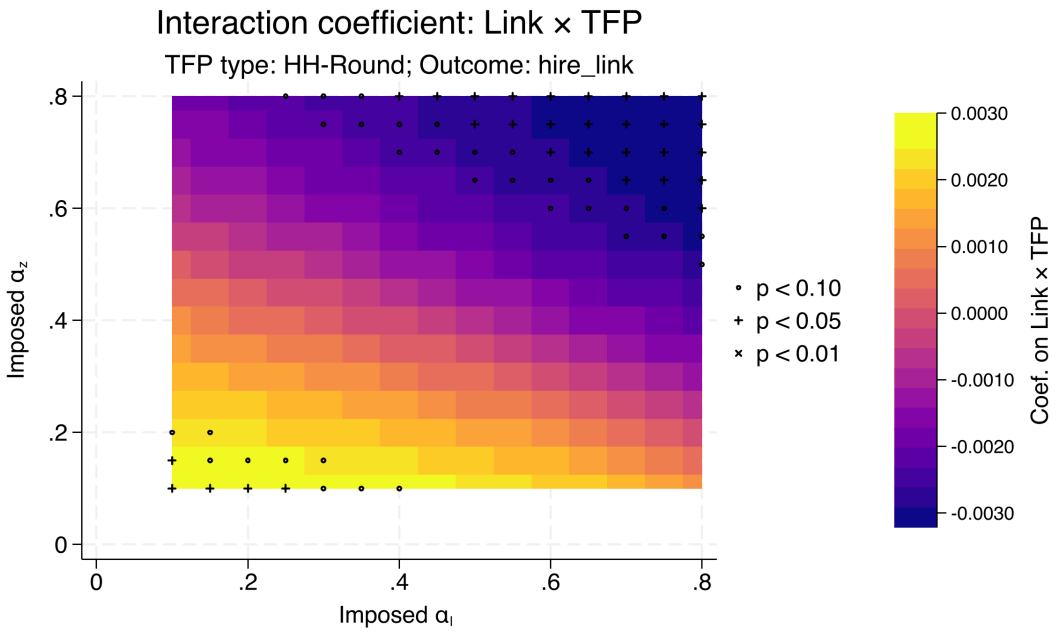
The significance of β_4 in Equation 10 is robust to constraining factor loadings when estimating TFP.[20] Below we present two heatmaps, one for Rent In and one for Hire, that document this robustness. The coordinates of each cell represent imposed values for α_l and α_z used to estimate TFP at the household-survey level. The color of each cell indicates the β_4 coefficient value from Equation 10 when estimated with the corresponding TFP variable. Black indicators in the cells indicate coefficient significance levels.

[20] Similar figures for β_5 are available upon request.

Figure A2: Robustness to constrained production functions



(a) Rent In



(b) Hire

Notes: XXXX

The positive interaction between social links and TFP in predicting land rental-in is robust throughout the empirically relevant neighborhood or CRS and across a broad range of alternative factor loadings. In contrast, the hiring interaction is statistically insignificant in the relevant range, with significance only under relatively extreme returns-to-scale assumptions. The coefficient also changes signs when moving from extreme DRS to IRS.

C Appendix proofs

C.1 Productivity gains from partial reallocation

Let Z_i and Z_{ii} denote the area cultivated and non-rented area cultivated for household i at baseline, A_i denote total factor productivity, and L_i denote labor used. Define autarkic area cultivated to be $Z_i^a \equiv \frac{Z_{ii}}{\sum_j Z_{jj}} \sum_j Z_j$, and autarkic production to be $Y^a \equiv \sum_i A_i \left(Z_i^a\right)^{\alpha_Z} L_i^{\alpha_L}$. Define realized gains to be $(\sum_i A_i Z_i^{\alpha_Z} L_i^{\alpha_L}) - Y^a$, and traded land to be $\sum_i (Z_i - Z_i^a)\mathbf{1}\{Z_i > Z_i^a\}$. Potential productive efficiency gains solve

$$dY(p) \equiv \max_z \left(\sum_i A_i z_i^{\alpha_Z} L_i^{\alpha_L} \right) - Y^a$$

subject to the constraints $\sum_i z_i \leq \sum_i Z_i$ and $\sum_i (z_i - Z_i^a)\mathbf{1}\{z_i > Z_i^a\} \leq p \sum_i Z_i^a$ for some fraction p. Define λ^- and $\lambda^+ - \lambda^-$ to be the Lagrange multipliers on these constraints.

We are primarily interested in potential productive efficiency gains as a function of p, as a share of gains absent constraints on reallocated land. That is $dY(p)/dY(1)$.

Let $\text{MPZ}_i(z) \equiv \alpha_Z A_i z^{\alpha_Z - 1} L_i^{\alpha_L}$, and let $\text{MPZ}_i^a \equiv \text{MPZ}_i(Z_i^a)$. The first order condition for the optimization problem is

$$\text{MPZ}_i(z_i) = \lambda^- + \mathbf{1}\{z_i > Z_i^a\}(\lambda^+ - \lambda^-)$$

This yields three types of solutions across i.

$z_i < Z_i^a$: In this case, $\text{MPZ}_i(z_i) = \lambda^-$. Since $z_i < Z_i^a$, this implies $\text{MPZ}_i^a < \lambda^-$. Solving, we find $z_i / Z_i^a = (\text{MPZ}_i^a / \lambda^-)^{1/(1-\alpha_Z)}$.

$z_i = Z_i^a$: In this case, $\text{MPZ}_i(z_i) \in [\lambda^-, \lambda^+]$. As $z_i = Z_i^a$, this implies $\text{MPZ}_i^a \in [\lambda^-, \lambda^+]$.

$z_i > Z_i^a$**:** In this case, $\text{MPZ}_i(z_i) = \lambda^+$. Since $z_i > Z_i^a$, this implies $\text{MPZ}_i^a > \lambda^+$. Solving, we find $z_i/Z_i^a = (\text{MPZ}_i^a/\lambda^+)^{1/(1-\alpha_Z)}$.

The above fully characterizes z_i as a function of MPZ_i^a, Z_i^a, λ^-, and $\lambda^+ \geq \lambda^-$. Note that this has transformed the original optimization problem, which depended on p, into an optimization problem which depends on λ^- and λ^+. As we are interested in $dY(p)/dY(1)$, we take the following approach to solve for $dY(p)$.

1. For a grid $\mathcal{G}$ over (λ^-, λ^+) with $\lambda^+ > \lambda^-$:
   (a) Use the above expressions to calculate $z_i(\lambda^-, \lambda^+)$
   (b) Calculate $\widetilde{dY}(\lambda^-, \lambda^+) = (\sum_i A_i z_i(\lambda^-, \lambda^+)^{\alpha_Z} L_i^{\alpha_L}) - Y^a$
   (c) Calculate $\widetilde{p}(\lambda^-, \lambda^+) \equiv \frac{\sum_i (z_i(\lambda^-, \lambda^+) - Z_i^a)\mathbf{1}\{z_i(\lambda^-, \lambda^+) > Z_i^a\}}{\sum_i Z_i^a}$
   (d) Calculate $\widetilde{dZ}(\lambda^-, \lambda^+) \equiv \sum_i z_i(\lambda^-, \lambda^+) - Z_i^a$
2. Define $\widehat{dY}(p) \equiv \max_{\lambda^-, \lambda^+ \in \mathcal{G}} \widetilde{dY}(\lambda^-, \lambda^+)\mathbf{1}\{\widetilde{dZ}(\lambda^-, \lambda^+) \leq 0\}\mathbf{1}\{\widetilde{p}(\lambda^-, \lambda^+) \leq p\}$

C.2 Proof of Theorem 1

Let $\underline{\epsilon} \equiv \min_{i,j} \epsilon_{ij}$, $\overline{\epsilon} \equiv \max_{i,j} \epsilon_{ij}$, and $\epsilon^* \equiv (\overline{\epsilon} + \underline{\epsilon})/2$. First, we rewrite the farm's rent posting equation $R_i = A_i Z_i^{-(1-\alpha)}$ as

$$R_i = A_i^{\frac{1}{1+(1-\alpha)\epsilon^*}} (Z_i R_i^{-\epsilon^*})^{-\frac{1-\alpha}{1+(1-\alpha)\epsilon^*}}$$

Second, we substitute Equation 7 into labor market clearing $Z_i = \sum_j \overline{Z}_j P_{ji}$ and multiply both sides by $R_i^{-\epsilon^*}$ to derive

$$Z_i R_i^{-\epsilon^*} = \sum_j \overline{Z}_j \delta_{ji}^{-\epsilon_{ji}} R_i^{\epsilon_{ji} - \epsilon^*} \Lambda_j^{-\epsilon_{ji}}$$

We apply Theorem 1 of Allen et al. (2024) and Remark 1 to $(\Lambda_i, Z_i R_i^{-\epsilon^*}, R_i)$, which characterize equilibrium uniqueness using the spectral radius of the matrix $\mathbf{A}$ of suprema of cross-elasticities.

$$\mathbf{A} \equiv \begin{pmatrix} 0 & 0 & 1 \\ \overline{\epsilon} & 0 & \overline{\epsilon} - \epsilon^* \\ 0 & \frac{1-\alpha}{1+(1-\alpha)\epsilon^*} & 0 \end{pmatrix}$$

In the first row, Λ_i is an implicit and increasing function of R. As it is homothetic, the sum over j of the absolute values of elasticities of Λ_i to R_j is 1. In the second row, the maximum absolute value of the elasticities of the expression for $Z_i R_i^{-\epsilon^*}$ to Λ_j is $\bar{\epsilon}$ and to R_j is $\bar{\epsilon} - \epsilon^* = \epsilon^* - \underline{\epsilon}$. In the third row, the absolute value of the elasticity of the expression for R_i to $Z_i R_i^{-\epsilon^*}$ is $\frac{1-\alpha}{1+(1-\alpha)\epsilon^*}$.

Suppose $\bar{\epsilon} = \epsilon^* + \frac{1}{2}\frac{1}{1-\alpha}$, and denote $a \equiv \frac{1}{1-\alpha}$. In this case, the matrix $\mathbf{A}$ simplifies to

$$\mathbf{A}(a) \equiv \begin{pmatrix} 0 & 0 & 1 \\ \epsilon^* + \frac{1}{2}a & 0 & \frac{1}{2}a \\ 0 & \frac{1}{\epsilon^*+a} & 0 \end{pmatrix}$$

The eigenvalues of this matrix are 1 and $-\frac{1}{2} \pm \sqrt{\frac{3}{4} - \frac{1}{2}\frac{a}{\epsilon^*+a}}$. The absolute values of the second two eigenvalues are less than 1, so $\mathbf{A}(a)$ has spectral radius of 1. As the spectral radius is strictly increasing in nonnegative entries for an irreducible matrix, whenever $\bar{\epsilon} < \epsilon^* + \frac{1}{2}\frac{1}{1-\alpha}$ the spectral radius of $\mathbf{A}$ will be less than 1. By Theorem 1 and Remark 1 of Allen et al. (2024), there is a unique equilibrium.

C.3 Proof of Theorem 1 with two factors

Environment Consider the following two factor extension of the model in Section 4.1, for factor $W \in \{Z, L\}$ where Z represents land and L represents labor.

$$P_{ij}^W = \left(\frac{R_j^W}{\Lambda_i^W \delta_{ij}^W} \right)^{\epsilon_{ij}^W} \tag{11}$$

$$R_j^W = \frac{\partial}{\partial W} A_j Z_j^\alpha L_j^\beta \tag{12}$$

$$W_j = \sum_i \overline{W}_i P_{ij}^W \tag{13}$$

Equation 11 is the land and labor supply equation, Equation 12 is the land and labor demand equation (posted factor prices are marginal products), and Equation 13 is the land and labor market clearing condition.

Useful definitions Let $\bar{\epsilon}^W \equiv \max_{i,j} \epsilon_{ij}^W$ and $\underline{\epsilon}^W \equiv \min_{i,j} \epsilon_{ij}^W$ denote the largest and smallest factor supply elasticities for W. Let $\Delta^W \equiv \frac{\bar{\epsilon}^W - \underline{\epsilon}^W}{2}$ denote half the range of the factor supply elasticities for W, and $\epsilon^W \equiv \frac{\bar{\epsilon}^W + \underline{\epsilon}^W}{2}$ denote the midpoint of the range. Note that $\bar{\epsilon}^W = \epsilon^W + \Delta^W$.

Factor market access We transform the factor market clearing condition in Equation 13 by multiplying both sides by substituting Equation 11 and multiplying both sides by $(R_j^W)^{-\epsilon^W}$. This yields

$$W_j (R_j^W)^{-\epsilon^W} = \sum_i \overline{W}_i (\delta_{ij}^W)^{-\epsilon_{ij}^W} (R_j^W)^{\epsilon_{ij}^W - \epsilon^W} (\Lambda_i^W)^{-\epsilon_{ij}^W} \tag{14}$$

Equation 14 can roughly be interpreted as factor market access for farm j.

Transformed factor demand We will see below that it will be useful to express posted factor prices as a function of factor market access, rather than factor allocations. First, note that

$$R_j^Z = \alpha A_j Z_j^{-(1-\alpha)} L_j^{\beta} \tag{15}$$

$$R_j^L = \beta A_j Z_j^{\alpha} L_j^{-(1-\beta)} \tag{16}$$

We claim that

$$R_j^Z = \kappa^Z A_j^{\frac{1+\epsilon^L}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}} \left(Z_j (R_j^Z)^{-\epsilon^Z}\right)^{-a} \left(L_j (R_j^L)^{-\epsilon^L}\right)^{b} \tag{17}$$

where

$$\kappa^Z \equiv \alpha^{\frac{1+(1-\beta)\epsilon^L}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}} \beta^{\frac{\beta\epsilon^L}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}}$$

$$a \equiv \frac{(1-\alpha)+(1-\alpha-\beta)\epsilon^L}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}$$

$$b \equiv \frac{\beta}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}$$

This is straightforward but tedious to verify by substituting Equations 15 and 16 for R_j^Z and R_j^L into the right hand side of Equation 17, which after simplification is equivalent to Equation 15.

By symmetry

$$R_j^L = \kappa^L A_j^{\frac{1+\epsilon^Z}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}} \left(Z_j(R_j^Z)^{-\epsilon^Z}\right)^d \left(L_j(R_j^L)^{-\epsilon^L}\right)^{-c} \tag{18}$$

where

$$\kappa^Z \equiv \alpha^{\frac{\alpha\epsilon^Z}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}} \beta^{\frac{1+(1-\alpha)\epsilon^Z}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}}$$

$$c \equiv \frac{(1-\beta)+(1-\alpha-\beta)\epsilon^Z}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}$$

$$d \equiv \frac{\alpha}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}$$

Uniqueness condition We apply Theorem 1 of Allen et al. (2024) and Remark 1 to the equilibrium conditions on the vector $(\Lambda_i^Z, Z_i(R_i^Z)^{-\epsilon^Z}, R_i^Z, \Lambda_i^L, L_i(R_i^L)^{-\epsilon^L}, R_i^L)$, which characterizes equilibrium uniqueness using the spectral radius of the matrix $\mathbf{A}$ of suprema of cross-elasticities. We derive

$$\mathbf{A} \equiv \begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ \epsilon^Z & 0 & \Delta^Z & 0 & 0 & 0 \\ 0 & a & 0 & 0 & b & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & \epsilon^L & 0 & \Delta^L \\ 0 & d & 0 & 0 & c & 0 \end{pmatrix} \tag{19}$$

In the first and fourth rows, Λ_i^W is an implicit and increasing function of R^W from Equation 11. As it is homothetic, the sum over j of the absolute values of elasticities of Λ_i^W to R_j^W is 1. In the second and fifth rows, seen in Equation 14, the maximum absolute value of the elasticities of factor market access $W_i(R_i^W)^{-\epsilon^W}$ to Λ_j is ϵ^W and to R_j^W is $\bar{\epsilon}^W - \epsilon^W = \epsilon^W - \underline{\epsilon}^W = \Delta^W$. In the third and sixth rows, the elasticities follow directly from Equations 17 and 18 respectively. Theorem 1 of Allen et al. (2024) and Remark 1 states that there is a unique equilibrium if the spectral radius of $\mathbf{A}$ is less than 1, and it can be solved for by iteratively applying the equilibrium conditions.

Two necessary conditions from spectral radii of principal submatrices As $\mathbf{A}$ is nonnegative, its spectral radius is weakly larger than the spectral radii of all principal submatrices.

Suppose 1 is an eigenvalue of the top left principal submatrix, that is

$$\begin{vmatrix} -1 & 0 & 1 \\ \epsilon^Z & -1 & \Delta^Z \\ 0 & a & -1 \end{vmatrix} = 0$$

Simplifying yields

$$a(\epsilon^Z + \Delta^Z) - 1 = 0$$

As the spectral radius is strictly increasing in nonnegative entries for an irreducible matrix, whenever $a(\epsilon^Z + \Delta^Z) \geq 1$, then the spectral radius of the top left principal submatrix is weakly greater than 1. Applying an argument by symmetry, the following two conditions are necessary for the spectral radius of $\mathbf{A}$ to be less than 1:

$$a(\epsilon^Z + \Delta^Z) < 1 \tag{20}$$

$$c(\epsilon^L + \Delta^L) < 1 \tag{21}$$

One necessary condition for characteristic polynomial to have no zeros above 1 We next derive the characteristic polynomial for $\mathbf{A}$, and show that one additional condition is necessary and sufficient for it to have no zeros greater than 1 if Equations 20 and 21 hold. The characteristic polynomial for $\mathbf{A}$ is

$$g_A(\lambda) = \left[a(\lambda\Delta^Z + \epsilon^Z) - \lambda^3\right]\left[c(\lambda\Delta^L + \epsilon^L) - \lambda^3\right] - bd(\lambda\Delta^L + \epsilon^L)(\lambda\Delta^Z + \epsilon^Z) \tag{22}$$

Note that $\lim_{\lambda\to\infty} g_A(\lambda) = \infty$, so it must be the case that $g_A(1) > 0$. Simplifying yields

$$\left[a(\Delta^Z + \epsilon^Z) - 1\right]\left[c(\Delta^L + \epsilon^L) - 1\right] - bd(\Delta^L + \epsilon^L)(\Delta^Z + \epsilon^Z) > 0 \tag{23}$$

The three conditions are sufficient Lastly, we show that Equations 20, 21, and 23 together imply that $g_A(\lambda) > 0$ for all $\lambda \geq 1$, and therefore the spectral radius of $\mathbf{A}$ is less than 1. As a consequence, these three equations are necessary and sufficient for the spectral radius of $\mathbf{A}$ to be less than 1.

Assume Equations 20, 21, and 23 hold. We then differentiate $g_A(\lambda)$, yielding

$$g_A^{(1)}(\lambda) = (a\Delta^Z - 3\lambda^2)(c(\lambda\Delta^L + \epsilon^L) - \lambda^3) + (a(\lambda\Delta^Z + \epsilon^Z) - \lambda^3)(c\Delta^L - 3\lambda^2) - bd(\Delta^L(\lambda\Delta^Z + \epsilon^Z) + \Delta^Z(\lambda\Delta^L + \epsilon^L))$$

$$g_A^{(2)}(\lambda) = -6\lambda(c(\lambda\Delta^L + \epsilon^L) - \lambda^3) + 2(a\Delta^Z - 3\lambda^2)(c\Delta^L - 3\lambda^2) - 6\lambda(a(\lambda\Delta^Z + \epsilon^Z) - \lambda^3) - 2bd\Delta^L\Delta^Z$$

$$g_A^{(3)}(\lambda) = -6(c(\lambda\Delta^L + \epsilon^L) - \lambda^3) - 18\lambda(c\Delta^L - 3\lambda^2) - 18\lambda(a\Delta^Z - 3\lambda^2) - 6(a(\lambda\Delta^Z + \epsilon^Z) - \lambda^3)$$

$$g_A^{(4)}(\lambda) = -24[c\Delta^L - 3\lambda^2] + 216\lambda^2 - 24[a\Delta^Z - 3\lambda^2] \qquad g_A^{(5)}(\lambda) = 720\lambda \qquad g_A^{(6)}(\lambda) = 720$$

We repeatedly apply Equations 20 and 21, which imply that $c(\Delta^L + \epsilon^L) - 1 < 0$ and $a(\Delta^Z + \epsilon^Z) - 1 < 0$, and make use of the observations that $a\Delta^Z - 3 < a(\Delta^Z + \epsilon^Z) - 1$ and $c\Delta^L - 3 < c(\Delta^L + \epsilon^L) - 1$.

We note in sequence that

$$\begin{aligned}
g_A^{(1)}(1) &= (a\Delta^Z - 3)(c(\Delta^L + \epsilon^L) - 1) + (a(\Delta^Z + \epsilon^Z) - 1)(c\Delta^L - 3) - bd(\Delta^L(\Delta^Z + \epsilon^Z) + \Delta^Z(\Delta^L + \epsilon^L)) \\
&> 2(a(\Delta^Z + \epsilon^Z) - 1)(c(\Delta^L + \epsilon^L) - 1) - 2bd(\Delta^L + \epsilon^L)(\Delta^Z + \epsilon^Z) = 2g_A(1) > 0 \\
g_A^{(2)}(1) &= -6(c(\Delta^L + \epsilon^L) - 1) + 2(a\Delta^Z - 3)(c\Delta^L - 3) - 6(a(\Delta^Z + \epsilon^Z) - 1) - 2bd\Delta^L\Delta^Z \\
&> 2(a\Delta^Z - 3)(c\Delta^L - 3) - 2bd\Delta^L\Delta^Z \\
&> 2(a(\Delta^Z + \epsilon^Z) - 1)(c(\Delta^L + \epsilon^L) - 1) - 2bd(\Delta^L + \epsilon^L)(\Delta^Z + \epsilon^Z) = 2g_A(1) > 0 \\
g_A^{(3)}(1) &= -6(c(\Delta^L + \epsilon^L) - 1) - 18(c\Delta^L - 3) - 18(a\Delta^Z - 3) - 6(a(\Delta^Z + \epsilon^Z) - 1) > 0 \\
g_A^{(4)}(1) &= -24[c\Delta^L - 3] + 216 - 24[a\Delta^Z - 3] > 0 \\
g_A^{(5)}(1) &= 720 > 0 \\
g_A^{(6)}(1) &= 720 > 0
\end{aligned}$$

As $g_A(\lambda)$ is a polynomial and all order derivatives are weakly positive at $\lambda = 1$, it is increasing for all $\lambda > 1$. Since $g_A(1) > 0$, $g_A(\lambda) > 0$ for all $\lambda \geq 1$.

Simplifying the three conditions Lastly, we substitute Equations 17 and 18 into the conditions in Equations 20, 21, and 23.

First, substituting into Equation 20

$$\frac{(1-\alpha)+(1-\alpha-\beta)\epsilon^L}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}(\epsilon^Z+\Delta^Z)-1<0$$

$$\frac{\left[(1-\alpha)+(1-\alpha-\beta)\epsilon^L\right]\Delta^Z-(1+(1-\beta)\epsilon^L)}{1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z}<0$$

$$\Delta^Z<\frac{1+(1-\beta)\epsilon^L}{(1-\alpha)+(1-\alpha-\beta)\epsilon^L}$$

By symmetry, Equation 21 simplifies to

$$\Delta^L<\frac{1+(1-\alpha)\epsilon^Z}{(1-\beta)+(1-\alpha-\beta)\epsilon^Z}$$

Lastly, we apply the first step of the simplification of Equation 20, and the same step to Equation 21, and substitute into Equation 23. This yields

$$\left[\left[(1-\alpha)+(1-\alpha-\beta)\epsilon^L\right]\Delta^Z-(1+(1-\beta)\epsilon^L)\right]\left[\left[(1-\beta)+(1-\alpha-\beta)\epsilon^Z\right]\Delta^L-(1+(1-\alpha)\epsilon^Z)\right]$$
$$-\beta\alpha(\Delta^L+\epsilon^L)(\Delta^Z+\epsilon^Z)>0$$

$$\left[1+(1-\alpha)\epsilon^Z+(1-\beta)\epsilon^L+(1-\alpha-\beta)\epsilon^L\epsilon^Z\right]\left[(1-\alpha-\beta)\Delta^L\Delta^Z-(1-\beta)\Delta^L-(1-\alpha)\Delta^Z+1\right]>0$$

$$(1-(1-\alpha)\Delta^Z)(1-(1-\beta)\Delta^L)-\alpha\beta\Delta^L\Delta^Z>0$$

Theorem 1 with two factors Suppose Equations 11, 12, and 13 hold. Let $\epsilon^W\equiv\frac{\max_{i,j}\epsilon^W_{ij}+\min_{i,j}\epsilon^W_{ij}}{2}$ and $\Delta^W\equiv\frac{\max_{i,j}\epsilon^W_{ij}-\min_{i,j}\epsilon^W_{ij}}{2}$. Then if

$$\Delta^Z<\frac{1+(1-\beta)\epsilon^L}{(1-\alpha)+(1-\alpha-\beta)\epsilon^L}$$

$$\Delta^L<\frac{1+(1-\alpha)\epsilon^Z}{(1-\beta)+(1-\alpha-\beta)\epsilon^Z}$$

$$(1-(1-\alpha)\Delta^Z)(1-(1-\beta)\Delta^L)-\alpha\beta\Delta^L\Delta^Z>0$$

there is a unique equilbrium. The unique equilbrium can be solved for by iterating Equations 11 (to solve for household factor market access given posted factor prices), 14 (to solve for farm factor market access given household factor market access and posted factor prices), and 17 and 18 (to solve for posted factor prices given farm factor market demand).

A brief corollary When $\Delta^L = 0$, these conditions simplify to $\Delta^Z < \frac{1}{1-\alpha}$.

C.4 Match destruction in a dynamic model

We consider the following dynamic version of the household's factor problem in Equation 4. Following a separation, a unit of household i's land is immediately matched to a new farm with probabilities that solve

$$V_i = \max_{\sum_j q_{ij}=1} \sum_{j \in \mathcal{I}} q_{ij} V_{ij} - \sum_{j \in \mathcal{I}} m(q_{ij}) \tag{24}$$

$$V_{ij} = \int_0^\infty \underbrace{\left[\int_0^t \rho e^{-\rho s} u_{ij} ds + \int_t^\infty \rho e^{-\rho s} V_i ds \right]}_{\text{utility if separation after } t} \underbrace{\phi_{ij} e^{-\phi_{ij} t}}_{\text{separation density}} dt \tag{25}$$

In Equation 24, household i maximizes expected utility ($\sum q_{ij} V_{ij}$) net of search costs ($\sum m(q_{ij})$). In Equation 25, i's utility from matching with j is V_{ij}. After matching, separation occurs at exogenous rate ϕ_{ij}, after which i experiences utility V_i in expectation. i experiences flow utility u_{ij} until separation. Future utility is discounted exponentially with discount factor ρ.

Integrating, we simplify match utility in Equation 25 to

$$\begin{aligned} V_{ij} &= \frac{\rho}{\rho + \phi_{ij}} u_{ij} + \frac{\phi_{ij}}{\rho + \phi_{ij}} V_i \\ &= \frac{\rho}{\rho + \phi_{ij}} (u_{ij} - V_i) + V_i \end{aligned} \tag{26}$$

Substituting match utility V_{ij} from Equation 26 into Equation 24, and substituting $\sum_{j \in \mathcal{I}} q_{ij} = 1$ and subtracting V_i from both sides, yields

$$0 = \max_{\sum_j q_{ij}=1} \sum_{j \in \mathcal{I}} q_{ij} \frac{\rho}{\rho + \phi_{ij}} (u_{ij} - V_i) - \sum_{j \in \mathcal{I}} m(q_{ij}) \tag{27}$$

We next take the first order condition for utility maximization with respect to q_{ij}. Let λ_i denote the multiplier on the constraint $\sum_{j\in\mathcal{I}} q_{ij} = 1$. The first order condition is therefore $\partial V_i/\partial q_{ij} = \lambda_i$. Simplifying yields

$$m'(Q_{ij}) = \frac{\rho}{\rho+\phi_{ij}}\left(u_{ij} - V_i\right) - \underbrace{\left(1 + \sum_{k\in\mathcal{I}} Q_{ik}\frac{\rho}{\rho+\phi_{ik}}\right)\lambda_i}_{\equiv\lambda_i^*} \tag{28}$$

As in Proposition 1, we consider the case $m'(r) = a\log r + b$, and therefore $m(r) = ar\log r + (b-a)r + c$. In this case, choices simplify to

$$\log Q_{ij} = \frac{1}{a}\Big(\frac{\rho}{\rho+\phi_{ij}}(u_{ij} - V_i) - \lambda_i^* - b\Big)$$

Substituting into Equation 27, we derive

$$\begin{aligned} 0 &= \sum_{j\in\mathcal{I}} Q_{ij}\left(\frac{\rho}{\rho+\phi_{ij}}(u_{ij} - V_i) - a\log Q_{ij} - (b-a)\right) - c \\ &= \sum_{j\in\mathcal{I}} Q_{ij}\left(\lambda_i^* + a\right) - c \\ \lambda_i^* &= -a + |\mathcal{I}|c \end{aligned}$$

and choices therefore satisfy

$$\log Q_{ij} = \frac{1}{a}\Big(\frac{\rho}{\rho+\phi_{ij}}(u_{ij} - V_i) + a - b - |\mathcal{I}|c\Big) \tag{29}$$

Lastly, we note that when i matches to j, i spends on average $1/\phi_{ij}$ time before separating. Letting P_{ij} denote the fraction of time a unit of factor from i is observed working at j,

$$P_{ij} = \frac{Q_{ij}/\phi_{ij}}{\sum_k Q_{ik}/\phi_{ik}}$$

Substituting, we derive

$$\log P_{ij} = \frac{1}{a}\Big(\frac{\rho}{\rho+\phi_{ij}}(u_{ij} - V_i) + a - b - |\mathcal{I}|c\Big) - \log\phi_{ij} - \log\left(\sum_k Q_{ik}/\phi_{ik}\right) \tag{30}$$

Note that demand in Proposition 1 is identical to matching probabilities in Equation 29, but distinct from employment probabilities in Equation 30. Employment probabilities in Equation 30 depend on an additional aggregator $\sum_k Q_{ik}/\phi_{ik}$.[21] However, both Equations 29 and 30 imply identical estimating equations for our analysis in Section 5.2.

Matching frictions and separation rates play identical roles in the static and dynamic models, with a factor trade elasticity proportional to $1/\mu_{ij}$ in the static model and $\rho/(\rho+\phi_{ij})$ in the dynamic model. These are identical in the no discounting limit ($\rho \to 0$) as in Prediction 1.

C.5 Predictions 2 and 3 under general c

Section 4.2 demonstrates that iceberg frictions decrease bilateral trade while matching frictions have an indeterminate effect (Prediction 2), but matching frictions decrease the factor trade elasticity while iceberg frictions have no effect (Prediction 3). These predictions were derived under a parametric specification of c; below we show similar predictions hold for general c.

Prediction A.2. *Hold fixed the shadow value of land λ_i. Iceberg frictions decrease bilateral trade. Matching frictions decrease bilateral trade if and only if marginal search costs are positive.*

$$\left.\frac{dP_{ij}}{d\log\tau_{ij}}\right|_{\lambda_i} = -\frac{\eta}{\mu_{ij}c''(P_{ij})} < 0 \qquad \left.\frac{dP_{ij}}{d\log\mu_{ij}}\right|_{\lambda_i} = -\frac{c'(P_{ij})}{c''(P_{ij})}$$

Prediction A.3. *Hold fixed the shadow value of land λ_i. Matching frictions decrease the factor trade elasticity if and only if the elasticity of marginal search costs to factor trade is decreasing.*

$$\frac{d}{d\log\mu_{ij}}\left.\frac{d\log P_{ij}}{d\log R_j}\right|_{\lambda_i} < 0 \Leftrightarrow \frac{d}{dP_{ij}}\frac{d\log c'(P_{ij})}{d\log P_{ij}} < 0$$

Proof. Prediction A.2 implies

$$\left.\frac{d\log P_{ij}}{d\log\mu_{ij}}\right|_{\lambda_i} = -\frac{c'(P_{ij})}{c''(P_{ij})P_{ij}} = -\left(\frac{d\log c'(P_{ij})}{d\log P_{ij}}\right)^{-1}$$

This expression is increasing in the elasticity of marginal search costs to P_{ij}. Since P_{ij} is increasing in R_j holding fixed λ_i, this expression is decreasing in R_j if and only if the elasticity of marginal

[21] Fally (2022) characterize demand systems that depend both on indirect utility and a price aggregator.

search costs is decreasing in P_{ij}. □

Prediction A.2 is identical to Prediction 2. Prediction A.3 demonstrates that matching frictions decrease the factor trade elasticity under the additional assumption that the elasticity of marginal search costs to factor trade is decreasing, which is satisfied by $c'(q) = a \log q + b$. A decreasing elasticity implies that directing trade is relatively less costly than intensifying trade at higher levels of trade—that is, if moving from 1% of labor hired by both A and B to 1.5% by A and 0.5% by B is equally costly as increasing to 1.2% of labor hired by both A and B, then moving from 10% of labor hired by both A and B to 15% by A and 5% by B must be less costly than increasing to 12% of labor hired by both A and B.

Prediction A.3 does not speak to the effect of iceberg frictions on the factor trade elasticity. Below, we show that iceberg frictions do not robustly impact the effect of posted factor prices $\log R_j$ on factor trade in a generalized linear model across specifications of the link function, and therefore interpret non-robust impacts as potentially consistent with iceberg frictions.

Prediction 6. *Holding fixed the shadow value of land λ_i, and for some increasing link function g,*

$$\left.\frac{d^2 g(P_{ij})}{d\mu_{ij} d\log R_j}\right|_{\lambda_i} < 0$$

$$\left.\frac{d^2 g(P_{ij})}{d\tau_{ij} d\log R_j}\right|_{\lambda_i} = 0$$

That is, matching frictions decrease the factor trade elasticity, while iceberg frictions do not.

Proof. Fix $g(q) \equiv \frac{1}{\eta} c'(q)$. $c''(q) > 0$ by assumption, so g is increasing. Differentiating yields

$$\left.\frac{dg(P_{ij})}{d\log R_j}\right|_{\lambda_i} = \frac{1}{\mu_{ij}}$$

Prediction 6 trivially follows. □

C.6 Proof of Prediction 5

Let $\text{MPZ}_i \equiv A_i \overline{Z}_i^{-(1-\alpha)}$. The change in production from rentals in, relative to a benchmark with randomly allocated rentals in, is equal to

$$\begin{aligned}
&\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} P_{ji} \overline{Z}_j \\
&= \Big(\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} C_{ij} P_{ji} \overline{Z}_j \Big) + \Big(\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} (1 - C_{ij}) P_{ji} \overline{Z}_j \Big)
\end{aligned}$$

Leveraging independence of MPZ_i and C_{ij} to substitute $\overline{\text{MPZ}} = \mathbf{E}[\text{MPZ}_i | C_{ij}]$ and $\mathbf{Var}[\text{MPZ}_i | C_{ij}] = \mathbf{Var}[\text{MPZ}_i]$, we derive

$$\begin{aligned}
&\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} C_{ij} P_{ji} \overline{Z}_j \\
&= \frac{\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} C_{ij} P_{ji} \overline{Z}_j}{\sum_{i, j \neq i} C_{ij}} \sum_{i, j \neq i} C_{ij} \\
&= \mathbf{Cov}[\text{MPZ}_i, P_{ji} \overline{Z}_j | C_{ij} = 1, j \neq i] \sum_{i, j \neq i} C_{ij} \\
&= \frac{\mathbf{Cov}[\text{MPZ}_i, P_{ji} \overline{Z}_j | C_{ij} = 1]}{\mathbf{Var}[\text{MPZ}_i | C_{ij} = 1]} \mathbf{Var}[\text{MPZ}_i] \sum_{i, j \neq i} C_{ij} \\
&= \frac{\mathbf{Cov}[\text{MPZ}_i, P_{ji} \overline{Z}_j | C_{ij} = 1]}{\mathbf{Var}[\text{MPZ}_i | C_{ij} = 1] \mathbf{E}[P_{ji} \overline{Z}_j | C_{ij} = 1]} \mathbf{Var}[\text{MPZ}_i] \sum_{i, j \neq i} C_{ij} P_{ji} \overline{Z}_j
\end{aligned}$$

We then apply the approximation $\mathbf{Cov}[A, B] \approx \mathbf{E}[A] \mathbf{Cov}[\log A, B]$ to derive

$$\begin{aligned}
&\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} C_{ij} P_{ji} \overline{Z}_j \\
&= \frac{\mathbf{Cov}[\log \text{MPZ}_i, \log P_{ji} + \log \overline{Z}_j | C_{ij} = 1]}{\mathbf{Var}[\log \text{MPZ}_i | C_{ij} = 1]} \overline{\text{MPZ}} \mathbf{Var}[\log \text{MPZ}_i] \sum_{i, j \neq i} C_{ij} P_{ji} \overline{Z}_j \\
&= \frac{\mathbf{Cov}[\log \text{MPZ}_i, \log P_{ji} | C_{ij} = 1]}{\mathbf{Var}[\log \text{MPZ}_i | C_{ij} = 1]} \overline{\text{MPZ}} \mathbf{Var}[\log \text{MPZ}_i] \sum_{i, j \neq i} C_{ij} P_{ji} \overline{Z}_j
\end{aligned}$$

Note that our expression of interest

$$\frac{\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} C_{ij} P_{ji} \overline{Z}_j}{\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} P_{ji} \overline{Z}_j} = \left(1 + \frac{\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} (1 - C_{ij}) P_{ji} \overline{Z}_j}{\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} C_{ij} P_{ji} \overline{Z}_j} \right)^{-1}$$

Substituting and canceling yields our approximation

$$\begin{aligned} &\frac{\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} C_{ij} P_{ji} \overline{Z}_j}{\sum_i (\text{MPZ}_i - \overline{\text{MPZ}}) \sum_{j \neq i} P_{ji} \overline{Z}_j} \\ &\approx \left(1 + \frac{\sum_{j \neq i} (1 - C_{ij}) P_{ji} \overline{Z}_j}{\sum_{j \neq i} C_{ij} P_{ji} \overline{Z}_j} \frac{\mathbf{Cov}[\log P_{ji}, \log \text{MPZ}_i | C_{ij} = 0]_{j \neq i} / \mathbf{Var}[\log \text{MPZ}_i | C_{ij} = 0]_{j \neq i}}{\mathbf{Cov}[\log P_{ji}, \log \text{MPZ}_i | C_{ij} = 1]_{j \neq i} / \mathbf{Var}[\log \text{MPZ}_i | C_{ij} = 1]_{j \neq i}} \right)^{-1} \end{aligned}$$