Farm Household Misallocation

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Abstract

Agricultural markets often fail to allocate resources efficiently across farm households in developing countries. However, policymakers require knowledge of which markets fail and how the distortions they generate are correlated. Using data from rural Thailand, I characterize how distortions in land, labor, credit, and insurance markets each contribute to misallocation. I use moments in household consumption and production data to separately identify these distortions and develop a novel method using them to structurally estimate the production function. I find that the efficient allocation would increase aggregate productivity by 31% relative to the status quo, while only 16% (9%) gains could be achieved by eliminating financial (input) distortions in isolation. Positive interaction effects from addressing multiple distortions simultaneously account for the remaining 6% TFP gains. Meanwhile, other common methods would produce larger estimates of misallocation and suggest that a financial market intervention would decrease aggregate productivity. Accounting for multiple correlated distortions is therefore crucial for measuring misallocation and designing policies to address it.

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1 Introduction

Farm households in developing countries face many different market failures, but how does each matter for aggregate productivity? Decades of research in development economics has provided robust empirical evidence of incomplete credit, insurance, land, labor, fertilizer, equipment, seed, and other markets, often occurring simultaneously.[1] However, these market failures rarely operate in a vacuum; in equilibrium, they combine to misallocate resources across farms. While the resulting misallocation is extremely costly (Restuccia and Rogerson, 2008; Adamopoulos and Restuccia, 2014), how can policymakers distinguish between its many possible sources?

Doing so is especially important, yet challenging, because distortions generated by different market failures may compound or offset each other in equilibrium. The theory of the second best implies that the effects of reducing distortions in *any* market are ambiguous and depend on the underlying distribution of distortions in *all* markets (Lipsey and Lancaster, 1956). What determines a policy's effectiveness is not how much it reduces a particular distortion, but whether it moves producers closer to or further from the efficient allocation. For example, correcting distortions in land markets may have limited or negative effects if the households that expand their landholdings are already inefficiently large due to preferential access to credit. Since considering a single market failure in isolation can lead to inefficient and even harmful policy recommendations, it is important to distinguish them empirically.

This paper separately identifies a wide range of distortions in Thai agriculture and characterizing how they combine to generate misallocation in equilibrium. Such a task requires a structural model:[2] Specifically, I estimate distortions in input (e.g. land, labor, and equipment) and financial (credit and insurance) markets.[3] Under general production and utility functions, distortions in these markets each affect households' input demands through distinct wedges. However, the full set of input and financial wedges cannot be separately identified using solely production data (Hsieh and Klenow, 2009) — there generally is no way to tell whether a household uses less of an input because it cannot obtain it at the

[1] See Magruder (2018) and Suri and Udry (2022) for recent overviews.Goldstein and Udry (2008); Breza, Kaur, and Shamdasani (2021); Karlan et al. (2014); Mobarak and Rosenzweig (2013); Diop (2023); Caunedo and Kala (2021); and Bold et al. (2017) provide excellent examples of each of these market failures, respectively. Emerick et al. (2016) and Jones et al. (2022) are examples providing experimental evidence on how these market failures can compound each other.

[2] If there are K potential market failures, the ideal experiment would require 2^K treatment arms, at the village (or higher) level of aggregaation.

[3] These are the distortions I find to be most relevant in the Thai context. In general, the model I develop in Section 2 can accommodate distortions in financial markets and $K-1$ input markets if there are K inputs.

market price or because it is financially constrained. In particular, analyses that treat farm households as profit-maximizing firms cannot separately identify the distortions induced by uninsured risk.

However, unlike typical firms, farm households are also consumers. Under imperfect markets, household consumption enters their investment decisions and thus contains information about how production is distorted (Benjamin, 1992). I leverage this information to how credit constraints and uninsured risk distort households productive choices distinctly from frictions in input markets. In particular, credit constraints enter as a wedge between the marginal utilities of consumption at planting and at harvest (reflecting the inability to smooth consumption across time by borrowing against future harvests). Meanwhile uninsured risk enters through the covariance between production shocks and the marginal utility of consumption at harvest (reflecting the dependence of consumption on realizations of output when households cannot use insurance to smooth consumption across *states of the world).* On the other hand, input frictions function like a tax or subsidy and can be identified from dispersion in input *composition* across households.

Expanding on this theoretical framework, I develop a novel method to structurally estimate the production function from households' first-order conditions. Structural production function estimation can help overcome the endogeneity of inputs if firms' optimization problems are well-specified. The logic is that firms take all available information into account when choosing their inputs, including information unobservable to the econometrician. In this case, inverting demand for a flexible input can essentially proxy for unobserved productivity, which may be preferable to searching for an instrument that's uncorrelated with it. (e.g. Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Gandhi, Navarro, and Rivers, 2020).[4] The catch is that most of these approaches are invalid when unobserved distortions affect input demands. However, my estimates of these distortions from the previous step account for exactly *how* input and financial distortions affect input demands, making structural approaches valid again. Estimating the production function then amounts to identifying the parameters that rationalize these constrained optimal choices, as in a portfolio choice problem. To do so, I develop a linear GMM estimator in the spirit of Hansen and Singleton (1982) under the assumption of rational expectations.[5] To my knowledge, this is

[4]The simplest example of this is calibrating Cobb-Douglas coefficients to observed revenue shares. However, these are not valid under imperfect markets because firms do not maximize expected profits and do not face common prices.

[5]Much like a consumption-CAPM problem, I treat inputs as risky assets whose (marginal) returns covary with the return to a household's overall portfolio, captured by the marginal utility of expenditure. However in my case, the returns rather than marginal utilities (which have been estimated in the previous step, are

the first use of moments in consumption data to estimate a physical production function.

I then use estimates of the production function and distortions to calculate aggregate TFP under the observed allocation, the efficient allocation, and counterfactual distributions of distortions. Crucially, my estimation strategy is only possible when both input and financial distortions are well-specified. Otherwise, the common alternative is to calibrate the production function using revenue shares from a setting in which perfect markets are assumed to hold, such as the US or Canada (e.g. Adamopoulos and Restuccia, 2020; Chen, Restuccia, and Santaeulàlia-Llopis, 2023), or use lagged inputs as instruments (e.g. Shenoy, 2017, 2021; Manysheva, 2021).

I implement my approach with the Townsend Thai Data, which is a 196-month panel of rural households in 16 Thai villages (with annual surveys in another 48 villages over the same period) from 1998 to 2014. Many studies have used the Townsend Thai Data to provide evidence of credit constraints (Kaboski and Townsend, 2011, 2012) and imperfect risk-sharing (Kinnan and Townsend, 2012; Karaivanov and Townsend, 2014; Samphantharak and Townsend, 2018; Kinnan et al., 2024). Shenoy (2017) also estimates a lower bound on input misallocation of about 11% of TFP. I interpret these findings as evidence of both imperfect financial and input markets in Thailand and view this paper as the first full decomposition of their costs. However, many of the institutional features common in other studies of misallocation, such as restrictive land policy and absence of credit markets, do not apply.[6] This makes Thailand a useful benchmark for less developed countries; finding nontrivial amounts of misallocation suggests that favorable institutions alone do not guarantee efficiency. The level of misallocation in Thailand may therefore be a more realistic counterfactual for institutional reforms in these settings than full efficiency.

I present four main empirical findings: First, I find that going from the observed to efficient allocation increases aggregate TFP by 31%. This is similar to estimates of total misallocation of 19% in Shenoy (2017) from Thailand (albeit using different methodologies and data), but substantially lower than estimates of 53% from China (Adamopoulos et al., 2022b), 97% from Ethiopia (Chen, Restuccia, and Santaeulàlia-Llopis, 2022), 259% from Malawi (Chen, Restuccia, and Santaeulàlia-Llopis, 2023), and 286% from Uganda (Aragon, Restuccia, and Rud, 2022). These gains increase to about 35% when allowing the aggregate supply of tradable inputs to respond to increased aggregate TFP, as in Donovan (2021).

the estimands of interest.

[6] Thai agriculture features important distortions at the sectoral level, including heavy price supports for rice and fertilizer. However, this would only affect conclusions from the model in Section 2 to the extent it creates variation in prices across households in the same location, which is unlikely to be the case.

Second, I decompose these gains into the effects of eliminating either friction in isolation and the interaction effect from eliminating them simultaneously. I find that removing financial distortions while holding observed input wedges fixed would achieve 16-19% TFP gains relative to the observed allocation while removing input distortions alone would achieve 9-14% gains. Thus, TFP can be increased by a further 3-6% (relative to baseline) by addressing both sets of distortions together. While the sign of these interaction effects is theoretically ambiguous, in the data it is positive because more financially constrained households are relatively subsidized in input markets.[7]

Third, I model the effects of incrementally reducing distortions in one or more markets. This may represent a more realistic policy scenario when budgetary, political, or feasibility constraints make it impossible to eliminate some distortions entirely. I find that reducing both input and financial frictions by one-half (uniformly across households) would be much more effective than eliminating either distortion alone. This suggests that there are diminishing returns to addressing individual distortions in isolation and that a multi-pronged policy approach could achieve larger gains from the same amount of resources.

Finally, I analyze some distributional implications of reducing distortions. In the data, wealthier households tend to have much larger farm sizes. Each counterfactual leads to a more concentrated farm size distribution in which most households contract, but which households expand depends on which distortions are reduced. Reducing financial frictions weakens the correlation between farm size and baseline income by reallocating from the wealthiest households to those at the middle of the income distribution. However, removing input frictions alone further concentrates resources towards wealthier households, exacerbating inequality. Under the efficient allocation, the progressivity of financial reform outweighs the regressivity of input reform, reducing the correlation between farm size and baseline wealth.

This paper's main contribution is developing a framework and estimation strategy to attribute misallocation to failures in distinct markets. Doing so is important not only for understanding where misallocation comes from but for developing policies to address it. This is because unmodeled distortions can bias estimates of misallocation and even suggest harmful policies, depending on how the measured distortions are correlated with unmeasured ones. Recent advances in the misallocation literature (e.g. Carrillo et al., 2023; Sraer and Thesmar, 2023; Hughes and Majerovitz, 2023) show how misallocation can nonparametrically be es-

[7] This is consistent with evidence that poorer households over-supply labor to their own farms because the shadow value of their time is lower (Dillon, Brummund, and Mwabu, 2019; Jones et al., 2022).

timated from (quasi-)experimental variation but are generally unable to trace misallocation to its different sources. There is also a growing literature applying quantitative misallocation models to microdata in agriculture (Adamopoulos and Restuccia, 2020; Adamopoulos et al., 2022a,b; Aragon, Restuccia, and Rud, 2022; Chari et al., 2021; Chen, Restuccia, and Santaeulalia-Llopis, 2017; Chen, Restuccia, and Santaeulàlia-Llopis, 2022, 2023; Donovan, 2021; Gottlieb and Grobovšek, 2019; Manysheva, 2021; Shenoy, 2017). However, these papers typically model a single distortion in isolation or combine all distortions into a composite wedge. Notable exceptions are Manysheva (2021), who models the explicit dependence of credit constraints and land distortions through the collateral channel, and Shenoy (2017) who, also in Thailand, derives bounds for input and financial misallocation under assumptions on the joint distribution of distortions. In contrast, I estimate a more complete range of distortions and model how the effects of counterfactual policies depend on their underlying distribution. Importantly, I show how my results differ substantially from the conclusions one would draw under other methods.

An important advantage of this framework is that it allows me to remain agnostic towards the specific institutions that generate distortions. These distortions have many potential, possibly simultaneous, causes and conclusions may depend on which ones a model specifies. For example, recent empirical work has identified expropriation risk (Goldstein and Udry, 2008), incomplete contracting (Burchardi et al., 2019), an explicit cap on landholdings (Adamopoulos and Restuccia, 2020), lack of titling (Chen, Restuccia, and Santaeulàlia-Llopis, 2022), land fragmentation (Bryan et al., 2022), and others, as contributing to imperfect land markets. It would be impossible to capture all of these explicitly in a single model. Instead, my method allows me to diagnose how distortions in each market affect aggregate productivity without strong assumptions about their root causes.

Second, I contribute to the recent literature on how measurement error can inflate estimates of misallocation by using a model to separate between financial frictions and input mismeasurment. Rotemberg and White (2021) and Bils, Klenow, and Ruane (2021) find large upward biases due to measurement error in U.S. and Indian manufacturing. Meanwhile, Gollin and Udry (2021) argue that up to 70% of observed productivity dispersion in Ugandan and Tanzanian agriculture is due to measurement error and unobserved heterogeneity. This is supported by evidence of large and systematic measurement error in survey measures of agricultural land, labor, and output (e.g. Arthi et al., 2018; Desiere and Jolliffe, 2018; Abay et al., 2019; Abay, Bevis, and Barrett, 2021).

Estimating a wider range of distortions helps me overcome these concerns by avoiding having to infer them from a noisy residual. In particular, observed productivity dispersion is a (nonlinear) function of true misallocation and measurement error. When estimating a model with only a subset of distortions, e.g. only input distortions, the residual contains both financial distortions and measurement error. In other words, measurement error looks like a distortion in the data – and will tend to inflate estimates of misallocation.[8] However, directly estimating financial distortions allows me to distinguish between measurement error and true misallocation in this residual.[9] Without estimating both input and financial distortions, one would not be able to make this distinction.[10] I find that this would produce slightly larger estimates of misallocation than my model does and would suggest that eliminating financial distortions would *lower* aggregate productivity. This occurs due to the correlation between financial distortions and measurement error.

Third, I contribute to the literature on production function estimation when input choices are distorted. This has been done in previous work to address adjustment costs (Asker, Collard-Wexler, and De Loecker, 2014), input price dispersion (De Loecker et al., 2016; Grieco, Li, and Zhang, 2016), and markups (De Loecker and Warzynski, 2012; Asker, Collard-Wexler, and De Loecker, 2019; Cairncross et al., 2023), but not the types of distortions that farm households are likely to face, such as uninsured risk. My approach is to use a simple theory-consistent model of households' constrained optimal behavior to identify the production function given how input and financial frictions enter first-order conditions. Doing so ensures unobserved shocks' effects on input demands are subsumed by households' constrained-optimal choices of consumption and investment. The main difference between my estimator and dynamic panel estimators used elsewhere in the literature (Shenoy, 2017; Manysheva, 2021, e.g.) is that the bulk of my assumptions rests on household optimization rather than the dynamics of unobserved shocks.

The rest of the paper is organized as follows: In Section 2, I present the theoretical framework and derive expressions for financial and input wedges at the household level, showing how they map to aggregate misallocation. Section 3 provides more information

[8]The effect of measurement error on misallocation is theoretically ambiguous, but measurement error would need to be sufficiently negatively correlated with true distortions to create a downward bias.

[9]Of course, estimated quantities (TFP and wedges) contain error as well. However, TFP estimates (by design) remove much of the error in raw input measurements and are therefore less noisy. Moreover, having estimates of financial frictions allows me to compute both TFP-based and input-based estimates of aggregate productivity under any allocation.

[10]In the expression I derive for misallocation in Section 2, mismeasurement in inputs appears like a distortion in the sense that moves inputs either away from or closer to the efficient allocation. If it is correlated with other distortions and household productivity, the effects on measured misallocation are ambiguous, much like with two correlated "true" distortions.

about the Thai data and context. Section 4 presents the estimation framework I develop and the results. Section 5 shows the counterfactuals that I evaluate and Section 6 concludes.

2 Model

I propose a dynamic farm household model to characterize how frictions in financial and input markets generate distinct wedges in households' input demands. In equilibrium, these create dispersion in marginal revenue products (TFPR in the language of Hsieh and Klenow (2009)) across households, lowering aggregate TFP relative to the case of perfect markets. The model is dynamic and features many possible sources of distortions, but allows their effects on each market to be separately identified from three sets of first-order conditions.

While this allows me to estimate distortions while remaining agnostic towards the specific institutions that generate them I cannot prescribe specific policies without further assumptions on the root causes of distortions in each market. However, this does not allow me to prescribe specific policies without further assumptions on the root causes of distortions in each market. Doing so would require distinguishing between, for example, limited commitment or asymmetric information in risk-sharing networks and expropriation risk and lack of titling in land markets. While further research is required to further distinguish between these sources of distortions, quantifying the misallocation within each market may nonetheless be useful for policymakers.

2.1 Environment

There are V villages[11] and time, indexed by t, is discrete. For simplicity, each village has a fixed number of households N_v, indexed by j. Agriculture is the only sector in the villages and uses $K \geq 3$ inputs to produce a single numéraire good[12] I assume for simplicity that the supply of land $\bar{Q}_{1vt}$ and labor $\bar{Q}_{2vt}$ is fixed within villages. There is an urban sector with stand-in firms that produce a vector of other consumption goods, indexed by i, and the remaining $K-2$ inputs used in agriculture.[13] Each of these can be imported to the village at exogenous prices p_{ivt} for goods i and $\bar{w}_{kvt}$ for inputs k. However, households may face

[11] I use the word villages for exposition but the unit of analysis I use in the empirical section is the tambon (township) (see Samphantharak and Townsend, 2018).

[12] This implicitly assumes that all farmers face the same output price, which I show in Section 4 is a reasonable approximation in the Thai setting.

[13] The urban sector plays no substantive role in the model but captures that many goods are not produced in the village.

different (effective) prices for each input, as I describe below.

2.2 Production

Production is given by

$$Y_{jt+1} = F(q_{jt}, \varphi_{jt+1}) \tag{1}$$

where q_{jt} is a vector of K inputs applied by j at time t, and φ_{jt+1} is a shock realized at $t+1$, prior to harvesting output Y_{jt+1}. As is standard, I assume that $F_k > 0, F_\varphi > 0$,and $F_{kk} < 0$ for each k. I assume that F is common across households and fixed over time, but households may have heterogeneous time-varying productivity. Note that I treat all inputs as static – in a benchmark economy with complete rental markets, households' input use at time t would not depend on their endowments or previous seasons' input choices.

I assume that $\bar{w}_{vkt}$ is the (endogenously determined) market price of each input k in village v at time t. However, households may face idiosyncratic taxes or subsidies such that they face prices $s_{jkt}\bar{w}_{vkt}$. Households may also be subject to upward or downward rations on inputs such that $\underline{q}_{jkt} \leq q_{jkt} \leq \bar{q}_{jkt}$.

While I only directly model the agricultural sector, allowing households to earn income from other sources is important to match the income diversification observed in the data. Households can invest in a portfolio of assets b_{jmt} with uncertain returns r_{jmt+1}. They may also be subject to borrowing constraints such that $\sum_m b_{jmt} \geq \bar{B}_{jt}$. B should also be thought of as capturing formal and informal insurance with state-contingent payouts. Like with inputs, frictions in the asset market can be modeled by writing returns as $r_{jmt+1} \equiv \chi_{jmt}\bar{r}_{vmt+1}$, where $\bar{r}_{vmt+1}$ is the (endogenously determined and possibly stochastic) average return in village v.[14] Let B_{jt} denote a household's portfolio of assets and R_{jt+1} be the return to that portfolio. I denote the set of primitive taxes and rations that generate the distortions I derive below as $\mathcal{D} \equiv \{\chi, s, \underline{q}, \bar{q}, \bar{B}\}$.[15] Note that the estimation strategy I develop in section 4 does not depend on which frictions in $\mathcal{D}$ generate λ and τ. In section 5, I discuss how whether input frictions act as taxes or rations affects counterfactuals and compute results both ways.

[14] $\chi_{jmt} = -\infty$ implies a household never purchases asset m.

[15] While the elements of $\mathcal{D}$ cannot be separately identified without many additional assumptions, they microfound the distortions the markets in credit, insurance and the k input markets I derive below.

2.3 Dynamic Program

I assume households j have time-separable, von Neumann-Morgenstern preferences with discount factor δ and per-period utility function $u(c,l)$, which I assume is continuously differentiable, strictly increasing, and concave in consumption c and leisure l. At time t, they maximize

$$\mathrm{E}_t\left[\sum_{s=t}^{\infty}\delta^{s-t}u(c_{js},l_{js})\right]$$

subject to the following budget constraint,

$$M_{jt+1} = M_{jt} + Y_{jt+1} - w'_{jt}q_{jt} - p'_t c_{jt} + R_{jt+1}B_{jt+1} - B_{jt} \tag{2}$$

which holds in each state of the world.

The household's value function satisfies the Bellman equation

$$V(Y,M,w,p,\varphi,R,\mathcal{D}) = \max_{c,q,B} u(c) + \delta \mathrm{E}_t V(Y',M',w',p',\varphi',R',\mathcal{D}') \tag{3}$$

subject to the budget constraint (2), borrowing constraint $\bar{B}$, and possible rations on hiring inputs in or out, $\underline{q}, \bar{q}$. Taking first-order conditions with respect to the choice variables c, q, and B:

$$(c) \qquad u_i(c) = \lambda p_i \tag{4}$$

$$(q) \qquad \delta \mathrm{E}\left[\frac{\partial V}{\partial Y}(Y',k',w',p',\varphi',R',\mathcal{D})F_k(q,\varphi')\right] = \lambda w_k + \underline{\mu}_k - \bar{\mu}_k \tag{5}$$

$$(B) \qquad \delta R \mathrm{E}\left[\frac{\partial V}{\partial B}(Y',k',w',p',\varphi',R',\mathcal{D}')\right] + \mu^B = \lambda \tag{6}$$

where λ, μ^B, $\underline{\mu}_k$, and $\bar{\mu}_k$ are the Lagrange multipliers on the budget constraint, borrowing constraint $\bar{B}$, and rations on hiring inputs in and out, $\underline{q}, \bar{q}$, respectively. The first FOC simply states that households equate the marginal utility of expenditure on each good consumed within a period to a common Lagrange multiplier λ. The second implies that households equate the marginal utility of expenditure on each input to the expected marginal utility of its marginal product, unless an input ration binds. The third is simply the Euler equation with the possibility of binding borrowing constraints.

2.4 Input Demands and Wedges

Applying the envelope theorem to the first-order condition for q with simple substitutions yields the following expression for input demands:

$$\bar{w}_{vkt}\tau_{jkt} = \delta \mathrm{E}_t \left[F_k(q_{jt}, \varphi_{jt+1})\right]\Lambda_{jkt} \tag{7}$$

in which

$$\tau_{jkt} \equiv s_{jkt} + \frac{\underline{\mu}_{jkt} - \bar{\mu}_{jkt}}{\lambda_{jt}\bar{w}_{vkt}} \tag{8}$$

$$\Lambda_{jkt} \equiv \frac{\mathrm{E}_t[\lambda_{jt+1}]}{\lambda_{jt}} + \frac{cov_t(\lambda_{jt+1}, F_k(q_{jk}, \varphi_{jt+1}))}{\lambda_{jt}} \tag{9}$$

(7) simply states that households equate the marginal utility of expenditure on input k to the discounted expected marginal utility of its marginal product. Under input frictions, the (shadow) cost of each input k differs from the common market price by τ_{jkt} as defined by (8). Meanwhile, Λ captures how credit constraints and uninsured risk affect input demands through the two terms in (9), respectively. When credit constraints bind, (5) implies that $\lambda_{jt} > \mathrm{E}_t[\lambda_{jt+1}]$ since households cannot borrow against expected future earnings. Likewise, absent full insurance, consumption at $t+1$ will depend on the realization of production shocks, creating a non-zero covariance between λ_{jt+1} and (stochastic) marginal products, $F_k(q_{jt}, \varphi_{jt+1})$. This covariance may differ across inputs for a general production function. However, it will be negative if households are prudent ($u'''(c) > 0$), input k does not reduce risk ($F_{k\varphi} \geq 0$), and agriculture is not a hedge against overall portfolio risk. In this case, both mechanisms would reduce input demands relative to the case of perfect financial markets.

Λ_{jkt} and τ_{jkt} fully characterize the distortions generated by $\mathcal{D}$ in the markets for each input k. To see this, compare (7) to the benchmark of perfect markets, in which it reduces to expected profit maximization.

$$\bar{w}_{vkt} = \delta \mathrm{E}_t[F_k(q_{jt}, \varphi_{jt+1})] \tag{10}$$

This is identical to (7) when $\Lambda_{jkt} = \tau_{jkt} = 1$ for all j, k, t. In this case, ratios of marginal utilities λ are constant across households and cancel out and all households equalize expected marginal products to the common price of each input ($\tau = 1$). The equalization of marginal products across households implies the allocation is efficient. Note how deviations from efficiency are completely characterized by Λ_{jkt} and τ_{jkt}, which together define the distortions in the market for each input k.

I have thus far kept the model as general as possible to illustrate how financial and input frictions create distinct wedges under very general conditions. However, estimating the model requires functional form assumptions for F and u. While I discuss functional forms for utility in Section 4, I assume output is determined by the following Cobb-Douglas production function:

$$F(q,\phi) = A_{jt}\varphi_{jt+1}\prod_k q_{jkt}^{\alpha_k} \tag{11}$$

where A_{jt} is (possibly time-varying) household-specific TFP that is known ex-ante and φ_{jt+1} is an unanticipated shock with mean 1 realized after input decisions are made.[16] I assume decreasing returns to scale with $\gamma \equiv \sum_k \alpha_k < 1$.[17]

Under the Cobb-Douglas assumption. I can rewrite (7) to obtain the demand function for each input k.

$$q_{jkt} = \frac{\delta\alpha_k}{\bar{w}_{vkt}\tau_{jkt}}\frac{\mathrm{E}_t[\lambda_{jt+1}Y_{jt+1}]}{\lambda_{jt}} \tag{12}$$

(12) can also be expressed as

$$q_{jkt} = \frac{\delta\alpha_k}{\bar{w}_{vkt}\tau_{jkt}}\mathrm{E}_t[Y_{jt+1}]\Lambda_{jt} \tag{13}$$

where $\Lambda_{jt} = \dfrac{\mathrm{E}_t[\lambda_{jt+1}\varphi_{jt+1}]}{\lambda_{jt}}$ is now constant across inputs k.[18]

Meanwhile, distortions in the market for each input k enter through τ_{jkt}. In contrast,

[16] This is equivalent to writing

$$Y_{jt+1} = \tilde{A}_{jt}e^{\phi}_{jt+1}\prod_{k=1}^{K} q_{jkt}^{\alpha_k}$$

where $A_{jt} = \tilde{A}_{jt}\mathrm{E}_t[e^{\phi_{jt+1}}]$ and and $\varphi_{jt+1} \equiv \dfrac{e^{\phi_{jt+1}}}{\mathrm{E}_t[e^{\phi_{jt+1}}]}$. The normalization I use more clearly delineates the expected and unexpected components of TFP and guarantees that φ is strictly positive with mean 1.

[17] If $\gamma \geq 1$, then the efficient allocation is degenerate with only the most productive producer producing.

[18] To see this, it is useful to write the expectation in the numerator as $\mathrm{E}_t[\lambda_{jt+1}] + cov_t(\lambda_{jt+1},\varphi_{jt+1})$ (since φ is mean 1 by construction). Also note that (13) can be written in closed-form by substituting (11) for Y_{jt+1} and solving the system of equations implied by (12)

$$q_{jkt} = \frac{\alpha_k}{\bar{w}_{vkt}\tau_{jkt}}\left(A_{jt}\Lambda_{jt}\prod_l\left(\frac{\alpha_l}{\bar{w}_{vlt}\tau_{jlt}}\right)^{\alpha_l}\right)^{\eta}$$

where $\eta \equiv \frac{1}{1-\gamma}$

financial frictions Λ_{jt} distort the *scale* of production while the *composition* of inputs is only distorted by τ. To see this, take the ratio of demands for any two inputs, k and l:

$$\frac{q_{jkt}}{q_{jlt}} = \frac{\alpha_k}{\alpha_l}\frac{\bar{w}_{vlt}}{\bar{w}_{vkt}}\frac{\tau_{jlt}}{\tau_{jkt}} \tag{14}$$

Input ratios are solely a function of technology and relative market prices, which under perfect markets are constant across households in the same village-year. Thus any dispersion in input ratios can be attributed to τ.[19] This is a feature of any homothetic production function.[20]

2.4.1 Nonhomothetic Production

While the misallocation literature typically assumes a homothetic production function with Hicks-neutral shocks, this implies that all inputs contribute proportionally to the variance as outputs. Maintaining this assumption not only increases tractability, but allows me to directly compare my results to others in the literature, showing how modeling the consumption side produces drastically different conclusion, holding the model fixed. However, a stark implication of homotheticity is that households facing the same input prices would use the same input mix and financial distortions would only affect the scale of production. To relax this assumption, I assume production takes the following generalized Cobb-Douglas form following Just and Pope (1978, 1979).

$$Y_{jt+1} = A_{jt}\prod_{k}^{K} q_{jkt}^{\alpha_k} + \varphi_{jt+1}B_t\prod_{k}^{K} q_{jkt}^{\beta_k} \tag{15}$$

where Y_{t+1} is output realized the period following production, q_{kt} is the quantity of input k at time t, A is TFP, and φ_{t+1} is a mean 0 shock realized before harvest and consumption at $t+1$. I assume that expected returns to scale $\gamma \equiv \sum_k \alpha_k < 1$ to ensure the socially optimal allocation is nondegenerate. The main difference between this and the workhorse Cobb-Douglas specification is that the variance of output now depends on input composition. Inputs are differentially risky if $\alpha \not\propto \beta$. In particular, α_k can be thought of as the elasticity of the expectation of output with respect to input k, while β_k is the elasticity of the *standard deviation* of output with respect to input k.[21]

[19] Note that $s, \underline{q}, \bar{q}, \bar{B}$, and χ are the primitives that determine the distortions τ and Λ.

[20] Note that under CES production, the ratio of τs on the right-hand side of (14) is raised to the elasticity of substitution σ.

[21] I prefer this specification to that recently introduced by Bohr, Mestieri, and Robert-Nicoud (2023), since this functional form allows for a first order effect of uninsured risk on input demand as shown below. Note

$$q_{jkt} = \frac{\alpha_k \mathrm{E}_t[Y_{jt+1}]\mathrm{E}_t[\lambda_{jt+1}] + \beta_k cov_t(\lambda_{jt+1}, Y_{jt+1})}{\lambda_{jt}\bar{w}_{kvt}\tau_{jkt}} \tag{16}$$

Note how when $\alpha = \beta$ this reduces to (12). The only difference is that (16) assigns different coefficients to the expected and stochastic components of $\mathrm{E}_t[\lambda_{jt+1}Y_{jt+1}]$. Inputs with higher β contribute more to the variability of output, causing their demand to be disproportionately affected by imperfect insurance. In contrast, the separability of the shocks in the standard Cobb-Douglas means that the same Λ_{jt} applies to demand for each input.[22] The first term can be thought of as the wedge created by the inability to intertemporally smooth consumption and is constant across inputs. For example, if a household faces a binding borrowing constraint, then $\mathrm{E}_t[\lambda_{t+1}]$ would generally be lower than λ_{t+1}. The second term captures how uninsured risk affects demand. Again, one would expect the covariance term to be negative,[23] but this is amplified by how risky a given input is.

However, this no longer allows the straightforawrd identification of τ from (14), requiring an alternative set of identification assumptions, which I discuss in Appendix B. I also show results from this more general specification and the results are broadly similar to those under the standard Cobb-Douglas.

2.5 Equilibrium

I now show how this model of farm-household distortions maps to aggregate misallocation. Let $\eta \equiv \frac{1}{1-\gamma}$, which is a nonlinear transformation of returns to scale that approaches ∞ as production approaches CRS. In what follows, I drop time subscripts to ease notation. A decentralized allocation yields the following expression for the share of factor k in a given location allocated to household j.[24]

$$\omega_{jk} \equiv \frac{\frac{1}{\tau_{jk}}\left(A_j\Lambda_j \prod_l \tau_{jl}^{-\alpha_l}\right)^\eta}{\sum_{h=1}^{N_v} \frac{1}{\tau_{hk}}\left(A_h\Lambda_h \prod_l \tau_{hl}^{-\alpha_l}\right)^\eta} \tag{17}$$

that this functional form nests the workhorse Cobb-Douglas specification $Y_{t+1} = A_t e^{\phi_{t+1}} \prod_{k=1}^K q_{kt}^{\alpha_k}$ if $\alpha = \beta$ and $B = A/\mathrm{E}[e^\phi]$.

[22]This is true for any homothetic production function.

[23]unless $u'''(c) \leq 0$ or returns from agriculture are sufficiently negatively correlated with those from other investments

[24]Note that both the constant market price of each input $\bar{w}_{vkt}$ and aggregate supply $\bar{Q}_{kvt}$ are constants that cancel out of (17).

(17) is obtained by aggregating household first-order conditions (13) and implies that any allocation can be defined as a function of technology α, household TFP A, and distortions Λ and τ.[25]

An important distinction is whether factor stocks are fixed within locations or determined through general equilibrium.[26] In the base case, I assume that stocks of all inputs are fixed at the township level. I then continue to assume that land and labor are fixed but allow fertilizer, equipment, and seeds to be supplied from outside the village at an exogenous price while maintaining fixed stocks of land and labor at the township level.[27] In this case, which essentially treats villages as small open economies, demand for each input is pinned down by exogenous import prices $\bar{w}$ rather than endowments $\bar{Q}$. Definition 1 formalizes an equilibrium in either case.

Definition 1. *A decentralized equilibrium is defined by a set of prices $\{\bar{w}_{vkt}, p_{it}, R_v t\}$, an input allocation $\{q_{jkt}\}$, and a consumption allocation $\{c_{jt}\}$ such that*

1. *Households optimize following (4)-(6)*
2. *Input demands q_{jkt} equal $\omega_{jkt}\bar{Q}_{vkt}$, where ω_{jkt} is given by (17) and $\sum_{j=1}^{N_v} \omega_{jkt} = 1$ for each v*
3. *Λ_{jt} and τ_{jkt} are defined as in (8) and* (13)

given a set of initial asset holdings M_{jt} and primitive distortions $\mathcal{D}$.

This also implies that when there are no distortions (i.e. $\Lambda_j = \tau_{jk} = 1$ for all inputs and households), the optimal allocation is

$$\omega_j^* \equiv \frac{A_j^\eta}{\sum_{i=1}^{N_v} A_j^\eta} \; \forall k \in \{1, \ldots, K\}. \tag{18}$$

In this case, each input is allocated proportionally to household TFP, transformed by returns to scale.[28] However, deviations of Λ and τ away from 1 in either direction lead to misallocation.

[25] Again, note that τ and Λ capture how primitive distortions $\mathcal{D}$ affect the equilibrium input allocation.

[26] The latter is the mechanism through which uninsured risk generates dispersion in fertilizer intensity even with perfect input markets in Donovan (2021).

[27] In a full spatial model, trade costs would determine the response of market-level demand to changes in within-market aggregate TFP, while migration costs would also be needed to determine counterfactual reallocation of labor across villages.

[28] This is a standard result in the misallocation literature.

In equilibrium, expected aggregate productivity in a given village is:

$$\mathrm{E}[TFP_v] = \sum_{j=1}^{N_v} A_j \prod_k \omega_{jk}^{\alpha_k} = \frac{\sum_j \left(A_j \Lambda_j^\gamma \prod_l \tau_{jl}^{-\alpha_l}\right)^\eta}{\prod_k \left(\sum_{j\in v} \frac{\Lambda_{jk}}{\tau_{jk}} \left(A_j \Lambda_j^\gamma \prod_l \tau_{jk}{}^{-\alpha_l}\right)^\eta\right)^{\alpha_k}} \tag{19}$$

as opposed to the case of perfect markets in which this reduces to

$$\mathrm{E}[TFP_v^*] = \left(\sum_{j=1}^{N_v} A_j^\eta\right)^{\frac{1}{\eta}} \tag{20}$$

My base definition of misallocation is the percentage by which aggregate TFP would need to be increased to attain the efficient allocation, summed across locations and time periods.[29] Formally:

$$\mathcal{M} \equiv \frac{\sum_{v=1}^V \sum_{t=1}^T \mathrm{E}[TFP_{vt}^*]}{\sum_{v=1}^V \sum_{t=1}^T \mathrm{E}[TFP_{vt}]} - 1 \tag{21}$$

3 Empirical Setting and Data

I use monthly survey data from the Townsend Thai Monthly Survey, which covers 196 months of production and consumption in 16 villages from four tambons (townships), each in a different changwat (province). Two changwats (Chachoengsao and Lobpuri) are located in relatively developed Central Thailand and the other two (Buriram and Sisaket) are in the more rural North. The data span 1998 to 2014, during which substantial growth and structural change occurred after the Asian financial crisis. Table C4 and Table C5 provide some summary statistics of household demographics and agricultural production. There are a total of 791 households in the data, of which 568 engage in agriculture during the sample period. Over 68% of plots are grown with rice. In addition to crop production, households also earn income from wages, livestock and aquaculture, and other businesses. The average agricultural household sample in the household earns slightly less than half its income from crop cultivation. Importantly, the estimation procedure I develop in the following section can account for this feature of the data. In particular, it is robust to households endogenously selecting into production in a given year and does not impose a 1-to-1 mapping between farm income and consumption.

The data in Table C5 show that markets for land, labor, equipment (mainly tractors,

[29] Note that in the case where all inputs are in fixed supply within each location, aggregate TFP is proportional to aggregate output. Otherwise, aggregate demand for intermediate inputs is increasing in allocative efficiency, which further augments aggregate TFP.

power tillers, and pumps), fertilizer, and seed exist. However, land and labor markets are much more active in the Central region and appear quite thin in the North. The average farm (defined as all of a household's plots in a given year) hires about 28% of its labor input, although more than two-thirds of farms hire some labor in a given season. Fertilizer, commercial seed, and mechanization use is widespread and is frequently acquired from outside the tambon. Land market participation is fairly low, with about 16% of farms renting any plots in a given season. However, this masks substantial regional heterogeneity: nearly 40% of farms rent land in Chachoengsao while only 2.5% rent land in Sisaket. About 89% of farms use fertilizer and over 90% of farms use equipment, which can be owned or hired.

There is quite active participation in both formal and informal finance, with people obtaining loans from government banks and credit schemes as well as neighbors and informal lenders. However, only 5.7% of loans are collateralized. The data include input quantities and expenditures (for transacted inputs), which allows me to calculate prices even though I do not observe them directly.[30] With this in mind, the data show a large degree of price dispersion in land and labor transacted on the market in all tambons, while the law of one price appears to hold for other inputs and output. In Table C7, I plot the coefficients of variation for the price of each input and output for the average year in each tambon. There is very little variation in the prices of fertilizer, seed and rice, but large variation in wages, land rents and tractor rental rates.[31] This lends support to my assumption that output, fertilizer, and seed are perfectly tradable within townships while other factors are not.[32]

For the main analysis, I treat the township as the level of aggregation, since villages within townships are often quite integrated (Kaboski and Townsend, 2011; Samphantharak and Townsend, 2018). I focus on the sample of households cultivating annual crops during the main season, which I define as crops taking fewer than 8 months from planting to harvesting I drop all plots that do not report using land or labor. In the main analysis, I also differentiate between labor at different stages of the production process, essentially treating planting, weeding, and harvest labor as separate inputs.[33] While stopping short of

[30]I discuss how I value households' own inputs in the following section. While it is unclear to what extent input market frictions are pecuniary distortions that show up in these expenditures, I only need to take an explicit stand on this for the nonhomothetic generalization in Appendix B.

[31]Much of this variation may also be coming from imputing prices as expenditures divided by quantities and averaging across months.

[32]Thailand did not have a targeted fertilizer subsidy during the sample period. While price controls were enacted in 2008 and 2011 (with the latter not binding), these would not violate my assumption since price controls would apply equally to all farmers in a township.

[33]I use "weeding" as a shorthand for all midseason labor tasks, including fertilizing, irrigating, and pest control.

a fully sequential production function, this allows me to capture some of the seasonality in rural labor markets, where there may be tightness in planting and harvesting seasons but slack at other times. This gives me a total of 7 inputs: land, fertilizer, equipment, seed, and planting, weeding, and harvesting labor. I then aggregate inputs up to the farm-season level, since the model implies that the shadow prices of inputs and consumption apply to all plots cultivated by a household at a given time.[34] This gives me a panel of 6,223 farm-level observations across 16 years. Marginal utilities of consumption, λ are estimated using the procedure I describe in Section 4.1 from monthly expenditures on 47 food and non-food goods. I merge these estimates into the production panel to match the months of input use and harvests.

3.1 Evidence of Imperfect Markets in Thailand

Other authors have used the Townsend Data to study imperfect risk-sharing, borrowing constraints, and factor market imperfections. Kaboski and Townsend (2011, 2012) find that a microcredit expansion that occurred during the sample period partially relaxed binding credit constraints. Meanwhile, several papers suggest that kinship networks manage to share idiosyncratic risk fairly well (Kinnan and Townsend, 2012; Karaivanov and Townsend, 2014; Samphantharak and Townsend, 2018) but far from perfectly, as idiosyncratic shocks propagate through labor supply and financial networks (Kinnan et al., 2024). Meanwhile, Shenoy (2017) argues that input frictions reduce aggregate productivity by at least 6%.

Additionally, I implement two canonical tests of complete markets before imposing the structure of my model. First, Townsend (1994) provides a test of full insurance, under which a regression of log consumption on log income with household and village-year fixed effects should yield a coefficient of 0. Second, Benjamin (1992) tests the null hypotheses of a full set of complete markets, under which households' production decisions should be fully separable from their consumption decisions. In this case, household composition (and other variables associated with households' preferences) should be independent of labor use. While rejection of this null hypothesis does not identify which market fails, the common interpretation in Benjamin (1992) and related papers (Dillon, Brummund, and Mwabu, 2019, e.g.) is frictions in labor markets causing households with larger labor endowments to use more farm labor. Column (1) of Table C1 presents the results of the Townsend (1994) test while columns

[34] See Gollin and Udry (2021) and Aragón, Restuccia, and Rud (2022) for further discussion of aggregation at different levels and its advantages/disadvantages with regard to measurement error. For robustness, I also compute all results using plots as the unit of aggregation.

(2) and (3) present the results of the Benjamin (1992). The former rejects at all levels of significance while the latter rejects at the 10% level when using household size as the single right-hand side variable and at the 5% level when using the counts of household members in different age-sex bins.

While the regression coefficients in these tests do not have structural interpretations, it is useful to examine whether consumption is more or less sensitive to income shocks in villages where labor intensity depends more on household endowments. To test this, I run both tests cutting the sample into 64 village×4-year blocks and plot each of the coefficients against each other in Figure C1. The coefficients appear negatively correlated with each other, suggesting that the joint distribution of distortions merits further structural analysis.

4 Estimation Framework

I now describe how each of the key components of the model λ, τ, α, A, and Λ are estimated in four steps. First, I estimate realized marginal utilities λs from the full sample of expenditure data in Section 4.1. I do so under the assumption of CRRA preferences as well as under the more flexible Constrant Frisch Elasticity system of Ligon (2020). Second, I estimate input wedges τ from dispersion in input ratios within a township-year, as in (14), in Section 4.2. While inferring input distortions from factor ratios is standard in the misallocation literature, I discuss additional steps I take to avoid misattributing measurement error and unobserved heterogeneity to τ. Having estimated λ and τ, the production coefficients α are now identified from the moment conditions for input demands (12). In Section 4.3, I use a linear GMM to estimate α from these moment conditions and show the robustness of results to several alternative specifications. This allows me to back out TFP A and production shocks φ. The last step, which I discuss in Section 4.4 is to estimate the composite financial wedge Λ_{jt}, which depends on the covariance between the realizations of φ_{jt+1} and the marginal utility of consumption at harvest λ_{jt+1}.

4.1 Estimating marginal utilities (λ)

While the model in Section 2 doesn't require any particular structure on preferences over goods, estimation requires mapping disaggregated expenditure data into a measure of welfare, λ_{jt}.[35] This requires choosing a functional form for utility. To place as minimal structure as

[35]Since all households are assumed to face constant prices for output and other goods, what matters for misallocation in the model are intertemporal and risk preferences. How different consumption goods are

possible on preferences, I use the constant Frisch elasticity (CFE) demand system proposed by Ligon (2020). I discuss the theoretical properties and estimation of this demand system in Appendix D. An advantage of the CFE demand system is that it flexibly accounts for non-homotheticity and can be estimated from incomplete data on expenditures and prices. However, I obtain very similar results when estimating λ assuming CRRA preferences, which, like many other commonly used demand systems, are a special case of CFE.

I estimate λ using the full 196-month panel featuring 47 food and non-durable consumption goods.[36] The estimation also allows demands to vary with household composition, as measured by the counts of members in different age-sex bins. Figure C13, which plots the time series of the average $\log \lambda$ in each township, shows that the estimates capture substantial variation in the MUE across tambons, over time, and across seasons. I also compute results using CRRA for robustness. Figure C14 plots estimated $\log \lambda$ against log consumption expenditure, controlling for month fixed-effects. The elasticity of λ to total consumption value is (minus) the coefficient of relative risk aversion under von Neumann-Morgenstern preferences. Imposing CRRA preferences leads to an estimate of $\theta = 1.5$. To ensure that my results are not being driven by the choice of demand system, I compute all results using both CFE and CRRA λs. Reassuringly, the estimates of both the production function and counterfactuals are extremely similar.

4.2 Identifying factor frictions

I now describe how I use the dispersion in input ratios to separately identify τ.[37] Recall that Λ_{jt} is common across all inputs and plots used by a household in a given period. Therefore, it affects the overall scale of production but not input composition and cancels out of *relative* input demands (14). However, input ratios may be measured with error ν, such that we observe

$$\frac{\tilde{q}_{jkt}}{\tilde{q}_{jlt}} = \frac{\alpha_k}{\alpha_l} \frac{\bar{w}_{vlt}}{\bar{w}_{vkt}} \frac{\tau_{jlt}}{\tau_{jkt}} e^{\nu_{jkt} - \nu_{jlt}} \tag{22}$$

where $\tilde{q}$ denotes measured inputs and ν may include misreported quantities of inputs or heterogeneous input quality.[38] Since α_k and $\bar{w}_{kvt}$ are not household-specific, (22) shows that

aggregated matters for accurately mapping disaggregated expenditures into MUEs, but does not otherwise influence misallocation.

[36] While consumption of durable goods may be a concern in other cases, the CFE demand system can be consistently estimated from only a subset of goods.

[37] While this approach leverages the assumption of a homothetic production function, I discuss an alternative method that relaxes this assumption in Appendix B.

[38] It may be useful to think of q as a measure of effective input quantity.

any dispersion in input ratios across households is either due to differences in the ratio of τs, unobserved quality or measurement error. However, (22) also highlights two challenges for identifying τ.

First, τs for K inputs cannot be identified with $K-1$ ratios. Because of this, most papers in the misallocation literature are only able to identify the *relative* distortion of land to labor (Hsieh and Klenow, 2009; Adamopoulos et al., 2022a). However, if at least one input, say K, were perfectly tradable within townships such that $\tau_{jKt} = 1$ for all households, the remaining $K-1$ τs are identified. This appears plausible for both seed and fertilizer in the Thai context. The survey asks households whether they have had trouble acquiring any inputs. Fewer than 1% of households answer yes for fertilizer or seed in a given year. Additionally, Table C7 shows minimal price dispersion for both fertilizer and seed within a given township-year.[39] This allows me to compute results using either fertilizer or seed as the normalizing input. I use fertilizer in the main specifications, since it is less susceptible to unobservable quality but show that results are quite similar when using seed.[40]

I now describe my approach to distinguish true input distortions, unobserved heterogeneity, and noise. Results in both micro and macro literatures recognize the potential for heterogeneous land quality to bias estimation (Benjamin, 1995; Gollin and Udry, 2021). I address this issue using a hedonic approach. Specifically, I train a model to predict rental values from observed plot features on a random sample of rented plots. These features include area, soil type and quality, histories of drought, flood, erosion, and fertilizer application, proximity to water sources, roads, and the household, and (self-reported) sale values.[41] I use cross-validated boosted trees and test the model's fit on a holdout sample, achieving an R^2 of 0.54. I then use the model to assign rental values to plots that were cultivated by the owner, for which no rental price is observed. I then use observed and predicted rental prices as a measure of quality-adjusted land quantities.

There are some caveats to this procedure. First, distorted land markets may not accurately reflect true land quality in prices. While this approach allows for land distortions to take the form of either an implicit tax or a ration, it essentially assumes that there is no distortion to the *relative* prices of observable plot attributes, such as soil and proximity to water sources. Nevertheless, there is no a priori reason to assume that relative prices of

[39] Much of this dispersion may also come from imputing prices by dividing expenditures by quantities.

[40] Although farmers use different varieties of fertilizer, for simplicity I use the market value of the total fertilizer used by households to compute τs. Note that since τs are computed relative to the village-year average, this does not affect the results under the model's assumptions as long as farmers' mix of fertilizer varieties is not distorted.

[41] A similar approach is applied by Gordeev and Singh (2023).

different attributes should be distorted in a particular direction. Another concern is that transacted plots may be selected on unobservable physical attributes. However, the model would capture the value of these attributes to the extent they are correlated with observable attributes.

I then turn to input measurement. There is evidence of considerable misreporting of inputs in household surveys (e.g. Beegle, Carletto, and Himelein, 2012; Carletto, Savastano, and Zezza, 2013; Carletto, Gourlay, and Winters, 2015; Arthi et al., 2018; Abay et al., 2019; Abay, Bevis, and Barrett, 2021). However, other papers in the misallocation literature either attribute all variation in observed input ratios to τ or only attribute the time average of distortions for each household in a panel to τ.[42] I therefore take a more intermediate approach and attempt to capture only the systematic variation in τs.[43] Although τs are unlikely to be fixed over time, they are likely to be highly serially correlated and also depend on household composition.[44] I therefore model τ as following an AR(1) process, conditional on household characteristics X_{jt}, with the following equation of motion.

$$\tau_{jkt} = \rho\tau_{jkt-1} + \kappa_k X_{jt} + \xi_{jkt} \tag{23}$$

The AR(1) model can be thought of as a coarse way of capturing how τ depends on unobserved market institutions and household state variables that may evolve over time. Substituting into (14) implies that $\log \tau_{jkt}$ can be written:

$$\begin{aligned} \log \tau_{jkt} &= \log\left(\frac{\bar{w}_{Kvt} q_{jKt}}{\bar{w}_{kvt} q_{jkt}}\right) + \log(\alpha_k/\alpha_K) + \nu_{jkt} \\ &= \rho_k \left(\log\left(\frac{\bar{w}_{Kvt-1} q_{jKt-1}}{\bar{w}_{kvt-1} q_{jkt-1}}\right) + \log(\alpha_k/\alpha_K) + \kappa_k \Delta X_{jt} + \nu_{jkt}\right) + \xi_{jkt} \end{aligned} \tag{24}$$

This simply states that τ, net of measurement error, is proportional to the ratio of the *market* value of input K to k used by household j at time t,[45] which can be expressed

[42]While more conservative with respect to measurement error, the latter approach discards the time-varying components of true distortions. If τ represents a binding input ration, then the *shadow* price implied by the ration will depend on other time-varying state variables even if the ration itself stays fixed. Moreover, household fixed-effects may pick up permanent differences in land quality in addition to average input distortions.

[43]This exercise is in a similar spirit to Bils, Klenow, and Ruane (2021), who leverage time-series variation to isolate the predictable part of distortions.

[44]LaFave and Thomas (2016) show that even mechanical changes to household composition in Indonesia due to the aging of members significantly predict land/labor ratios.

[45]Note that since $\bar{w}_{kvt}$ is constant across households in the same location-year by construction, they can also be subsumed into location-time fixed effects.

as a lagged dependent variable model after moving measurement and constants ν_{jkt} to the right-hand side.

$$\log(q_{jKt}/q_{jkt}) = \rho_k \log\left(q_{jKt-1}/q_{jkt-1}\right) + \kappa_k \Delta X_{jt} + \iota_{kvt} + \upsilon_{kvt} \tag{25}$$

where ι_{kvt} is a location-input-time fixed effect that combines constants and υ_{kvt} is the composite error term corresponding to $\rho\nu_{jkt-1} - \nu_{jkt} + \xi_{jkt}$.

I estimate this using both 2SLS and standard dynamic panel GMM approaches (Blundell and Bond, 1998). I use the predicted values of $\frac{q_{jKt}}{q_{jkt}}$ — normalizing by their location year averages — as my estimate of τ_{jkt}.[46]

4.2.1 τ Estimation Results

In Figure C11, I plot kernel densities of the estimated τs for land and labor from different specifications. Each of these specifications reduces the variation in measured input ratios relative to the raw data. The standard deviations of the estimated τs for land and labor are about one-third of those calculated from raw input ratios. Much of this difference is likely due to error in raw input measurements. Figure C11 and Figure C12 also show the density of τ for land and labor using the time-series average input ratio for each household and for the estimated τ for land not accounting for heterogeneous land quality. Overall, my preferred estimates may offer a more moderate approach to dealing with measurement error in inputs without discarding time variation in input wedges. Nevertheless, it is possible that they do not capture all of the idiosyncratic variation in the true underlying τ. However, the estimation and counterfactual results are quite robust across various specifications.

4.3 Production function estimation

A reasonable estimate of the production function is crucial for any analysis of misallocation. As in similar models, the elasticity of aggregate output to wedges is $\eta \equiv \frac{1}{1-\gamma}$, which goes to infinity as returns to scale approach 1. This means that even small biases in production can greatly affect estimates of misallocation.

[46]This normalization implies that τ is the deviation from village-average factor ratios. While this is consistent with a one-sector model, it rules out common cases in which the shadow wage for farm-households is below the market wage, such as labor rationing (Breza, Kaur, and Shamdasani, 2021; Agness et al., 2022). In this case, the τs I estimate would be too high and this would bias the production function coefficients upward in the procedure I describe in Section 4.3. However, the coefficients I estimate for labor are already quite low, suggesting that this may not be a major issue in my sample.

The first-order conditions for input demands provide moment conditions that can be exploited to recover the production function parameters under rational expectations using linear GMM in the spirit of Hansen and Singleton (1982). In a sense, I treat inputs as assets in a consumption-CAPM problem whose returns $\alpha_k Y$ covary with a household's overall portfolio captured by λ. The intuition behind this approach is simple. If all markets are perfect, then all households maximize expected profits and choose inputs to equate marginal revenue products with the common input price. Under Cobb Douglas, this means that α_k can simply be inferred as input k's revenue share. Note that this follows simply from expected-profit maximization under complete markets — it doesn't rely on any assumptions about anticipated shocks, since these are accounted for by optimal input choices. However, as in Section 2, this is a special case that only holds under perfect markets. More generally, households maximize expected utility rather than expected profits and may not face common (shadow) prices for all inputs However, estimates of λ and τ account for *how* input choices are distorted and allow α to be identified from the correctly-specified first order conditions for input demands (12).

Let $x_{jkt} \equiv \bar{w}_{kvt}\tau_{kt}q_{jkt}$. x_{jkt} can be interpreted as household j's "shadow" expenditure on input k at time t. This can either represent actual expenditure under possibly household-specific prices or as the cost of input k such that the household would choose q_{jkt} under perfect markets. Let $\mathcal{I}_{jt}$ denote household j's information set at time t. Rearranging constrained-optimal input demands (12) and making the dependence on households' time t information sets explicit yields the moment condition

$$\delta\alpha_k \mathrm{E}[\lambda_{j,t+1}Y_{j,t+1}|\mathcal{I}_{jt}] - \lambda_{jt}x_{jkt} = 0 \tag{26}$$

for each input k where input $x_{jkt} = \bar{w}_{vt}\hat{\tau}_{jkt}q_{jkt}$ is (shadow) expenditure on input k is applied at time t and $\hat{\tau}$ is estimated as described in Section 4.2. Note that both λ_{t+1} and Y_{t+1} are unknown as of time t, as they both depend on the yet-to-be-realized φ_{t+1}.

(26) holds simply by households' optimization. Therefore, any deviations between expected and realized $\lambda_{jt+1}Y_{jt+1}$ are mean-zero forecast errors. While x_{jkt}, λ_{jt}, λ_{jt+1}, and Y_{jt+1} are all either observed or estimated, using (26) to identify the α_k requires mapping the unobserved *subjective* expectation $\mathrm{E}[\lambda_{jt+1}Y_{jt+1}|\mathcal{I}_{jt}]$ to data. Proposition 1 states that α can be estimated from (26) (up to the time-preference discount factor δ with a simple linear GMM procedure under rational expectations. The intuition is that if expectations are rational, then subjective expectations $\mathrm{E}[\lambda_{jt+1}Y_{jt+1}|\mathcal{I}_{jt}]$ will *on average* equal the observed $\lambda_{jt+1}Y_{jt+1}$. Substituting realized $\lambda_{jt+1}Y_{jt+1}$ into (26) identifies the α_k up to the time-preference discount

factor δ. Moreover, optimization implies that any element of $\mathcal{I}_{jt}$ should be mean-independent of forecast errors, creating a large set of potential overidentifying instruments. In particular, lagged values of λ_{jt} are natural candidates.

Proposition 1. *Assume households have rational expectations and let $h(z_{jt})$ be a measurable function of variables $z_{jt} \in \mathcal{I}_{jt}$. Then the estimator defined by*

$$\arg\min_{a} J(a) \equiv g_{NT}(a)' W g_{NT}(a)$$

where

$$g_{NT}(a) \equiv \frac{1}{NT} \sum_{t} \sum_{j} \delta a(\lambda_{j,t+1} Y_{j,t+1} - \lambda_{jt} x_{jkt}) \otimes h(z_{jt})$$

is a consistent estimator of the vector of coefficients α up to the time-preference discount factor δ for a symmetric and positive-definite weighting matrix W, for large N and T.

Proof. See Appendix A □

The proof is a straightforward application of Hansen and Singleton (1982), albeit with the requirement that both N and T are large. With small T, the realizations of aggregate shocks may have a mechanical non-zero correlation with the instrument set.[47] If this is the case then the average household forecast error within each period will converge to the aggregate shock, which is a random variable with mean zero but is not necessarily zero in a given period. However, I show in Figure C15 using Monte Carlo simulations that the resulting finite-sample bias is likely to be negligible, especially with 16 years of panel data.

A caveat with this procedure is that it only identifies α up to the time-preference discount factor δ, which is distinct from the stochastic discount generated by incomplete insurance. One approach to recover the αs is to calibrate the model with an assumed value from the literature, including those using the Townsend Thai Data (Kaboski and Townsend, 2011). I discuss other approaches in Section 4.3.1 and show how sensitive the results are to alternate assumptions.[48]

[47] Note that serial correlation of the shocks is not an issue under rational expectations, since the moment restriction is only that *unexpected deviations* from anticipated shocks are mean-independent of the instruments. An example of the potential bias would be if the years in which aggregate shocks were unexpectedly large were those in which aggregate wealth (as captured by the lagged marginal utilities in the instrument) was particularly high or low.

[48] Note that the discount factor cancels out of expressions for aggregate TFP when aggregate resource constraints bind, since it is constant across all households by assumption.

4.3.1 Production Function Estimates

With estimates of λ and τ, I am able to estimate the production function following the procedure in Section 4.3. In the main specification, I use continuously updated GMM (Hansen, Heaton, and Yaron, 1996) with planting, weeding, and harvesting labor, land, fertilizer, equipment, and seed as inputs, with lags of λ from the previous 5 months and tambon dummies as instruments.[49] Given that the estimator relies on generated variables, I compute standard errors by block bootstrapping the entire estimation procedure, including estimates of λ and τ, at the household level.

I compute the main results assuming the annual time-preference discount factor $\delta = .95$. I also show robustness to Kaboski and Townsend (2011)'s estimate of $\delta = .926$ using the same data and 1. Since the median season covers 5 months, I convert the annual δ to its 5-month equivalent. Note that δ doesn't affect the results qualitatively, since it is constant across households and cancels out of (17). However, lower values of δ would lead to higher estimates of returns to scale and larger estimates of misallocation across specifications.[50]

The results are presented in Table 1. Column 1 presents the main results, using the CFE demand system to estimate λs and fertilizer as the normalizing input, restricting the sample to rice plots and aggregating to the farm level. The coefficients all take reasonable values for agricultural production functions and together imply returns to scale $\gamma \approx 0.83$, which is larger than other papers in the literature.[51] I test the overidentifying restrictions of the full model against one with a single lag of λ and tambon dummies as instruments. While I reject the null hypothesis that all instruments are exogenous, this appears to arise from the Cobb-Douglas specification struggling to capture heterogeneity across regions. I fail to reject the validity of the lagged λs as instruments when applying a difference-in-J test (what Hayashi (2011) calls a C test). In Table C2, I also show robustness to using seed rather than fertilizer as the normalizing input for τ, using CRRA to estimate λs instead of the more general CFE specification, restricting to rice plots, treating all labor as a single input, and aggregating to the plot rather than farm level. All specifications produce extremely similar results.

In Columns 2 and 3, I show the estimates of α and β from the generalized Cobb-Douglas

[49] Given that t corresponds to a season in the model in Section 2, the lagged λs should be thought of as occurring within different subperiods prior to planting.

[50] I show in Section 5 that while a lower δ increases my estimates of misallocation by a few percentage points, it doesn't alter any of the qualitative conclusions.

[51] Note that a lower value of γ would lower estimated misallocation because inputs are optimally allocated proportionally to $1/(1-\gamma)$.

Table 1: GMM results

	α CD	α NH	β NH
Equip.	0.084	0.161	0.144
	(0.005)	(0.013)	(0.048)
Fert.	0.089	0.103	0.110
	(0.002)	(0.004)	(0.016)
Harv. Labor	0.225	0.175	0.181
	(0.006)	(0.028)	(0.077)
Land	0.208	0.219	0.362
	(0.004)	(0.069)	(0.208)
Plant. Labor	0.117	0.120	0.210
	(0.004)	(0.045)	(0.430)
Seed	0.092	0.087	0.130
	(0.002)	(0.005)	(0.028)
Weed. Labor	0.013	0.041	0.050
	(0.001)	(0.017)	(0.029)
J-stat	35.06	36.41	
p-val	0.465	0.132	
γ	0.828	0.906	
s.e.	(0.01)	(0.09)	

This table presents results from the main GMM specifications used to estimate the production function under both the Hicks-neutral Cobb-Douglas specification in the main text and the generalized Cobb-Douglas in Appendix B. Column 1 shows the estimates of the Cobb-Douglas coefficients α from (26) The second and third columns show estimates of α and β from (31), which are the elasticities of the mean and standard deviation of output with respect to each input. All specifications use tambon dummies and lags of λ_{jt} from the 5 months before input k is first applied as instruments. An annual discount factor of $\delta = .95$ is assumed. Results are computed using fertilizer and seed as the reference input for the estimation of τ from (25) (only relevant for Column 1), using rice plots only and CFE λs at the farm level. The J-statistic and p-values reported are from a test of the model with the full instrument set against one with only tambon dummies and a single lag of λ_{jt}. γ is the returns to scale parameter implied by the sum of the production coefficients. Standard errors are computed from 234 bootstraps of the full estimation procedure at the household level.

specification in Appendix B. The αs are quite similar across specifications, suggesting that standard Cobb-Douglas would fit the data well if households were fully insured or risk-neutral. This suggests that the bias from failing to account for differentially risky inputs is relatively small. Nevertheless, there are important differences between the two specifications.

Recall that the generalized production function reduces to Hicks-neutral Cobb Douglas when $\alpha = \beta$, meaning that the elasticity of expected output with respect to input k is the same that of the standard deviation of expected output(Just and Pope, 1978, 1979). Inputs with larger β_k relative to α_k can be considered relatively "risk-augmenting." The results in Table 1 suggest that inputs chosen at planting (land, seed, fertilizer and planting labor) appear to be risk augmenting (although I cannot reject equality of α and β for land). The difference between β and α is most striking for planting labor, suggesting that its returns are highly variable. Meanwhile, other inputs appear neither risk-enhancing or risk-reducing, based on the similarities between α and β.[52]

4.4 Recovering TFP and financial wedges

With the production coefficients in hand, the next step is to recover household TFP A and financial wedges Λ. This is substantially more challenging than estimating the production function because it requires taking a more explicit stance on what households do and do not anticipate in each period, as opposed to relying on sample averages. Notably, these issues affect any quantitative analysis of misallocation.

I first take the average of realized TFP, computed using the estimated αs as $\bar{A}_j \equiv \frac{1}{T}\sum_{t=1}^{T} Y_{jt+1}/\prod_k q_{jkt}^{\alpha_k}$. I then try and predict deviations of realized household TFP in each period from $\bar{A}$ using variables in households' information sets $\mathcal{I}_{jt}$. Both ridge regressions and boosted trees using a rich set of features achieve an R^2 of close to zero, suggesting that $\bar{A}_j$ is a good approximation to anticipated TFP. Using this approximation means that production shocks $\varphi_{jt+1} = Y_{jt+1}/\prod_k \bar{A}_j q_{jkt}^{\alpha_k}$.

Recall from Section 2 that

$$\Lambda_{jt} = \frac{\mathrm{E}_t[\lambda_{jt+1}\varphi_{jt+1}]}{\lambda_{jt}}$$

While the denominator of Λ_{jt} has already been estimated, the numerator is an (unobserved) subjective expectation conditional on time t information. λ_{jt+1} is a function of φ_{jt+1} as well as households' other sources of income (including returns from other investments and payouts from insurance networks) which may be correlated with realizations of φ_{jt+1}. Therefore

[52] One might expect harvest labor to be fairly insensitive to risk. However, there is still substantial uncertainty over the value of output due to price fluctuations and postharvest losses in developing country agriculture (Aggarwal, Francis, and Robinson, 2018; Omotilewa et al., 2018; Burke, Bergquist, and Miguel, 2019; Channa et al., 2018). Also refer to work in progress by Ligon and Silver (2023a). While this paper uses a static production function that does not permit attributing risk to different stages of production, see (Felkner, Tazhibayeva, and Townsend, 2012) and Ligon and Silver (2023b) for estimates of a sequential production function that permits this.

$\mathrm{E}_t[\lambda_{jt+1}\varphi_{jt+1}]$ can also be thought of as a function of households' state variables at time t integrated over the distribution of φ_{jt+1}.[53] I use supervised machine learning to approximate this function as flexibly as possible using the rich set of time t information. This is a valid approximation under rational expectations under similar conditions as in Section 4.3 — essentially realized shocks must be uncorrelated on average with the state variables used as predictors. Dividing these predictions by the observed λ_{jt} identifies Λ_{jt}.[54]

I predict Λ_{jt} with boosted trees, using estimates of A_j, the lagged λs used as instruments in Section 4.3, and a rich set of information from household's balance sheets as features. This includes agricultural and non-agricultural assets, cumulative income from agricultural and non-agricultural investments. The R^2 of this prediction is 0.35, while the R^2 when predicting λ_{jt+1} alone is 0.63. Of course, a perfect model of households' subjective expectations of future consumption *shouldn't* have an R^2 close to 1 under incomplete insurance. Nevertheless, the results suggest that consumption is fairly predictable despite substantial uncertainty in production (the R^2 when predicting φ is negligible). I also obtain similar results when using a ridge regression instead of boosted trees.

In Tables C9 and C10, I show that these estimates of Λ are correlated with untargeted observables in the data on borrowing, saving and mutual gift-giving (insurance) networks. In particular, it appears that those with higher Λ (less constrained) have larger loans and make larger informal transfers (referred to as "gifts" in the survey) in typical years. This holds across specifications of Λ and also when splitting it into credit and risk wedges. I also show that positive (negative) production shocks are associated with gift outflows (inflows).[55]

Figure C9 shows the distribution of Λ. The mean of Λ in the main specification is 0.96, with a median of 0.88. While these estimates are close to 1, as would be the case under perfect financial markets, raising them to the elasticity $\eta \approx 5.2$ implies that the average (median) household only produces at 71% (40%) of its desired scale. This is consistent with evidence of functional but incomplete credit markets and risk-sharing in this setting (Kaboski

[53]For example, under CRRA utility

$$\mathrm{E}_t[\lambda_{jt+1}Y_{jt+1}] = \int_{\varphi} \frac{\varphi}{(R_{jt+1}(\varphi)B_{jt} + A_{jt}\varphi\prod_k q_{jkt}^{\alpha_k} - B_{jt+1}(\varphi) - \sum_k w_{jkt+1}(\varphi)q_{jkt+1}(\varphi))^{\theta}} d\varphi$$

where the possible dependence of $t+1$ variables on realizations of φ is made explicit.

[54]An alternative would be to model Λ as a function of returns to agriculture, other assets, and state-contingent transfers integrated over the distribution of the shocks. However, this would require further assumptions on preferences and the distribution of shocks, which is beyond the scope of this paper.

[55]By remaining agnostic to the primitives that cause distortions, it is unclear which moments in the data the wedges I estimate should map to. While taking such a stand may help discipline the model, it may rule out other important channels.

and Townsend, 2011; Karaivanov and Townsend, 2014; Samphantharak and Townsend, 2018; Kinnan et al., 2020). It also suggests that for the 40% of households with $\Lambda_{jt} > 1$, agriculture is a hedge against other sources of income, which is also consistent with evidence from other countries that households use off-farm labor to smooth consumption (Kochar, 1999) or substitute on-farm for off-farm labor when seasonal consumption constraints bind (Fink, Jack, and Masiye, 2020). Moreover, households in my sample have fairly diversified income streams that may be negatively correlated with returns to crop production.[56]

5 Results and Counterfactuals

Estimates of financial distortions Λ, input wedges τ, production coefficients α, and TFP A allow misallocation to be computed using the expression for aggregate TFP (19) relative to the efficient allocation (20). The model in Section 2 implies that overall misallocation depends on the joint distribution of Λ, τ and A.[57] Before delving into counterfactuals, I provide some descriptive graphical evidence to characterize this distribution.

Descriptive Results

Figure 1 plots 2D histograms of TFP-weighted input and financial distortions and reports their correlation coefficients.[58] The top left panel plots the Cobb-Douglas price index of τs, $\prod_l \tau_{jlt}^{\alpha_l}$ against the estimates of financial distortions Λ, each weighted by TFP A. The top right panel plots the τ for land against Λ while the bottom left plots the index of τ for the three types of labor (planting, weeding, and harvesting) considered. The bottom right panel plots the unweighted histogram of the τ price index and Λ. The positive correlation between τ and Λ suggests that, on average, more financially constrained households are relatively *subsidized* on inputs. More productive households also appear to be less financially constrained and more taxed on inputs. This corresponds to the conventional wisdom that poorer households oversupply labor to their own farms under imperfect labor markets (LaFave and Thomas, 2016; Breza, Kaur, and Shamdasani, 2021; Jones et al., 2022).

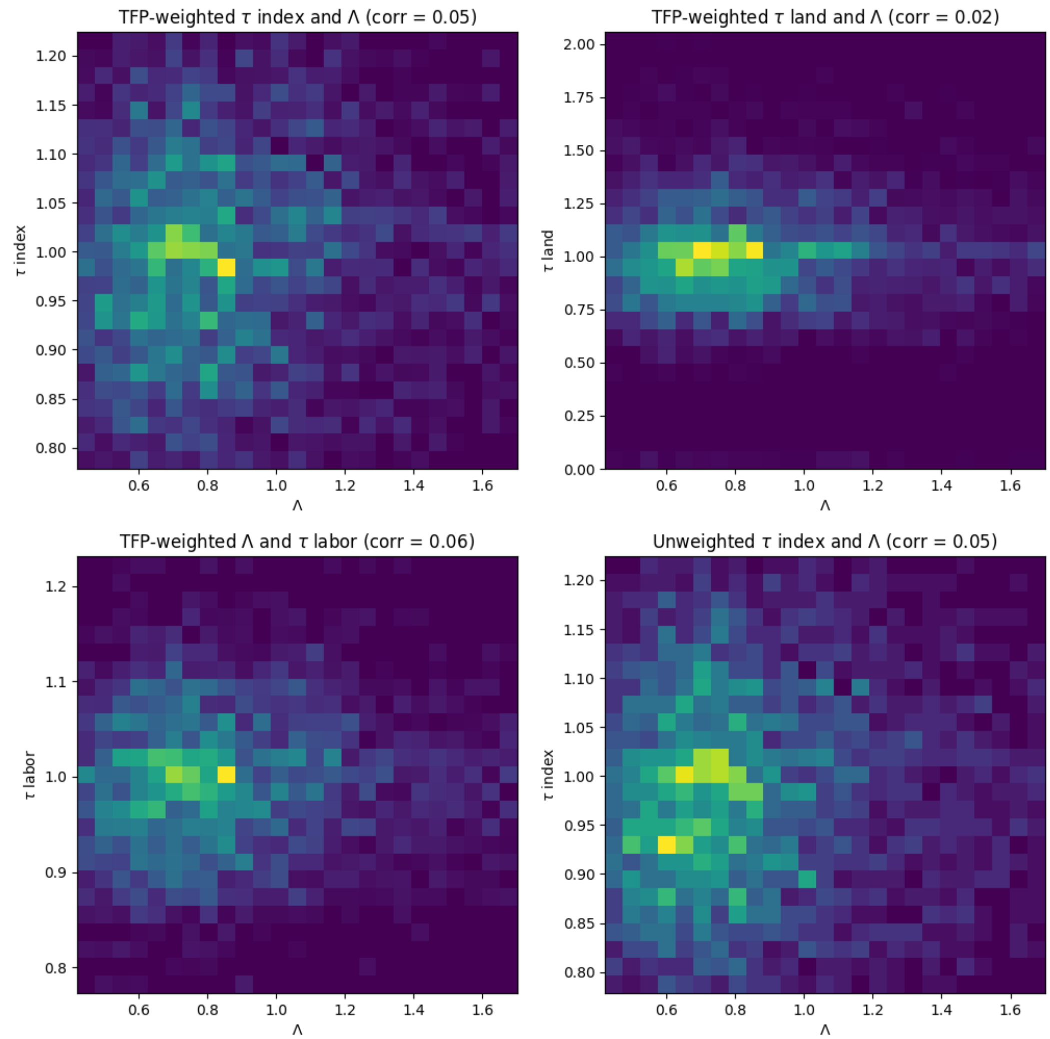
This implies that the observed distortions partially offset each other — relaxing credit constraints would disproportionately direct capital toward farms that are effectively subsi-

[56] Imposing that $\Lambda \leq 1$ does not change the qualitative conclusions in the counterfactuals in Section 5, although it lowers estimates of misallocation.

[57] This is an extension of results in Hsieh and Klenow (2009) and Adamopoulos et al. (2022b). regarding the covariance between wedges as a sufficient statistic for misallocation.

[58] In equilibrium, the influence of each of these distortions is weighted by household TFP.

Figure 1: Joint distribution of TFP-weighted τ and Λ



This figure plots TFP-weighted histograms of Λ and τ in 25×25 bins and reports their correlation coefficients. The top left panel plots the Cobb-Douglas price index of τs, $\prod_l \tau_{jlt}^{\alpha_l}$ against the estimates of financial distortions Λ, each weighted by TFP A. The top right panel plots the τ for land against Λ while the bottom left plots the index of τ for the three types of labor (planting, weeding, and harvesting) considered. The bottom right panel plots the price index of τs against Λ without weighting by TFP.

dized on inputs. The direct gains from relaxing credit constraints are large enough to swamp this effect but are smaller than they would be if credit constraints were uncorrelated with input distortions.[59] The results also show that distortions for land and labor are positively correlated. Most of the misallocation literature rules this out by assumption, modeling τ as a distortion in the *relative* price of land and labor. However, I am able to relax this assumption by using fertilizer and seed as normalizing inputs when estimating τs.

Main Counterfactuals

I now proceed to compute counterfactual *expected* aggregate productivity following (21) under the following four scenarios: (1) the first best allocation; (2) the baseline allocation, with all of the distortions I measure; (3) an allocation with perfect financial markets and the observed input wedges; (4) an allocation with perfect input markets and the observed financial wedge. I consider counterfactual allocations within township-years and then sum up these gains across townships in each of the 16 years of the sample.

I provide four main sets of results. First I characterize overall misallocation in Thailand. Second, I decompose misallocation into input distortions, financial distortions, and interactions between them. I then show other methods that are more susceptible to measurement error in inputs yield starkly different results. Finally, I use the model to approximate the marginal returns to incremental reductions in one or both sets of distortions. Note that the results below all refer to expected TFP, since the realizations of ex-post shocks cannot be considered misallocation.

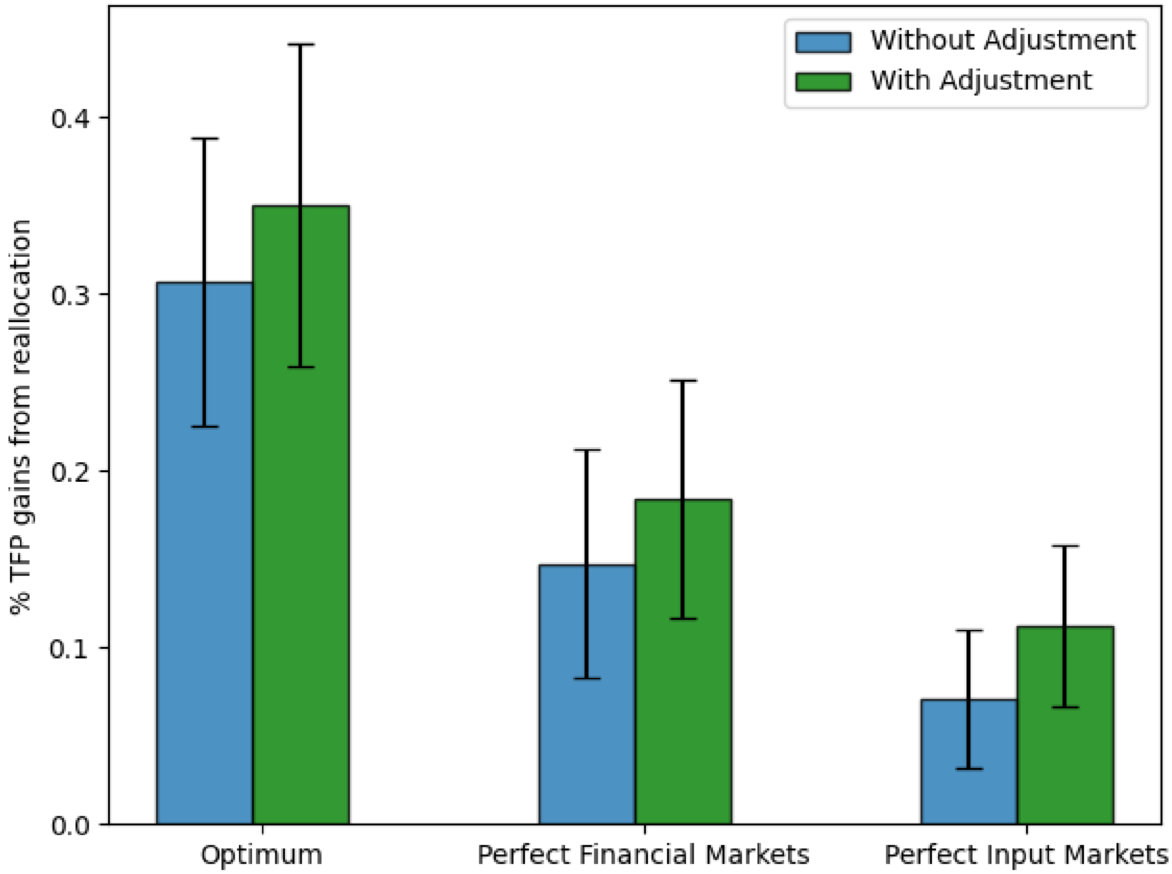
The gains from reallocation depend on whether one assumes that the stock of tradable inputs is held fixed or can respond to changes in counterfactual demand. The results also depend on whether one assumes input frictions take the form of implicit taxes or rations. I show how results depend on each of these cases below.

Baseline Misallocation

Figure 2 plots the gains from reallocation under each counterfactual as a percentage of (expected) aggregate TFP in the observed allocation. The three counterfactuals I consider are (1) eliminating financial distortions (i.e. setting $\Lambda = 1$) holding input frictions τ fixed; (2) eliminating input distortions (setting $\tau = 1$) while holding Λ fixed; and (3) eliminating

[59] TFP governs the incidence of these distortions; since it is the sole determinant of scale under the efficient allocation, multiplicative wedges such as Λ or τ exert a large influence on the aggregate economy when it affects firms that command more inputs.

Figure 2: Counterfactual TFP gains from reallocation



The figure shows the aggregate TFP gains from the main counterfactuals summed up across years, as a percentage of status quo aggregate TFP. The first group of columns shows results under perfect financial markets but with the observed input frictions. The second shows results under perfect input markets but with the observed financial distortions. The third shows the results under a full set of perfect markets. The blue (left) bars in each group show the gains holding aggregate supply fixed at the township level for all inputs while the green (right) bars show the gains allowing the aggregate supply of seed, fertilizer, and equipment to increase (holding their prices constant). The results are computed using fertilizer as the normalizing input for τ, CFE demands, and restricting the sample to rice plots , aggregated to the farm level.

all distortions. The blue (left) bars show results holding the aggregate supply of all inputs fixed, as if villages are in autarky. In this case, aggregate TFP is directly proportional to aggregate output. This is a relatively conservative assumption because it excludes gains from the increased aggregate demand for tradable inputs. The green (right) bars allow intermediate inputs (fertilizer, seed, and equipment) to be imported from outside the village at a constant price (as if the village were a small open economy). Confidence intervals from

200 bootstrap replications are shown for each specification.

The gains from full reallocation are 31% in the baseline case and 35% when the aggregate supply of tradable inputs is allowed to adjust. The baseline estimates are similar to Shenoy (2017)'s estimates from Thailand, which I discuss below. On the other hand, my results are an order of magnitude lower than some estimates from Africa of up to 286% gains from reallocation (Chen, Restuccia, and Santaeulàlia-Llopis, 2023; Aragon, Restuccia, and Rud, 2022). The additional gains from allowing the aggregate supply of tradable inputs to adjust are much smaller than those in Carrillo et al. (2023), where they account for almost all the estimated misallocation.[60]

Decomposing Misallocation

It is clear from the first two groups of bars in Figure 2 that both sets of markets contribute significantly to misallocation in isolation. Perfecting financial markets while holding observed input distortions intact achieves about 50% of the possible efficiency gains, or 16% of observed TFP. Similarly, removing input distortions holding observed financial frictions intact achieves about 30% of these gains (9% of TFP).

Notably, these two gains sum to less than 100%, meaning the gains from full reallocation are more than the sum of its parts. This is because Λ and τ are positively correlated (when weighted by TFP). In other words, the most financially constrained households are relatively subsidized in input markets, especially labor, as shown in Figure 1.[61] The effect of relaxing financial constraints is thus attenuated — but not offset — by reallocating resources to farms made inefficiently large by other distortions. Overall, these patterns suggest that the effects of policies targeting a single market failure would be attenuated, rather than amplified, by failures in other markets.

I also compute counterfactuals relaxing the distortions for some inputs but not others. Table 2 shows the results of removing wedges from each of these markets, with and without relaxing financial constraints. Reducing frictions in labor markets is slightly more effective than for land markets, despite them accounting for roughly equal expenditure shares. The sum of gains from reducing individual frictions is also more than the gains from reducing all of them simultaneously. While input frictions are negatively correlated with financial distortions, they are positively correlated with each other. In other words, reducing frictions

[60] See Donovan (2021) for a more detailed discussion of this channel where the price of intermediates is endogenous in general equilibrium.

[61] This reflects the common finding that poorer households tend to oversupply labor to their own plots.

Table 2: Decomposition of Gains by Input Market

	Financial Constraints	Perfect Financial Markets
All	0.095	0.313
Land	0.047	0.234
Total Labor	0.068	0.273
Plant. Labor	0.020	0.191
Weed Labor	0.003	0.161
Harv. Labor	0.055	0.248
Equip	0.011	0.174
None	0.000	0.157

This table shows the gains from removing distortions τ_{jkt} in individual input markets, both with the observed financial constraints and under perfect financial markets. This is shown for the closed economy case, using fertilizer as the normalizing input, CFE demands, and restricting the sample to rice crops at the farm level.

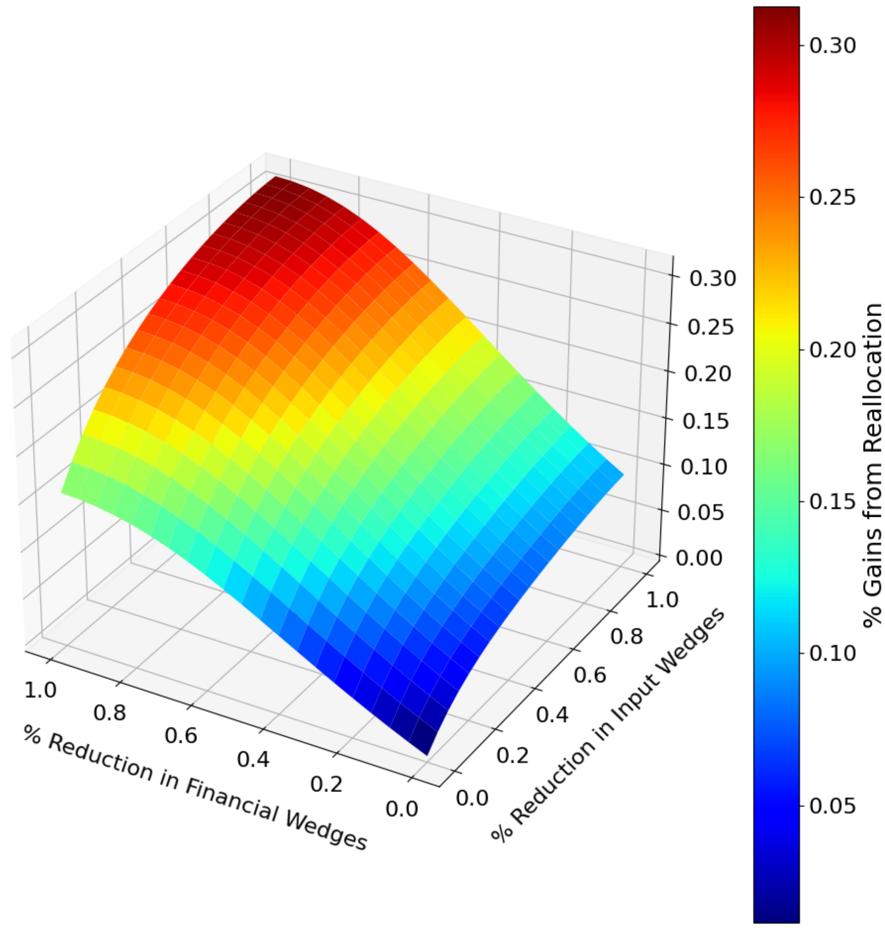
in land markets also indirectly addresses labor market distortions by reallocating resources toward households that are relatively taxed.

Intermediate Policies

The results above consider the gains from completely eliminating one set of distortions while holding others fixed at observed values. However, policymakers likely have a menu of policy instruments to choose from, but may not be able to fully eliminate distortions. The model allows me to estimate aggregate TFP under any values of Λ and τ. I therefore conduct a simple illustrative exercise in Figure 3, in which I plot the TFP gains from uniform partial reductions in τs and λs. This approximates the marginal returns to reductions in distortions. However, modeling the effects of a specific policy would require assumptions on the specific institutions underlying the distortions I measure, which also govern the second-order effects of how a change in τ affects Λ (and vice versa).

Figure 3 illustrates the complementarities between policies that reduce both sets of distortions. In particular, it shows that the marginal returns to reducing either set of distortions alone are limited, moving along either horizontal axis. However, the marginal returns are much higher after both sets of distortions have been reduced substantially, suggesting that small reductions to one or both sets of distortions may have limited effects and that significant improvements to both sets of markets may be required to unlock large gains. If one knew the relative costs of reducing each distortion, the gradient of Figure 3 would define an

Figure 3: Gains from partial reductions of τ and Λ



The figure shows counterfactual gains from reallocation using the TFP-based measure under different reductions of input and financial wedges. I compute aggregate TFP under each scenario shrinking Λ and τ towards unity by increments of .05. The origin corresponds to the status quo allocation and (1,1) corresponds to the efficient allocation. The vertical axis shows the percent increase in aggregate TFP relative to the status quo allocation. The figure uses fertilizer as the normalizing input for τs, CFE demands and restricts the sample to rice plots , aggregating to the farm level.

expansion path for the social planner in terms of which distortions to target as its budget shifts out. Additionally, Figure 3 shows that these marginal returns are not monotonic: at baseline levels of input (financial) distortions, going from 10% of observed financial (input) distortions to perfect financial (input) markets actually worsens efficiency.

5.1 Methodological Differences and Measurement Error

I now describe how estimating both Λ and τ helps alleviate concerns about measurement error. With both Λ and τ, counterfactual aggregate productivity can be computed in two ways: taking the observed allocation and then "removing" a distortion or taking the first-best allocation and "adding a distortion". To see this, note that the efficient allocation (18), which is just a function of A_{jt}, can also be written as a function of observed input demands and wedges by inverting (12) as a function of A and dividing out constants

$$\omega^*_{jt} = \frac{q_{jkt}\tau_{jkt}\left(\frac{\prod_l \tau_{jlt}^{\alpha_l}}{\Lambda_{jt}}\right)^{1-\gamma}}{\sum_{h=1}^{N_{vt}} q_{jkt}\tau_{jkt}\left(\frac{\prod_l \tau_{jlt}^{\alpha_l}}{\Lambda_{jt}}\right)^{1-\gamma}}. \tag{27}$$

Likewise, under the status quo, rewriting (17) should simply yield

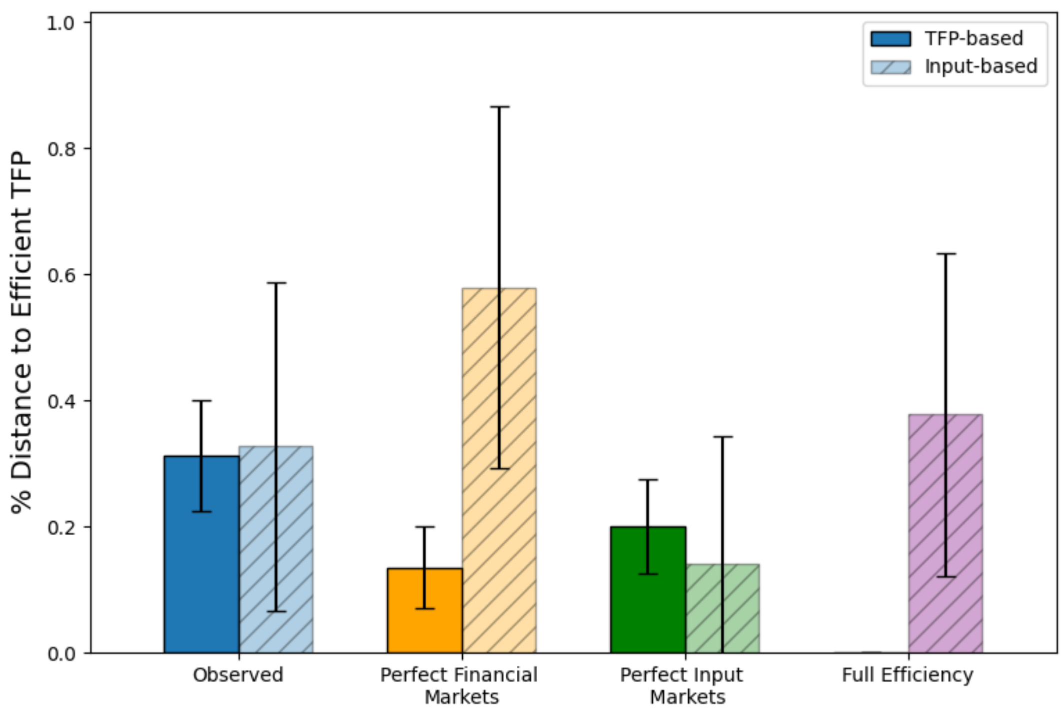
$$\omega_{jkt} = \frac{q_{jkt}}{\sum_{h=1}^{N_{vt}} q_{jkt}} \tag{28}$$

This allows me to compute TFP using either (17) or (27) and then aggregating using 19) for any counterfactual values of Λ and τ. However, this requires estimates of both Λ and τ.

If inputs were measured perfectly and τ and Λ were estimated without error, then these two approaches should produce identical estimates. The difference is that the former approach (17 and 18) uses estimated TFP while the latter (27 and 28) uses raw input measurements. Which estimate is preferable depends on how severe measurement error in inputs is relative to the errors in estimated objects. Given that estimates of TFP are less noisy than the raw inputs used to estimate them, one would therefore expect estimates using the TFP-based measures in (17) and (18) to be more reliable than the input-based measures in (27) and (28). I confirm this using Monte Carlo simulations in Figure C2, which shows that the TFP-based measure is approximately unbiased and less noisy than the input-based measure, which is biased upwards.

How different are the conclusions these measures produce in the data? To make this comparison, it will be useful to denominate misallocation by the *attainable* output (equivalent to TFP when aggregate input supply is fixed) forgone due to distortions in each scenario. Figure 4 compares results from the TFP-based results in the solid bars and the input-based results in the shaded bars. The solid bars simply recast the estimates from Figure 2. The blue bars show the percent of attainable output foregone in the observed allocation, while

Figure 4: Aggregate TFP relative to optimum, with and without input mismeasurement



The figure shows the percentage of foregone attainable output from the four main counterfactuals (observed allocation, efficient allocation, perfect financial markets with input wedges intact, and perfect input markets with financial wedges intact). The solid bars compute these using the TFP-based measure of misallocation, using (17). The shaded bars are calculated by taking raw input observed in the data and augmenting them by the estimated τ and Λ, where relevant. 95% confidence intervals from 200 bootstrap replications are plotted. Results are computed using CFE demands, fertilizer as the normalizing input for τs, only rice plots, and aggregating to the farm level.

the orange (green) bars show allocations with only the observed input (financial) frictions. By definition, the optimum allocation achieves all the attainable output so there is no solid purple bar.

Now contrast these TFP-based results with the shaded bars, which are computed using the input-based measure. As discussed in Section 2, these two panels would yield identical results if there were no measurement error and the model was perfectly specified. However, the differences between the two panels are quite striking when comparing bars of the same color in Figure 4. First, measured misallocation in the status quo is similar when using the input-based rather than the TFP-based measure, albeit much noisier. Second, it appears that perfecting financial markets would nearby *double* misallocation, rather than decreasing it. Most strikingly though, the implied "optimum" allocation is not only suboptimal but actually performs worse than the observed allocation.

How is this possible? Recall that counterfactuals using the input-based measure are computed by adding distortions to the observed allocation, which includes mismeasured inputs. The shaded green bar is calculated by equalizing factor ratios in a way that preserves scale across farmers: this is the model of an exchange economy that serves as a lower bound on factor misallocation in Shenoy (2017). The purple bar is then calculated by reweighting those demands by $1/\Lambda$, removing estimated financial frictions.[62] The input-based estimates are higher across the board than those using only estimated quantities. The conflicting result that removing financial frictions would worsen misallocation can be explained by their negative correlation with input measurement error. In other words, measurement error looks like a distortion that is partially offset by financial frictions — removing financial wedges thus makes this spurious distortion appear worse.[63]

Second, if there were no measurement error, then estimates of misallocation should be similar at the plot and farm level. Aragón, Restuccia, and Rud (2022) argue that plot-level data amplifies the potential for measurement error. Meanwhile Gollin and Udry (2021) argue that since optimization implies that households should be indifferent between allocating marginal expenditures towards one plot or another, differences in input intensity across plots of the same crop grown by the same farmers are likely to be either measurement error or unobserved heterogeneity. This suggests, that if households, or at least individuals, are truly optimizing and measurement error is not a concern, then plot-level data should not increase estimates of misallocation.

Figure C7 shows the main results using the plot rather than the household as the unit of analysis. This assumes that the same input and financial wedges apply equally to all plots a household cultivates simultaneously as in Gollin and Udry (2021). Table C2 shows that this produces nearly identical estimates of the production function as the farm-level specifications. Naturally, the solid bars in Figure C7 show slightly lower estimates of misallocation than the farm-level analysis in Figure 4. This is because the joint distribution of wedges and TFP is

[62] Note that the same wedges are used in each set of results but for different specifications. Input wedges are used to compute the orange and blue solid bars and the green and purple bars in the right panel. Meanwhile, financial wedges are used to compute the blue and green solid bars and the purple and orange shaded bars.

[63] Arthi et al. (2018) find that labor inputs are more upwardly biased for smaller farms. Since Figure 1 shows that these households are more financially constrained, financial constraints would then be negatively correlated with the measurement bias. Counterfactually relaxing these constraints would therefore allocate more resources to farms that appear artificially large in the raw data.

the same as in the farm-level analysis, except that the estimate of η is higher using plot-level data and that households with more plots (which tend to be less distorted) are oversampled. However, in the shaded bars, the estimates of misallocation using raw inputs nearly doubles. The reason for this is switching from farm-level aggregates to raw plot-level measurements introduces additional measurement error. Notably, there is no longer a significant difference between estimates from the observed allocation and when removing financial distortions.

These differences between the TFP and input-based measures are quite robust across specifications. Together, these results underscore the importance of separately identifying both input and financial distortions. Without a credible estimate of financial distortions, one would need to rely on noisily measured inputs and arrive at qualitatively different conclusions about the effects of counterfactual policies.

5.2 Alternative specifications and robustness checks

In Figures C4-C7, I show results under the alternative assumptions about the normalizing input for τ, the demand system used to estimate λ and sample restrictions. While the magnitudes of misallocation differ slightly across specifications, the qualitative results are broadly consistent.

Taxes vs. Rations

While the estimation procedure doesn't require taking a stand on whether input wedges operate as taxes or rations, this affects how households adjust different inputs under counterfactuals. In particular, a household facing a downward labor ration, as in Breza, Kaur, and Shamdasani (2021), would not use additional credit to hire more labor. The results in Figure 2 treat all inputs as flexible, as if input frictions functioned as taxes. Figure C3 shows the counterfactual gains from reallocation if land were a fixed factor or labor were rationed from below, relative to the case where both factors are mobile yet subject to distortions. The blue (left) bars in each group reproduce the results from the baseline case of Figure 2. The green (middle) bars show the results assuming land is a fully fixed factor in all specifications. However, the differences relative to the case of a tax are fairly small and statistically insignificant, as can be seen from the left-most group of bars in the figure. Even though households facing a downward labor ration would use additional credit to acquire other inputs until the ration no longer binds, the price of these other inputs also increases in equilibrium.

Levels of aggregation

So far I have assumed that reallocation occurs within townships, in which stocks of land and labor are fixed. I argue that this is a realistic level of aggregation since village boundaries within townships are fairly arbitrary (Kaboski and Townsend, 2011). However, I now consider how these results would change if reallocation could only occur within villages, or if reallocation could also take place across regions of Thailand. The latter should be viewed as an upper bound on the gains from reallocation since fundamental trade and migration costs cannot be considered misallocation. However, if these gains are large, it suggests that investments in roads and other infrastructure that promotes market integration may be effective at reducing misallocation.

Figure C16 shows the potential gains from full reallocation if allocation only occurs within villages or occurs at the national level.[64] The gains from reallocation across regions are more than three times as large as those from reallocation within townships. However, there appears to be very little misallocation across villages within townships, consistent with other evidence that villages in the same area are fairly integrated.

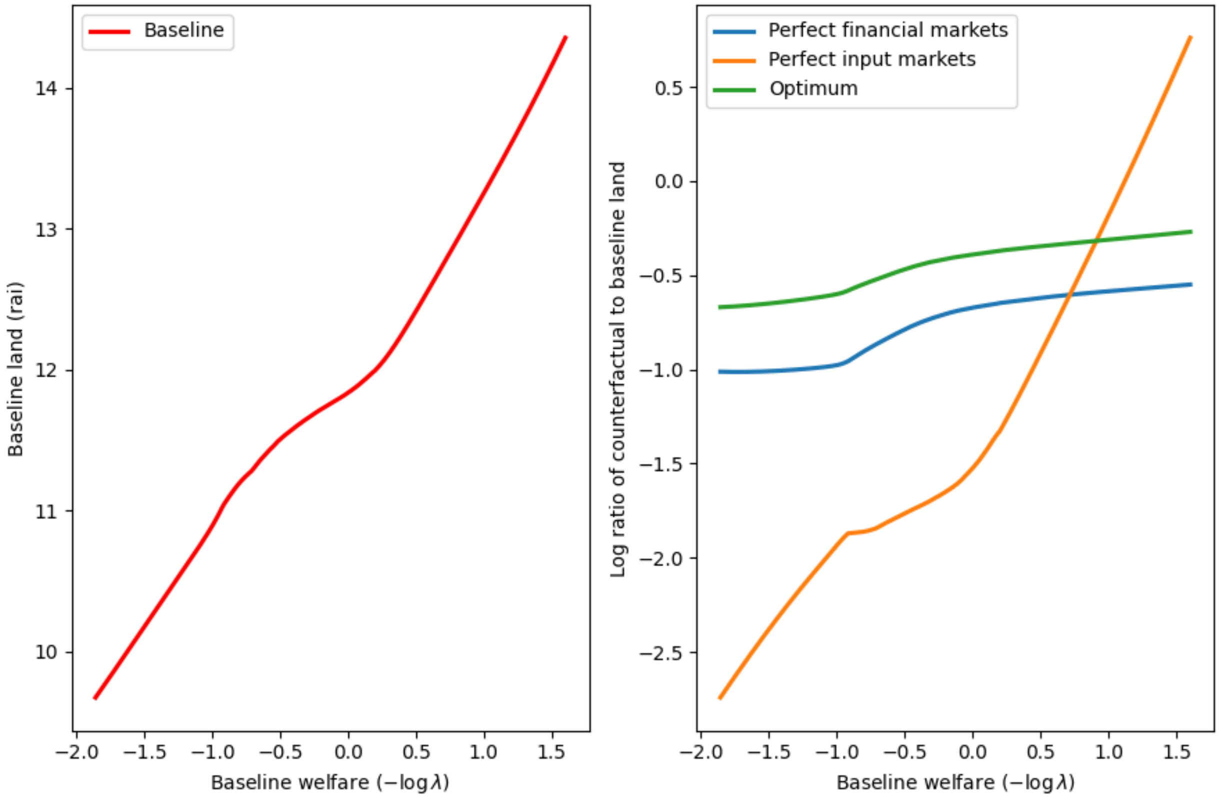
5.3 Distributional Effects

While the above counterfactuals only consider efficiency gains, what are the distributional implications of reallocation? Although a full treatment of welfare impacts is beyond the scope of this paper, Figure C8 and Figure 5 show how the distribution of land changes under the main counterfactuals. First, wealthier households tend to have much larger landholdings. While eliminating financial frictions makes the land distribution more equal across levels of baseline welfare, reducing frictions in land markets alone strengthens the correlation between welfare and farm size. This is because input frictions disproportionately affect wealthy households, who may wish to explain their landholdings but be unable to do so. However, many of these households are already inefficiently large ex ante because of their position in financial markets. Second, the concentration of farmland increases in all scenarios, meaning that the average household contracts its landholdings. This causes many farms to become infinitesimal, effectively exiting agriculture.[65] About 33% of households produce less than 1 rai (.125 ha) under perfect input markets and about 16% do under perfect financial markets.

[64]Note that since only 16 villages from 4 tambons are included in the sample, this should not be considered representative of a national-level reallocation.

[65]In the model, these households would continue to earn their non-agricultural income. However, I do not capture the potential entry by previously constrained households.

Figure 5: Changes in Land Distribution



The left panel shows the distribution of land under the baseline, denominated in rai (.125 ha), as a function of baseline welfare, which is the negative of the log MUE. The right panel shows the log ratio of land under the main counterfactuals to land at baseline. The plots show a lowess fit. This is shown for the closed economy case, using fertilizer as the normalizing input, CFE demands, and restricting the sample to rice crops at the farm level.

This is only 8% of farmers under the efficient allocation, in which the land distribution is more equal relative to reducing input frictions alone. This suggests that a single-market intervention may also induce inefficient levels of exit from agriculture. Nevertheless, I note that a richer model is required to fully capture the welfare effects of these channels.

6 Conclusion

In this paper, I estimate distinct distortions affecting farm households in Thailand and quantify how they each contribute to misallocation. This is necessary for policymakers to consider, as the welfare effects of interventions in a single market are ex-ante ambiguous.

First, the model yields a novel, theory-consistent production function estimation approach that holds when input choices are distorted. My approach flexibly allows for TFP shocks unobserved to the econometrician. Empirically, I find relatively low levels of misallocation in Thai agriculture: In my preferred specification, the gains from optimal reallocation are 31%. Perfecting financial markets while leaving input distortions unchanged would achieve 50% of these gains while perfecting financial markets holding input distortions fixed would achieve 30% of them. These gains sum to less than one because more financially constrained farmers are relatively subsidized in input markets, particularly for labor. This suggests that policies that seek to alleviate both distortions may be more effective than those targeted towards a single one.

Directly estimating financial distortions rather than inferring them from a residual allows me to avoid attributing measurement error in inputs to misallocation. I find that not accounting for measurement error using the full model would lead to 14% larger estimates of misallocation and, in contrast to my preferred approach, suggest that removing financial frictions alone would worsen misallocation. While the model explicitly allows for such a possibility, my preferred results show that this is not the case.

This paper leaves many additional topics for future research. In particular, more work is required to understand the distributional implications of productivity-enhancing policies. Another open question is how misallocation in agriculture interacts with climate change, given that it increases production uncertainty but increasing agricultural production may create climate externalities. Finally, while the paper provides a broad framework for diagnosing the effects of a general set of distortions, more research is needed to understand specific policies to address the relevant institutions in different contexts.

References

Abay, Kibrom, Gashaw Abate, Christopher Barrett, and Tanguy Bernard. 2019. “Correlated non-classical measurement errors, ‘Second best’ policy inference, and the inverse size-productivity relationship in agriculture.” *Journal of Development Economics* 139:171–184.

Abay, Kibrom., Leah Bevis, and Christopher Barrett. 2021. “Measurement Error Mechanisms Matter: Agricultural intensification with farmer misperceptions and misreporting.” *American Journal of Agricultural Economics* 103 (2):498–522.

Adamopoulos, Tasso, Loren Brandt, Chaoran Chen, Diego Restuccia, and Xiaoyun Wei.

2022a. "Land Security and Mobility Frictions." Tech. rep., National Bureau of Economic Research.

Adamopoulos, Tasso, Loren Brandt, Jessica Leight, and Diego Restuccia. 2022b. "Misallocation, selection, and productivity: A quantitative analysis with panel data from China." *Econometrica* 90 (3):1261–1282.

Adamopoulos, Tasso and Diego Restuccia. 2014. "The size distribution of farms and international productivity differences." *American Economic Review* 104 (6):1667–97.

———. 2020. "Land reform and productivity: A quantitative analysis with micro data." *American Economic Journal: Macroeconomics* 12 (3):1–39.

Aggarwal, Shilpa, Eilin Francis, and Jonathan Robinson. 2018. "Grain today, gain tomorrow: Evidence from a storage experiment with savings clubs in Kenya." *Journal of Development Economics* 134:1–15.

Agness, Daniel J, Travis Baseler, Sylvain Chassang, Pascaline Dupas, and Erik Snowberg. 2022. "Valuing the time of the self-employed." Tech. rep., National Bureau of Economic Research.

Anderson, Theodore Wilbur and Cheng Hsiao. 1981. "Estimation of dynamic models with error components." *Journal of the American Statistical Association* 76 (375):598–606.

Aragon, Fernando M, Diego Restuccia, and Juan Pablo Rud. 2022. "Are small farms really more productive than large farms?" *Food Policy* 106:102168.

Aragón, Fernando M, Diego Restuccia, and Juan Pablo Rud. 2022. "Assessing misallocation in agriculture: plots versus farms." Tech. rep., National Bureau of Economic Research.

Arellano, Manuel and Stephen Bond. 1991. "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." *Review of Economic Studies* 58 (2):277–297.

Arthi, Vellore, Kathleen Beegle, Joachim De Weerdt, and Amparo Palacios-López. 2018. "Not your average job: Measuring farm labor in Tanzania." *Journal of Development Economics* 130:160–172.

Asker, John, Allan Collard-Wexler, and Jan De Loecker. 2014. "Dynamic inputs and resource (mis) allocation." *Journal of Political Economy* 122 (5):1013–1063.

———. 2019. “(Mis) allocation, market power, and global oil extraction.” *American Economic Review* 109 (4):1568–1615.

Beegle, Kathleen, Calogero Carletto, and Kristen Himelein. 2012. “Reliability of recall in agricultural data.” *Journal of Development Economics* 98 (1):34–41.

Benjamin, Dwayne. 1992. “Household composition, labor markets, and labor demand: testing for separation in agricultural household models.” *Econometrica* :287–322.

———. 1995. “Can unobserved land quality explain the inverse productivity relationship?” *Journal of Development Economics* 46 (1):51–84.

Bils, Mark, Peter J Klenow, and Cian Ruane. 2021. “Misallocation or mismeasurement?” *Journal of Monetary Economics* 124:S39–S56.

Blundell, Richard and Stephen Bond. 1998. “Initial conditions and moment restrictions in dynamic panel data models.” *Journal of Econometrics* 87 (1):115–143.

Bohr, Clement, Martí Mestieri, and Frédéric Robert-Nicoud. 2023. “Heterothetic Cobb Douglas.” Tech. rep., Centre for Economy Policy Research.

Bold, Tessa, Kayuki C Kaizzi, Jakob Svensson, and David Yanagizawa-Drott. 2017. “Lemon technologies and adoption: measurement, theory and evidence from agricultural markets in Uganda.” *The Quarterly Journal of Economics* 132 (3):1055–1100.

Breza, Emily, Supreet Kaur, and Yogita Shamdasani. 2021. “Labor rationing.” *American Economic Review* 111 (10):3184–3224.

Bryan, Gharad, Jon de Quidt, Mariajose Silva-Vargas, Tom Wilkening, and Nitin Yadav. 2022. “Market Design for Land Trade: Evidence from Uganda and Kenya.” Tech. rep., London School of Economics, London.

Burchardi, Konrad B, Selim Gulesci, Benedetta Lerva, and Munshi Sulaiman. 2019. “Moral hazard: Experimental evidence from tenancy contracts.” *The Quarterly Journal of Economics* 134 (1):281–347.

Burke, Marshall, Lauren Falcao Bergquist, and Edward Miguel. 2019. “Sell low and buy high: arbitrage and local price effects in Kenyan markets.” *The Quarterly Journal of Economics* 134 (2):785–842.

Cairncross, John, Peter Morrow, Scott Orr, and Swapnika Rachapalli. 2023. "Robust Markups." *Unpublished manuscript* .

Carletto, Calogero, Sydney Gourlay, and Paul Winters. 2015. "From guesstimates to GPStimates: Land area measurement and implications for agricultural analysis." *Journal of African Economies* 24 (5):593–628.

Carletto, Calogero, Sara Savastano, and Alberto Zezza. 2013. "Fact or artifact: The impact of measurement errors on the farm size–productivity relationship." *Journal of Development Economics* 103:254–261.

Carrillo, Paul, Dave Donaldson, Dina Pomeranz, and Monica Singhal. 2023. "Misallocation in Firm Production: A Nonparametric Analysis Using Procurement Lotteries." Tech. rep., National Bureau of Economic Research.

Caunedo, Julieta and Namrata Kala. 2021. "Mechanizing agriculture." Tech. rep., National B ureau of Economic Research.

Channa, Hira, Jacob Ricker-Gilbert, Feleke Shiferaw, and Tahirou Abdoulaye. 2018. "Helping Smallholder Farmers Make the Most of Maize through Harvest Loans and Storage Technology: Insights from a Randomized Control Trial in Tanzania." *Unpublished* .

Chari, Amalavoyal, Elaine M Liu, Shing-Yi Wang, and Yongxiang Wang. 2021. "Property rights, land misallocation, and agricultural efficiency in China." *The Review of Economic Studies* 88 (4):1831–1862.

Chen, Chaoran, Diego Restuccia, and Raul Santaeulalia-Llopis. 2017. "Land misallocation and productivity." Tech. rep., National Bureau of Economic Research.

Chen, Chaoran, Diego Restuccia, and Raül Santaeulàlia-Llopis. 2022. "The effects of land markets on resource allocation and agricultural productivity." *Review of Economic Dynamics* 45:41–54.

———. 2023. "Land misallocation and productivity." *American Economic Journal: Macroeconomics* 15 (2):441–465.

De Loecker, Jan, Pinelopi K Goldberg, Amit K Khandelwal, and Nina Pavcnik. 2016. "Prices, markups, and trade reform." *Econometrica* 84 (2):445–510.

De Loecker, Jan and Frederic Warzynski. 2012. “Markups and firm-level export status.” *American Economic Review* 102 (6):2437–2471.

Desiere, Sam and Dean Jolliffe. 2018. “Land productivity and plot size: Is measurement error driving the inverse relationship?” *Journal of Development Economics* 130:84–98.

Dillon, Brian, Peter Brummund, and Germano Mwabu. 2019. “Asymmetric non-separation and rural labor markets.” *Journal of Development Economics* 139:78–96.

Diop, Binta Zahra. 2023. “Upgrade or Migrate: The Consequences of Input Subsidies on Household Labor Allocation.” .

Donovan, Kevin. 2021. “The equilibrium impact of agricultural risk on intermediate inputs and aggregate productivity.” *The Review of Economic Studies* 88 (5):2275–2307.

Emerick, Kyle, Alain De Janvry, Elisabeth Sadoulet, and Manzoor H Dar. 2016. “Technological innovations, downside risk, and the modernization of agriculture.” *American Economic Review* 106 (6):1537–61.

Felkner, John, Kamilya Tazhibayeva, and Robert Townsend. 2012. “The Impact of Climate Change on Rice Yields: the Importance of Heterogeneity and Family Networks.” .

Fink, Gunther, B Kelsey Jack, and Felix Masiye. 2020. “Seasonal Liquidity, Rural Labor Markets, and Agricultural Production.” *American Economic Review* 110 (11):3351–92.

Gandhi, Amit, Salvador Navarro, and David A Rivers. 2020. “On the identification of gross output production functions.” *Journal of Political Economy* 128 (8):2973–3016.

Goldstein, Markus and Christopher Udry. 2008. “The profits of power: Land rights and agricultural investment in Ghana.” *Journal of Political Economy* 116 (6):981–1022.

Gollin, Douglas and Christopher Udry. 2021. “Heterogeneity, measurement error, and misallocation: Evidence from african agriculture.” *Journal of Political Economy* 129 (1):1–80.

Gordeev, Stepan and Sudhir Singh. 2023. “Misallocation and Product Choice.”

Gottlieb, Charles and Jan Grobovšek. 2019. “Communal land and agricultural productivity.” *Journal of Development Economics* 138:135–152.

Grieco, Paul LE, Shengyu Li, and Hongsong Zhang. 2016. “Production function estimation with unobserved input price dispersion.” *International Economic Review* 57 (2):665–690.

Hansen, Lars Peter, John Heaton, and Amir Yaron. 1996. "Finite-sample properties of some alternative GMM estimators." *Journal of Business & Economic Statistics* 14 (3):262–280.

Hansen, Lars Peter and Kenneth J Singleton. 1982. "Generalized instrumental variables estimation of nonlinear rational expectations models." *Econometrica: Journal of the Econometric Society* :1269–1286.

Hayashi, Fumio. 2011. *Econometrics*. Princeton University Press.

Hsieh, Chang-Tai and Peter J Klenow. 2009. "Misallocation and manufacturing TFP in China and India." *The Quarterly Journal of Economics* 124 (4):1403–1448.

Hughes, David and Jeremy Majerovitz. 2023. "Measuring Misallocation with Experiments."

Jones, Maria, Florence Kondylis, John Loeser, and Jeremy Magruder. 2022. "Factor market failures and the adoption of irrigation in Rwanda." *American Economic Review* 112 (7):2316–52.

Just, Richard E and Rulon D Pope. 1978. "Stochastic specification of production functions and economic implications." *Journal of econometrics* 7 (1):67–86.

———. 1979. "Production function estimation and related risk considerations." *American Journal of Agricultural Economics* 61 (2):276–284.

Kaboski, Joseph P and Robert M Townsend. 2011. "A structural evaluation of a large-scale quasi-experimental microfinance initiative." *Econometrica* 79 (5):1357–1406.

———. 2012. "The impact of credit on village economies." *American Economic Journal: Applied Economics* 4 (2):98–133.

Karaivanov, Alexander and Robert M. Townsend. 2014. "Dynamic Financial Constraints: Distinguishing Mechanism Design from Exogenously Incomplete Regimes." *Econometrica* 82 (3):887–959.

Karlan, Dean, Robert Osei, Isaac Osei-Akoto, and Christopher Udry. 2014. "Agricultural decisions after relaxing credit and risk constraints." *Quarterly Journal of Economics* 129 (2):597–652.

Kinnan, Cynthia, Krislert Samphantharak, Robert Townsend, and Diego A Vera Cossio. 2020. "Propagation and insurance in village networks." Tech. rep., National Bureau of Economic Research.

Kinnan, Cynthia, Krislert Samphantharak, Robert Townsend, and Diego Vera-Cossio. 2024. "Propagation and insurance in village networks." *American Economic Review* 114 (1):252–284.

Kinnan, Cynthia and Robert Townsend. 2012. "Kinship and financial networks, formal financial access, and risk reduction." *American Economic Review* 102 (3):289–93.

Kochar, Anjini. 1999. "Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India." *Review of Economics and Statistics* 81 (1):50–61.

LaFave, Daniel and Duncan Thomas. 2016. "Farms, families, and markets: New evidence on completeness of markets in agricultural settings." *Econometrica* 84 (5):1917–1960.

Levinsohn, James and Amil Petrin. 2003. "Estimating production functions using inputs to control for unobservables." *The Review of Economic Studies* 70 (2):317–341.

Ligon, Ethan. 2020. "Estimating household welfare from disaggregate expenditures." .

Lipsey, Richard G and Kelvin Lancaster. 1956. "The general theory of second best." *The Review of Economic Studies* 24 (1):11–32.

Magruder, Jeremy R. 2018. "An assessment of experimental evidence on agricultural technology adoption in developing countries." *Annual Review of Resource Economics* 10:299–316.

Manysheva, Kristina. 2021. "Land Property Rights, Financial Frictions, and Resource Allocation in Developing Countries." Tech. rep., mimeo.

Mobarak, Ahmed Mushfiq and Mark R Rosenzweig. 2013. "Informal risk sharing, index insurance, and risk taking in developing countries." *American Economic Review* 103 (3):375–380.

Olley, G Steven and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 64 (6):1263–1297.

Omotilewa, Oluwatoba J, Jacob Ricker-Gilbert, John Herbert Ainembabazi, and Gerald E Shively. 2018. "Does improved storage technology promote modern input use and food security? Evidence from a randomized trial in Uganda." *Journal of Development Economics* 135:176–198.

Restuccia, Diego and Richard Rogerson. 2008. "Policy distortions and aggregate productivity with heterogeneous establishments." *Review of Economic Dynamics* 11 (4):707–720.

Rotemberg, Martin and T Kirk White. 2021. "Plant-to-table (s and figures): Processed manufacturing data and measured misallocation."

Samphantharak, Krislert and Robert M Townsend. 2018. "Risk and return in village economies." *American Economic Journal: Microeconomics* 10 (1):1–40.

Shenoy, Ajay. 2017. "Market failures and misallocation." *Journal of Development Economics* 128:65–80.

———. 2021. "Estimating the production function under input market frictions." *Review of Economics and Statistics* 103 (4):666–679.

Sraer, David and David Thesmar. 2023. "How to use natural experiments to estimate misallocation." *American Economic Review* 113 (4):906–938.

Suri, Tavneet and Christopher Udry. 2022. "Agricultural technology in Africa." *Journal of Economic Perspectives* 36 (1):33–56.

Townsend, Robert M. 1994. "Risk and insurance in village India." *Econometrica* .

A Proofs

Proposition 1. *Assume households have rational expectations and let $h(z_{jt})$ be a measurable function of variables $z_{jt} \in \mathcal{I}_{jt}$. Then the estimator defined by*

$$\arg\min_{a} J(a) \equiv g_{NT}(a)' W g_{NT}(a)$$

where

$$g_{NT}(a) \equiv \frac{1}{NT}\sum_{t=1}^{T}\sum_{j=1}^{N} \delta a(\lambda_{j,t+1}Y_{j,t+1} - \lambda_{jt}x_{jkt}) \otimes h(z_{jt})$$

is a consistent estimator of the vector of coefficients α up to the time-preference discount factor δ for a symmetric and positive-definite weighting matrix W.

Proof. The proof is an application of Hansen and Singleton (1982) with a few modifications.

Let $\zeta_{jt+1} \equiv \mathrm{E}[\lambda_{jt+1}Y_{t+1}|\mathcal{I}_{jt}]$, which is the difference between household j's subjective expectation of $\lambda_{jt+1}Y_{jt+1}$ conditional on time t information $\mathcal{I}_{jt}$. Under rational expectations, differences between expectations and realizations of random variables are mean 0 forecast errors. Therefore $\mathbf{E}[\zeta_{jt+1}] = 0$, where $\mathbf{E}$ denotes unconditional population expectations. Furthermore, let $z_{jt} \in \mathcal{I}_{jt}$ be a vector of observed elements of household j's time t information set with finite second moments and let $h(z_{jt})$ be a measurable function of z. Rational expectations then implies that $\mathbf{E}[\zeta_{jt+1}] \otimes h(z_{jt}) = 0$, where $\otimes$ is the Kronecker product. Substituting $\zeta_{jt+1} + \lambda_{j,t+1}Y_{t+1}$ for $\mathrm{E}_t[\lambda_{jt+1}Y_{jt+1}]$ implies

$$\mathbf{E}[(\delta\alpha\lambda_{j,t+1}Y_{j,t+1} + \zeta_{jt+1} - \lambda_{jt}x_{jkt}) \otimes h(z_{jt})] = 0 \tag{29}$$

The sample counterpart of is

$$g_{NT}(a) \equiv \frac{1}{NT}\sum_{j}\sum_{t} \delta a(\lambda_{j,t+1}Y_{j,t+1} + \zeta_{jt+1} - \lambda_{jt}x_{jkt}) \otimes h(z_{jt}) = 0 \tag{30}$$

$\frac{1}{N}\sum_{j=1}^{N}\zeta_{jt+1}$ itself can be thought of as the aggregate shock within each period. Let $\psi_{t+1} \equiv \frac{1}{N}\sum_{j=1}^{N}\zeta_{jt+1} \otimes h(z_{jt})$, which is the sample covariance of unanticipated shocks in each period with the lagged instruments in each period.

Since (by definition) idiosyncratic forecast errors by household are on average equal to the common forecast error, $g_{NT}(a) \to \frac{1}{T}\sum_{t=0}^{T}\psi_{t+1}$ as $N \to \infty$. If shocks are purely idiosyncratic, then average forecast error is zero in *each* period $\psi_{t+1} \to 0\ \forall t$ as $N \to \infty$. However, even there are aggregate shocks within each period, rational expectations still imply that are they are mean-zero. Therefore $\frac{1}{T}\sum_{t=0}^{T}\psi_{t+1} \to 0$ as $T \to \infty$. In this case, the GMM estimate of α is

$$\arg\min_{a} J(a) \equiv g_{NT}(a)' W g_{NT}(a)$$

where W is a symmetric and positive-definite weighting matrix. The efficient choice of W is $\mathbf{E}[g_{NT}(a)g_{NT}(a)']^{-1}$. □

B Generalized Cobb-Douglas Production

B.1 Estimating α and β

I now describe how each of the key components of the model λ, τ, α,β A, and Λ are estimated. Since the estimation of marginal utilities, λ, doesn't depend on the production function, I follow the same procedure as in Section 4.1. I then estimate (16) from a subsample of households' input demands. Once I recover α and β, I then recover τ, Λ and A for the full sample of households.

I use GMM to estimate α and β from the system of input demand equations defined by (16). In this approach, inputs are analogous to assets in a CAPM model and λ_t/λ_{t+1} is analogous to the portfolio's return (Hansen and Singleton, 1982). Under rational expectations, this yields a straightforward approach to estimation. a

Let $x_{jkt} \equiv \bar{w}_{kvt}\tau_{kt}q_{jkt}$. x_{jkt} can be interpreted as household j's "shadow" expenditure on input k at time t. This can either represent actual expenditure under possibly household-specific prices or as the cost of input k such that the household would choose q_{jkt} under perfect markets. Let $\mathcal{I}_{jt}$ be a vector of variables in household j's information set at time t. Rearranging constrained-optimal input demands (16) and making the dependence on households' time t information sets explicit yields the moment condition.

$$\alpha_k \mathrm{E}[\lambda_{j,t+1}|\mathcal{I}_{jt}]\mathrm{E}[Y_{j,t+1}|\mathcal{I}_{jt}] + \beta_k cov(\lambda_{j,t+1}, Y_{j,t+1}|\mathcal{I}_{jt}) - \lambda_{jt}x_{jkt} = 0 \tag{31}$$

where $cov_t(\lambda_{j,t+1}Y_{j,t+1}) = \mathrm{E}_t[\lambda_{j,t+1}Y_{j,t+1} - \mathrm{E}_t[\lambda_{j,t+1}]\mathrm{E}_t[Y_{j,t+1}]]$ can be thought of as a measure of how households expect their utility at harvest to depend on the realizations of production shocks, conditional on their time t information. Estimation requires mapping the subjective expectations $\mathrm{E}[\lambda_{jt+1}|\mathcal{I}_{jt}], \mathrm{E}[Y_{jt+1}|\mathcal{I}_{jt}]$, and $\mathrm{E}[\lambda_{jt+1}Y_{jt+1}|\mathcal{I}_{jt}]$ to data. The nested case of $\alpha = \beta$ in Section 4 doesn't require distinguishing between $\mathrm{E}[\lambda_{jt+1}|\mathcal{I}_{jt}]\mathrm{E}[Y_{jt+1}|\mathcal{I}_{jt}]$ and $E[\lambda_{jt+1}Y_{jt+1}|\mathcal{I}_{jt}]$, which allows me to substitute realized $\lambda_{jt+1}Y_{jt+1}$ for $\mathrm{E}[\lambda_{jt+1}Y_{jt+1}|\mathcal{I}_{jt}]$

under rational expectations. More formally, Differences between the expected and realized products of output and marginal utilities can be expressed as:

$$\lambda_{j,t+1}Y_{t+1} - \mathrm{E}[\lambda_{j,t+1}Y_{t+1}|\mathcal{I}_{jt}] = \zeta_{j,t+1} \tag{32}$$

I assume households are fully forward-looking and have rational expectations over future shocks. In this case $\mathrm{E}_t[\zeta_{j,t+1}|\mathcal{I}_{jt}] = 0$, as ζ is simply prediction error that arises from the realization of shocks after households' optimal decisions are made in time t. The challenge is that $\mathrm{E}_t[\zeta_{j,t+1}|\mathcal{I}_{jt}]$ is the household's *subjective* expectation as of time t, conditional on its information set $\mathcal{I}_{jt}$ but prior to the realization of shocks, and is unobserved. I do observe $\lambda_{jt+1}Y_{jt+1}$ for N households in T years. In a given year, the *population* the mean of realized ζ_{jt+1}, which I denote as $\mathbb{E}[\zeta_{t+1}]$, may be nonzero if there are aggregate shocks that affect all households within a period.

This motivates a set of instruments

$$z_{jt} \equiv \{\lambda_{j,t-1}, \lambda_{j,t-2}, \ldots\}$$

that are plausibly orthogonal to prediction error. The logic of this is that past consumption is correlated with future consumption, making z_{jt} relevant.[66] However, whether $\mathbb{E}[\zeta_{jt+1}z_t] = 0$ depends on whether their covariance is stationary. Within a given year, realizations of shocks are likely to differentially affect households with different levels of wealth, and thus z_t. Intuitively, poorer households may be more risk-averse (under prudence) and less insured, and thus their marginal utilities will be more sensitive to the realizations of shocks. The stationarity of $\mathbb{E}[\zeta_{jt+1}z_t] = 0$ ensures that the effects of this greater sensitivity of poorer households averages out to zero in the panel.[67]

This assumption permits the substitution of (subjective) conditional expectations $\mathrm{E}[\lambda_{jt+1}Y_{jt+1}|\mathcal{I}_{jt}]$ with realizations. However, this substitution can't be used for both $\mathrm{E}[\lambda_{jt+1}|\mathcal{I}_{jt}]\mathrm{E}[Y_{jt+1}|\mathcal{I}_{jt}]$ and $\mathrm{E}[\lambda_{jt+1}Y_{jt+1}|\mathcal{I}_{jt}]$ Therefore, separately identifying α and β requires taking a stand on what shocks the household does and does not anticipate at time t.

[66] Importantly, these instruments are functions of consumption that takes place after the previous season's shocks are realized, meaning that they don't reflect uncertainty from previous seasons.

[67] This would be violated if households' mispredictions, conditional on time t information, were correlated with income prior to time t.[68] However, I show with Monte Carlo simulations that the estimator I derive below performs well with small T, even when there is a correlation between baseline wealth and the realizations of aggregate shocks in the finite sample.

One approach would be projecting realizations of λ_{jt+1} and Y_{jt+1} on to functions of $\mathcal{I}_{jt}$, say $l(\mathcal{I}_{jt})$ and $y(\mathcal{I}_{jt})$, and using the predicted values, $\hat{l}(\mathcal{I}_{jt})$ and $\hat{y}(\mathcal{I}_{jt})$,to substitute for $\mathrm{E}[\lambda_{jt+1}|\mathcal{I}_{jt}]$ and $\mathrm{E}[Y_{jt+1}|\mathcal{I}_{jt}]$, respectively. In this case

$$\begin{aligned}
\lambda_{jt+1} &= \mathrm{E}[\lambda_{jt+1}|\mathcal{I}_{jt}] + \pi^L_{jt+1} \\
Y_{jt+1} &= \mathrm{E}[Y_{jt+1}|\mathcal{I}_{jt}] + \pi^Y_{jt+1} \\
\lambda_{jt+1} &= \hat{l}(\mathcal{I}_{jt}) = +\upsilon^L_{jt+1} \\
Y_{jt+1} &= \hat{y}(\mathcal{I}_{jt}) + \upsilon^Y_{jt+1}
\end{aligned} \tag{33}$$

The household's prediction errors π are mean zero by rational expectations and the estimation errors υ are mean 0 by construction. This means that the difference these two errors $\psi^Y_{jt} \equiv \pi^L_{jt} - \upsilon^L_{jt}$ and $\psi^Y_{jt} \equiv \pi^L Yjt - \upsilon^Y_{jt}$ are each mean zero by linearity of expectations. However substituting the *product* of subjective $\mathrm{E}[\lambda_{jt+1}|\mathcal{I}_{jt}]\mathrm{E}[Y_{jt+1}|\mathcal{I}_{jt}]$ for realizations implies:

$$\begin{aligned}
&\mathbb{E}\left[\left(\alpha_k(\hat{l}(\mathcal{I}_{jt}) + \upsilon^L_{jt+1})(\hat{y}(I) + \upsilon^Y_{jt+1}) + \beta(\lambda_{jt+1}Y_{jt+1} - (\hat{l}(\mathcal{I}_{jt}) + \upsilon^L_{jt+1})(\hat{y}(I) + \upsilon^Y_{jt+1})) - \lambda_{jt}x_{jkt}\right) \otimes h(\mathcal{I}_{jt})\right] \\
&= (\alpha_k - \beta_k)(\psi^L_{jt+1}\hat{y}(\mathcal{I}_{jt}) + \psi^Y_{jt+1}\hat{l}(\mathcal{I}_{jt}) + \psi^L_{jt+1}\psi^Y_{jt+1} \otimes h(\mathcal{I}_{jt}) = 0
\end{aligned} \tag{34}$$

Assuming $\hat{l}(\mathcal{I}_{jt})$ and $\hat{y}(\mathcal{I}_{jt})$ provide accurate predictions of the true subjective expectations, $\mathrm{E}[\lambda_{jt+1}|\mathcal{I}_{jt}]$ and $\mathrm{E}[Y_{jt+1}|\mathcal{I}_{jt}]$, they will differ by estimation error υ_l and υ_y, respectively. Both of these are mean 0 and orthogonal to $\mathcal{I}_{jt}$, by construction. However, their product is not necessarily mean 0. Estimation errors are likely to be correlated absent full insurance or quadratic utility, negatively if $u'''(c) > 0$ and production is not used as a hedge against portfolio risk: any anticipated productivity shock not captured by functions of the observed elements of $\mathcal{I}_{jt}$ is likely to have opposite effects on $\mathrm{E}[\lambda_{jt+1}|\mathcal{I}_{jt}]$ and $\mathrm{E}[Y_{jt+1}|\mathcal{I}_{jt}]$.

I assume households are fully forward-looking and have rational expectations. Therefore, by virtue of optimization, any differences between realized shocks and households' conditional expectations as of time t are mean-zero prediction errors Denote households' conditional expectations of $\lambda_{j,t+1}$ and $Y_{j,t+1}$, respectively, as $\bar{\lambda}_{j,t+1}$ and $\bar{Y}_{j,t+1}$. This implies that households' subjective expectations of random variables, on average, equal their realizations, meaning that we can substitute the conditional expectations in (31) with their unconditional expectations (Hansen and Singleton, 1982).[69] Letting $\mathbb{E}$ denote the unconditional expectation

[69] Also note that $\mathrm{E}[\lambda_{t+1}Y_{t+1} - \hat{l}(\mathcal{I}_{jt})\hat{y}(\mathcal{I}_{jt})|\mathcal{I}_{jt}] = \mathbb{E}[\lambda_{t+1}Y_{t+1} - \hat{l}(\mathcal{I}_{jt})\hat{y}(\mathcal{I}_{jt})]$.

operator, this implies that estimating

$$
\begin{aligned}
&\mathbb{E}\left[\left(\alpha_k \hat{l}(\mathcal{I}_{jt})\hat{y}(I) + \beta(\lambda_{jt+1}Y_{jt+1} - \alpha_k \hat{l}(\mathcal{I}_{jt})\hat{y}(I)) - \lambda_{jt}x_{jkt}\right) \otimes h(\mathcal{I}_{jt})\right] \\
&= \mathbb{E}[(\alpha_k(\mathrm{E}[\lambda_{jt+1}|\mathcal{I}_{jt}]\mathrm{E}[Y_{jt+1}|\mathcal{I}_{jt}] + \upsilon_{jt}) + \beta_k(\mathrm{E}[\lambda_{jt+1}Y_{jt+1}|\mathcal{I}_{jt}] - \mathrm{E}[\lambda_{jt+1}|\mathcal{I}_{jt}]\mathrm{E}[Y_{jt+1}|\mathcal{I}_{jt}] - \upsilon_{jt} + \zeta_{jt+1}) \\
&- \lambda_{jt}x_{jkt}) \otimes h(\mathcal{I}_{jt})] \\
&= ((\alpha_k - \beta_k)\upsilon_{jt} + \zeta_{xi}) \otimes h(\mathcal{I}_{jt}) = 0
\end{aligned}
$$

where $\upsilon_{jt} \equiv \upsilon^l_{jt}\hat{y}(\mathcal{I}_{jt}) + \upsilon^y_{jt}\hat{l}(\mathcal{I}_{jt}) + \upsilon^l_{jt}\upsilon^y_{jt}$ collects errors from the auxiliary regressions and h is a measurable function of observed elements of $\mathcal{I}_{jt}$ and $\otimes$ is the Kronecker product. Intuitively, the difference between households' subjective prediction errors and the econometrician's estimation errors needs to average out to 0 in the sample.

Taking sample averages:

$$
g_N T(\alpha, \beta) \equiv \frac{1}{NT}\left(\sum_{j=1}^{N}\sum_{t=1}^{T}(\alpha_k - \beta_k)\hat{l}(\mathcal{I}_{jt})\hat{y}(\mathcal{I}_{jt}) + \beta_k(\lambda_{j,t+1}Y_{j,t+1}) - \lambda_{jt}x_{jkt}\right) \otimes h(\mathcal{I}_{jt}), \quad (35)
$$

which converges to 0 with large NT under similiar conditions as in 1. Thus, the GMM estimate of α is

$$
\arg\min_a J(a) \equiv \arg\min_a g_{NT}(a)' W g_{NT}(a) \quad (36)
$$

where W is the standard optimal weighting matrix.

A second challenge is separately identifying τ, since households facing common technology and prices will no longer necessarily have the same input ratios. To make progress, I draw on empirical IO methods to estimate product-level production functions with unobserved input prices. In the case of De Loecker et al. (2016), they observe single- and multi-product firms producing the same goods but only observe inputs at the firm level. Their solution is to estimate the production function restricting the sample to single-product firms, and then apply a selection correction to control for unobservable differences between these two types of firms.

The problem in my case is that τ is not necessarily observed. Depending on the nature of input distortions, τ may correspond to the difference between the market price of an input and the price actually paid by a household that purchases this input, or it may be a shadow price that a household faces when rationed. I observe both input expenditures and quantities in the data. I assume that when households hire labor or rent land, any distortion is reflected in the observed price they pay. In this case, τ_{jkt} is included in the x_{jkt} I observe, which is the appropriate variable for (35). Thus I restrict the sample to transacted inputs when estimating α and β, which I then use to recover τs for the households that do not transact these inputs. Note that I do not have to make such assumptions about the nature of τs when production is homothetic, as I can estimate these directly from factor ratios.[70]

Results using simple linear projections of each λ_{jt+1} and Y_{jt+1} onto variables in $\mathcal{I}_{jt}$[71] are presented in Table 1. In column (1), I show the homothetic Cobb Douglas estimates of α, while columns (2) and (3) show α and β from the non-homothetic specification. The coefficients all take reasonable values for agricultural production. The estimates of α in column (2) imply *expected* returns to scale of $\gamma = 0.82$, which is slightly higher than in the Hicks-neutral case. However, the sum of the βs is higher and close to 1.

[70]This approach relies on some strong assumptions — namely that there is no selection into hiring inputs, that transacted inputs have the same returns as those owned by the household, and that households who purchase positive amounts of inputs do not come up against a ration. To provide support for the first assumption, I can apply the control function approach in De Loecker et al. (2016). I can also restrict the sample to households that use their own inputs in some seasons and purchase inputs in others. To address the second, I observe individual laborer and plot identifiers and can test whether their observed productivity differs when they are used by their respective households or hired. The third assumption is more difficult to test, but I can attempt to restrict the sample to households that appear less likely to face a binding ration.

[71]These variables include 5 monthly lags of λ and a vector of household characteristics.

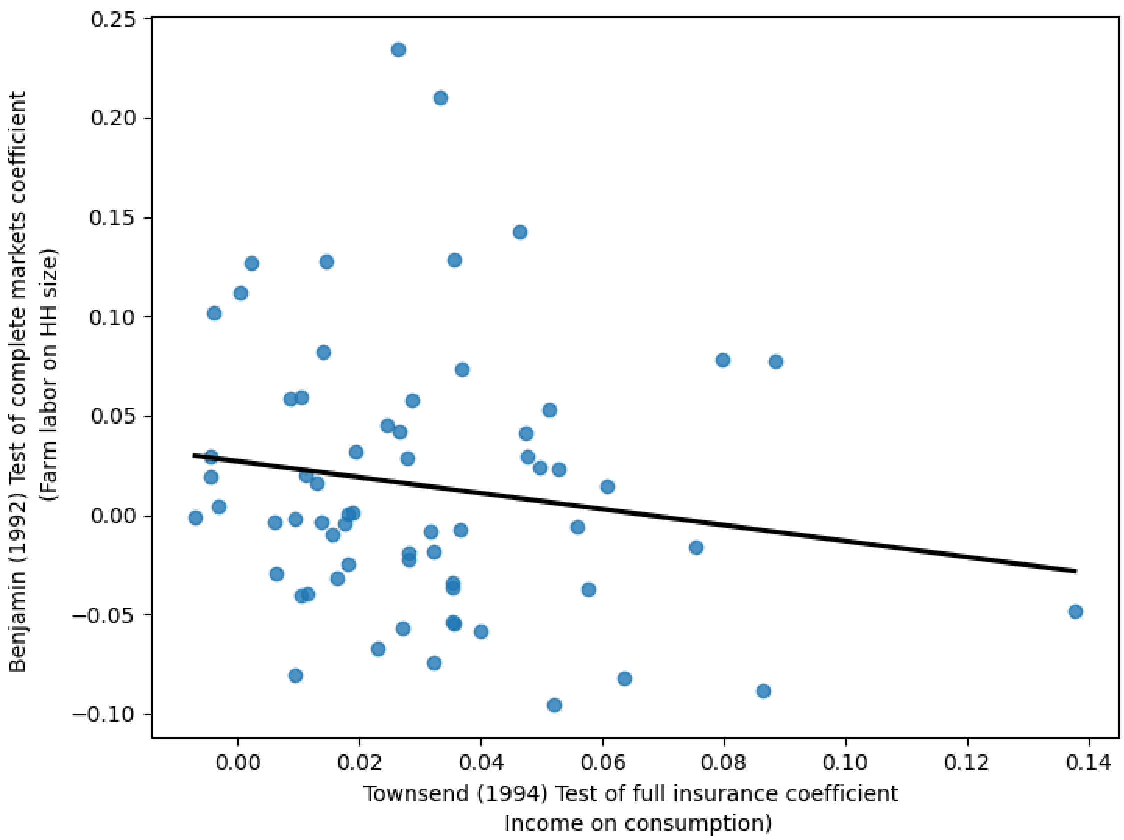
C Additional Tables and Figures

Table C1: Diagnostic Tests for Market Failures

	log Consumption Val.	log Labor Hrs.	
	(1)	(2)	(3)
log Income	0.0547***		
	(0.0037)		
HH Size		0.0211*	
		(0.0112)	
Male adults			0.0257
			(0.0258)
Female Adults			0.0269
			(0.0253)
Male children			0.0121
			(0.0217)
Female Children			0.0165
			(0.0210)
Household FE	Yes		
Village-month FE	Yes		
Village-year FE		Yes	Yes
F-stat			11.61**
p-val			0.0205
Observations	83,384	5,689	5,689

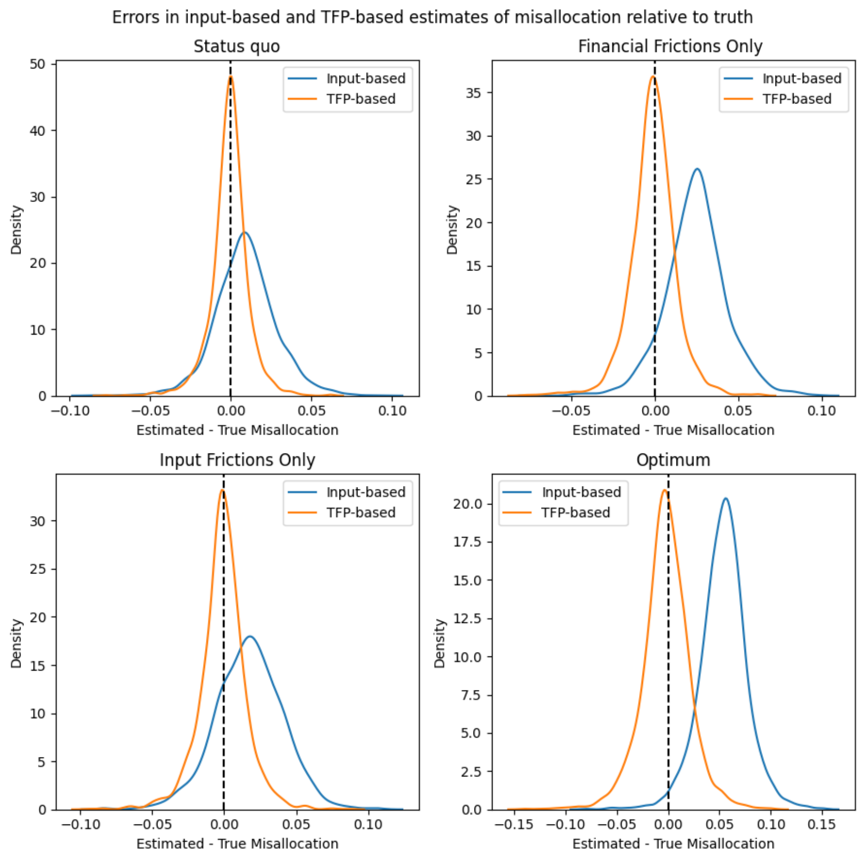
This table presents the results for two of the canonical tests of incomplete markets in the literature. Column (1) shows the results of a regression of (log) consumption on income with household and village-month fixed effects as in Townsend (1994). The full monthly sample of households (agricultural and non-agricultural) and monthly measures of total income and consumption are used. Column (2) shows the results of the Benjamin (1992) test of separability, which regresses (log) household labor hours on household characteristics, controlling for farm size. For simplicity, household size is the only measured included. Data from the full sample of producers aggregated to the household-year level are used.

Figure C1: Comparison of Test Coefficients Across Villages



This figure contains a scatter plot of the coefficients from the Townsend (1994) and Benjamin (1992) tests, run separately for each village in each 48-month block of the full panel. For the Townsend coefficients on the x-axis, the full monthly sample of households (agricultural and non-agricultural) and monthly measures of total income and consumption are used. Data from the full sample of producers aggregated to the household-year level are used to estimate the Benjamin coefficients on the y-axis.

Figure C2: Comparison of errors from input- and TFP-based estimates



These figures show the distribution of estimates of misallocation from 2,000 Monte Carlo simulations of the model. The model consists of 500 households observed for 16 years using a two-input production function with $\gamma = 0.7$. TFP, Λ and τ are drawn from a multivariate lognormal distortion with $\mu = 0$ and positively correlated distortions. Measurement error in inputs and production shocks are drawn from log normal distributions with $\sigma = .5$. The blue lines show the densities of estimates using the input-based measure from (27) and the orange lines show the densities using the TFP-based measure from (18). In all four scenarios, the TFP-based estimates have negligible bias while the input-based estimates are biased upwards and have larger variance. Similar patterns hold for other distributions of shocks and distortions.

Table C2: GMM results

	Fert τ	Seed τ	CRRA	Rice only
Equip.	0.084	0.080	0.165	0.094
	(0.005)	(0.004)	(0.005)	(0.005)
Fert.	0.089	0.089	0.100	0.084
	(0.002)	(0.002)	(0.002)	(0.002)
Harv. Labor	0.225	0.255	0.124	0.243
	(0.006)	(0.017)	(0.006)	(0.006)
Land	0.208	0.208	0.190	0.222
	(0.004)	(0.004)	(0.004)	(0.004)
Plant. Labor	0.117	0.125	0.050	0.121
	(0.004)	(0.003)	(0.004)	(0.004)
Seed	0.092	0.092	0.080	0.100
	(0.002)	(0.002)	(0.002)	(0.002)
Weed. Labor	0.013	0.014	0.016	0.019
	(0.001)	(0.001)	(0.001)	(0.001)
J-stat	35.06	45.53	36.64	37.93
p-val	0.465	0.11	0.393	0.337
γ	0.828	0.864	0.724	0.882
s.e.	(0.010)	(0.019)	(0.010)	(0.010)

This table presents results from the main GMM specifications used to estimate the production function. An annual discount factor of $\delta = .95$ is assumed. Columns (1) and (2) present results using fertilizer and seed as the reference input for the estimation of τ from (25), using rice plots only and CFE λs at the farm level. Column (3) presents results under CRRA preferences with a coefficient of relative risk aversion equal to 1.5. Column (4) includes all upland crops in the sample. Column (5) presents results using the plot rather than the farm level as the unit of aggregation. All specifications use tambon dummies and lags of λ_{jt} from the 5 months before input k is first applied. The J-statistic and p-values reported are from a test of the model with the full instrument set against one with only tambon dummies and a single lag of λ_{jt}. γ is the returns to scale parameter implied by the sum of the production coefficients. Standard errors are computed from 234 bootstraps of the full estimation procedure at the household level.

Table C3: Dynamic Panel Production Estimates

Dependent Variable:	Δlog Ouptut		
Model:	Just IDed	OverIDed 2SLS	OverIDed GMM
Variables			
Δlog Land	0.4641***	0.5239***	0.4314***
	(0.0399)	(0.0471)	(0.0480)
Δlog Labor	0.1033***	0.0604***	0.0839***
	(0.0225)	(0.0225)	(0.0217)
Δlog Equipment	0.0854***	0.1044***	0.1291***
	(0.0222)	(0.0265)	(0.0239)
Δlog Fertilizer	0.0561***	0.0452**	0.0273
	(0.0176)	(0.0182)	(0.0225)
Δlog Seed	0.0934***	0.1178***	0.1216***
	(0.0238)	(0.0253)	(0.0314)
Lagged instruments	1st	1st and 2nd	1st and 2nd
Observations	3,289	2,937	3,209
Within R^2	0.4579	0.4715	
Sargan test, p-value		0.0122	0.0027
AR(2) test, p-value			0.0001

Clustered (j) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table provides estimates of α following the Anderson and Hsiao (1981) (AH) procedure used by Shenoy (2017). To be consistent with Shenoy (2017), I group inputs into land, labor, and materials, where materials are the sum of expenditures on fertilizer, seed, and equipment. The first column shows the just-identified AH specification, in which the log differences in inputs are instrumented with their lagged values. The second shows the same specification with two first and second lags of inputs as instruments, estimated using two-stage least squares. The third estimates the same specification with GMM. The Sargan test rejects the null that both sets of lags are exogenous with p-values of 0.0122 and 0.0027, respectively and the Arellano-Bond test rejects the null of no second-order autocorrelation with a p-value of 0.0001 .

Table C4: Summary statistics for agricultural households by township

	All	Chachoengsao	Buriram	Lopburi	Sisaket
HH Size	5.564	5.827	5.622	5.03	5.923
	(2.333)	(2.857)	(2.214)	(2.018)	(2.389)
Age Head	56.037	59.792	53.295	53.756	59.597
	(13.259)	(13.515)	(13.275)	(12.387)	(12.745)
Sex Head	0.804	0.757	0.821	0.842	0.769
	(0.397)	(0.429)	(0.383)	(0.365)	(0.422)
Head Primary Educ	0.87	0.951	0.699	0.948	0.938
	(0.337)	(0.215)	(0.459)	(0.223)	(0.241)
Head Secondary Educ	0.1	0.07	0.08	0.121	0.115
	(0.3)	(0.255)	(0.271)	(0.326)	(0.319)
Formal Loan	0.341	0.149	0.432	0.368	0.307
	(0.519)	(0.361)	(0.573)	(0.493)	(0.519)
Any Loan	0.733	0.566	0.716	0.77	0.788
	(0.442)	(0.496)	(0.451)	(0.421)	(0.409)
Years in Ag	10.535	8.798	9.672	10.199	12.507
	(5.514)	(6.438)	(5.4)	(5.081)	(5.026)
N Households	568	71	174	161	162

This table shows summary statistics for agricultural households by township. The table displays means and standard deviations for each variable averaged across household-year observations.

Table C5: Summary statistics for agricultural households by township

	All	Chachoengsao	Buriram	Lopburi	Sisaket
Rice	0.691	0.884	0.966	0.007	0.937
	(0.462)	(0.32)	(0.182)	(0.081)	(0.243)
Maize	0.09	0.009	0.004	0.328	0.001
	(0.286)	(0.097)	(0.059)	(0.47)	(0.03)
Farm size	4.797	6.837	2.293	9.663	2.489
	(7.892)	(5.602)	(1.631)	(13.237)	(1.836)
# plots	3.227	3.078	2.097	4.704	3.026
	(2.787)	(2.424)	(1.28)	(4.069)	(1.944)
Any plot rented	0.16	0.395	0.144	0.267	0.025
	(0.367)	(0.489)	(0.351)	(0.443)	(0.155)
Any labor hired	0.682	0.76	0.781	0.849	0.461
	(0.466)	(0.427)	(0.414)	(0.358)	(0.499)
% labor hired	0.287	0.194	0.284	0.539	0.127
	(0.318)	(0.194)	(0.268)	(0.362)	(0.211)
Any fert.	0.89	0.929	0.92	0.803	0.92
	(0.313)	(0.256)	(0.271)	(0.398)	(0.271)
Any equip.	0.907	0.904	0.939	0.923	0.873
	(0.29)	(0.294)	(0.239)	(0.267)	(0.333)
Profit share	0.228	1.056	0.176	0.039	0.172
	(0.688)	(0.905)	(0.564)	(0.606)	(0.585)
N Households	578	73	177	165	163

This table shows summary statistics for agricultural households by township. The table displays means and standard deviations for each variable averaged across household-year observations.

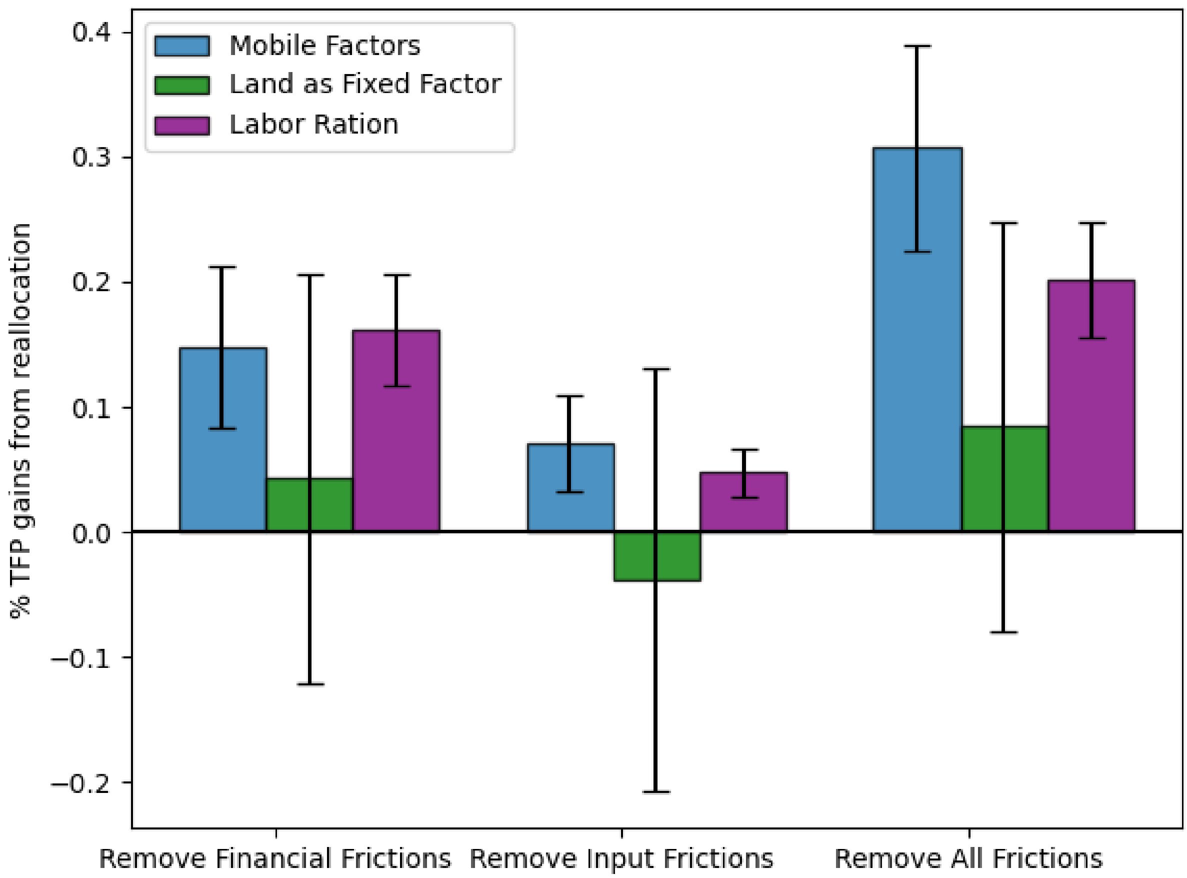
Table C6: Sys-GMM Estimates of τ

	Dependent variable:					
	Land	Labor	Plant Labor	Weed Labor	Harv Labor	Equip
	(1)	(2)	(3)	(4)	(5)	(6)
1st Lag log input ratio	0.2696***	0.3570***	0.3739***	0.2144***	0.3771***	0.2768***
	(0.0259)	(0.0250)	(0.0216)	(0.0310)	(0.0262)	(0.0263)
2nd Lag log input ratio	0.1216***	0.1606***	0.1692***	0.0515*	0.2088***	0.1056***
	(0.0204)	(0.0215)	(0.0228)	(0.0299)	(0.0240)	(0.0216)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
AR(2) p-value	0.4322	0.4506	0.0004	0.4750	0.2733	0.5004
J test p-value	0.4767	0.4263	0.3531	0.7404	0.4908	0.6048
HH	534	534	534	534	534	534

*p<0.1; **p<0.05; ***p<0.01

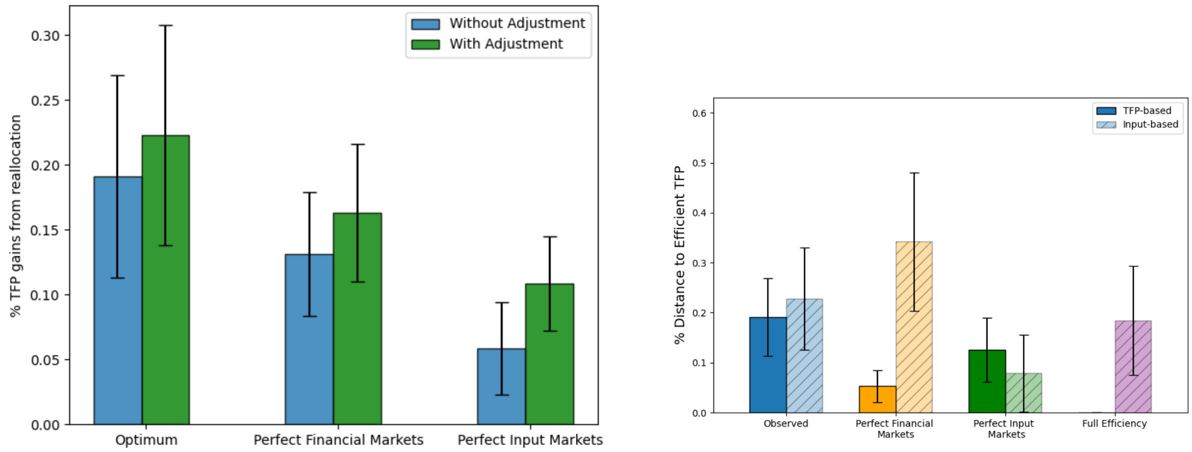
This figure presents the results from (25) estimated using the Sys-GMM procedure of Blundell and Bond (1998). The dependent variable is the log ratio of seed to the input indicated in the column heading and the independent variables are two lags of the input ratio from previous seasons. Controls include counts adult males, adults females, male children and female children. The full set of moment restrictions implied by the model is used. A heteroskedasticity-robust covariance matrix is used for the standard errors. p-values from the Arellano and Bond (1991) test for second-order autocorrelation and Sargan's J test of overidentifying restrictions are presented.

Figure C3: Counterfactual gains from reallocation under input rations



The figure shows the gains from reallocation under the main counterfactuals depending on which factors are mobile within townships. The blue (left) bars reproduce the baseline scenario, in which all factors are mobile and can be reallocated. The green (middle) bars show results holding land fixed at observed levels in all three scenarios, even when relaxing other input frictions. The purple (right) bars show results assuming households with $\tau < 1$ for each labor input face a binding downard ration. Results are computed using CFE demands, fertilizer as the normalizing input for τs, all crops, and aggregating to the farm level. 95% confidence intervals from 200 bootstrap replications are plotted.

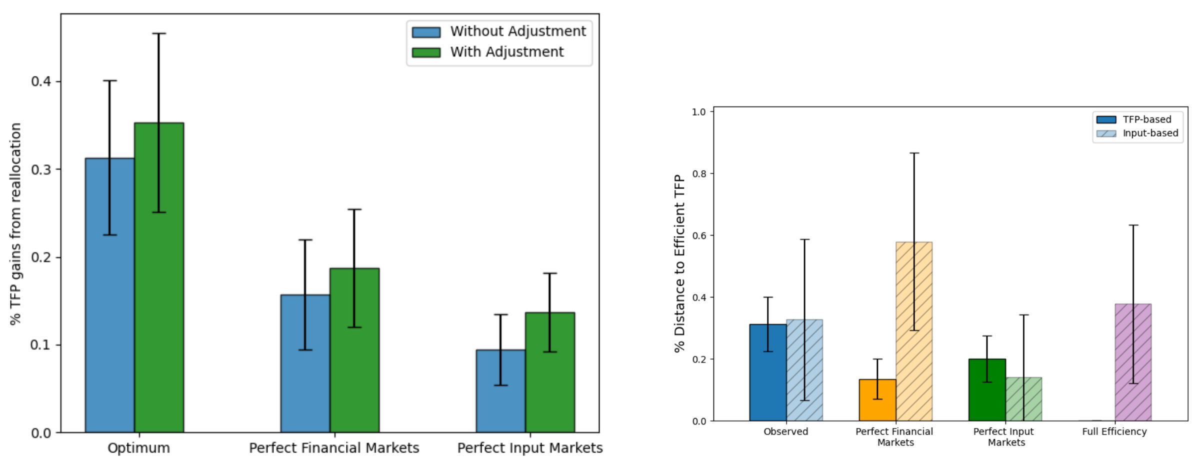
Figure C4: Main results with CRRA preferences



(a) (b)

The figure shows results from the main counterfactuals in Figure 2 and Figure 4 in panels (a) and (b). Results are computed using CFE demands, fertilizer as the normalizing input for τs, only rice plots, and aggregating to the farm level. The measure of misallocation is the difference between aggregate TFP under a given allocation and the efficient one, expressed as a percent of modeled TFP. The solid bars compute these using the TFP-based measure of misallocation, using (17). The shaded bars are calculated by taking raw input observed in the data and augmenting them by the estimated τ and Λ, where relevant. 95% confidence intervals from 200 bootstrap replications are plotted.

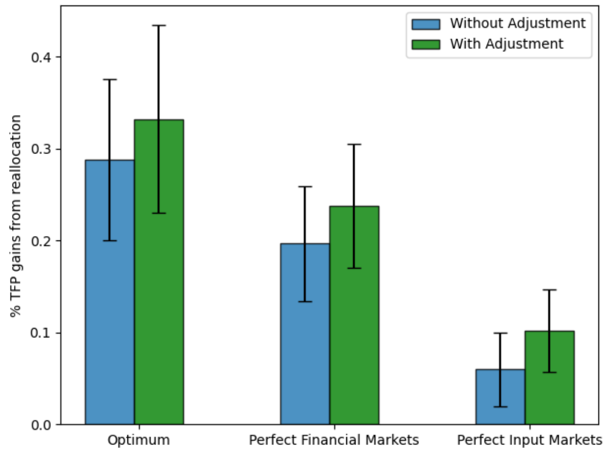
Figure C5: Results using only rice



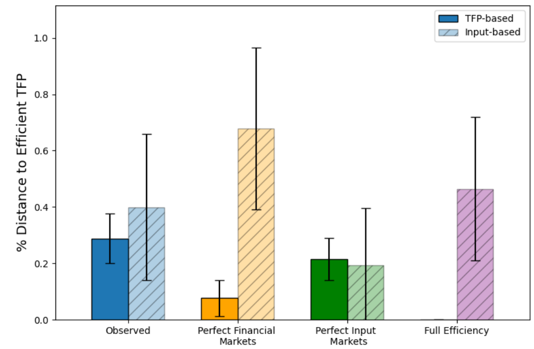
(a) (b)

The figure shows results from the main counterfactuals in Figure 2 and Figure 4 in panels (a) and (b). Results are computed using CFE demands, fertilizer as the normalizing input for τs, restricting the sample to rice plots, and aggregating to the farm level. The measure of misallocation is the difference between aggregate TFP under a given allocation and the efficient one, expressed as a percent of modeled TFP. The solid bars compute these using the TFP-based measure of misallocation, using (17). The shaded bars are calculated by taking raw input observed in the data and augmenting them by the estimated τ and Λ, where relevant. 95% confidence intervals from 200 bootstrap replications are plotted.

Figure C6: Main results using seed as the reference input



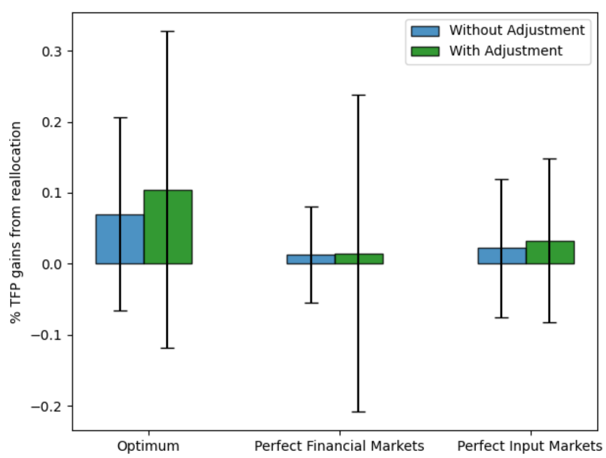
(a)



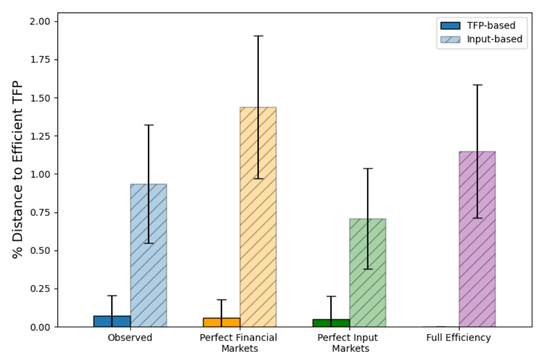
(b)

The figure shows results from the main counterfactuals in Figure 2 and Figure 4 in panels (a) and (b). Results are computed using CFE demands, seed as the normalizing input for τs, only rice plots, and aggregating to the farm level. The measure of misallocation is the difference between aggregate TFP under a given allocation and the efficient one, expressed as a percent of modeled TFP. The solid bars compute these using the TFP-based measure of misallocation, using (17). The shaded bars are calculated by taking raw input observed in the data and augmenting them by the estimated τ and Λ, where relevant. 95% confidence intervals from 200 bootstrap replications are plotted.

Figure C7: Plot-level estimates of misallocation



(a)



(b)

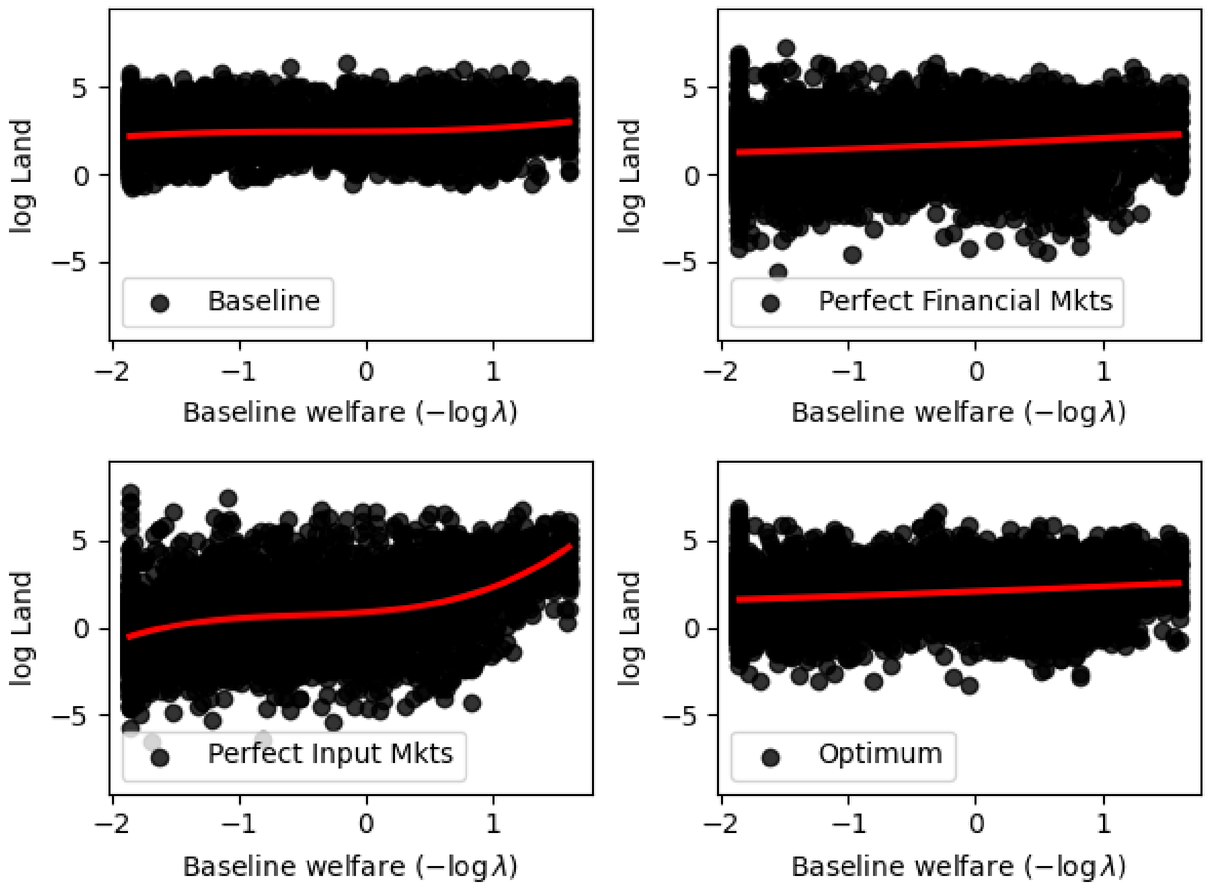
The figure shows results from the main counterfactuals in Figure 2 and Figure 4 in panels (a) and (b), respectively, using plot-level rather than farm-level data. Results are computed using CFE demands, fertilizer as the normalizing input for τs, restricting the sample to rice plots. The measure of misallocation is the difference between aggregate TFP under a given allocation and the efficient one, expressed as a percent of modeled TFP. The solid bars compute these using the TFP-based measure of misallocation, using (17). The shaded bars are calculated by taking raw input observed in the data and augmenting them by the estimated τ and Λ, where relevant. 95% confidence intervals from 200 bootstrap replications are plotted.

Table C7: Coefficients of variation in factor and output prices by township

	Chachoengsao	Lopburi	Srisaket
Land rent (per rai)	0.5197	0.4376	0.4552
Wage (hourly)	0.7179	0.5652	0.9919
Planting wage (hourly)	0.6822	0.4718	0.8543
Weeding wage (hourly)	0.5899	0.5312	0.5830
Harvest wage (hourly)	0.6151	0.5480	0.9213
Price of rice seed (per kg)	0.2663	0.2069	0.1096
Price of chem. fert. (per kg)	0.1780	0.1413	0.0946
Power tiller rental (per rai)	0.2749	0.4121	0.6040
Large tractor rental (per rai)	0.2093	0.3669	0.2870
Output price of rice (per kg)	0.0944	0.1148	0.0853

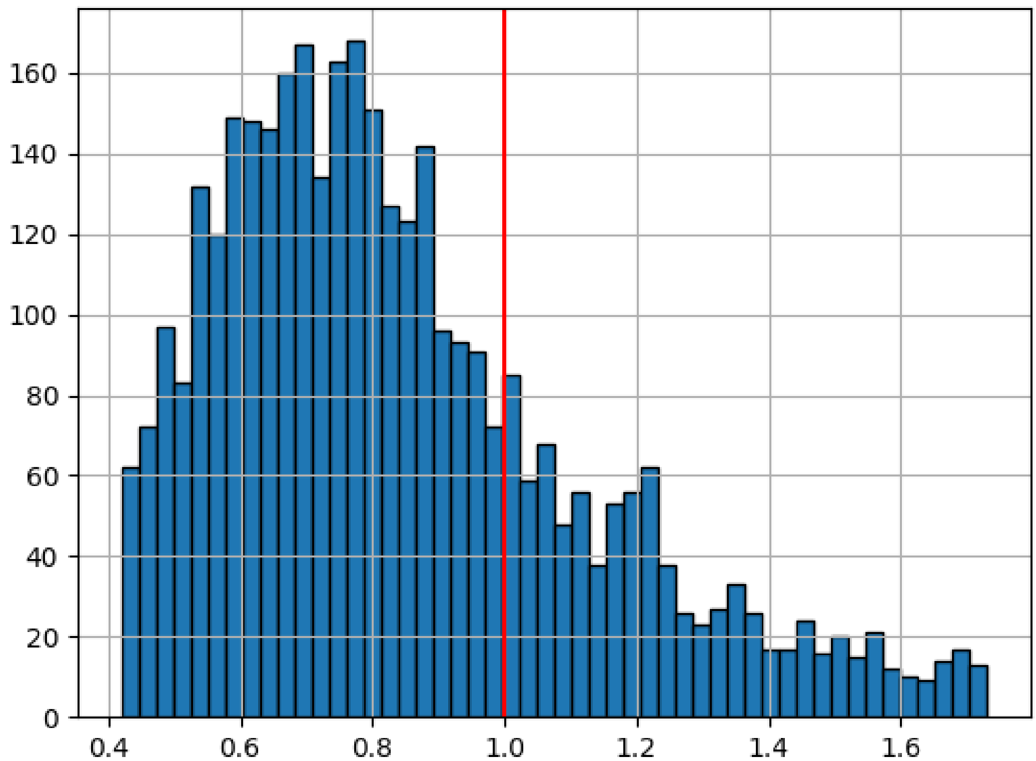
This table shows the coefficients of variation of input and output prices within each township averaged across years. The top panel shows the inputs that I assume are distorted, while the bottom panel shows those that I assume are freely traded. The coefficients of variation are computed at the township-year level after trimming outlier per-unit plot-level expenditures at the upper and lower 2.5% tails and restricting the sample to inputs/outputs with at least 20 observations within a township-year. The three townships shown are those that nearly universally produce rice. The data do not contain the number of days that tractors or power tillers are used — therefore the unit prices I compute are the total expenditure for each type of machinery at the plot level divided by the plot area. Therefore, much of the price dispersion depicted is likely to result from number of days used, machine sizes, or measurement error. Since a more diverse range of crops is grown in Buriram, there is additional heterogeneity due to varieties of seed and fertilizers used for different crops (which I observe). When accounting for this heterogeneity, similar patterns of high price dispersion in land and labor but low price dispersion for traded inputs and outputs emerge.

Figure C8: Land Distribution



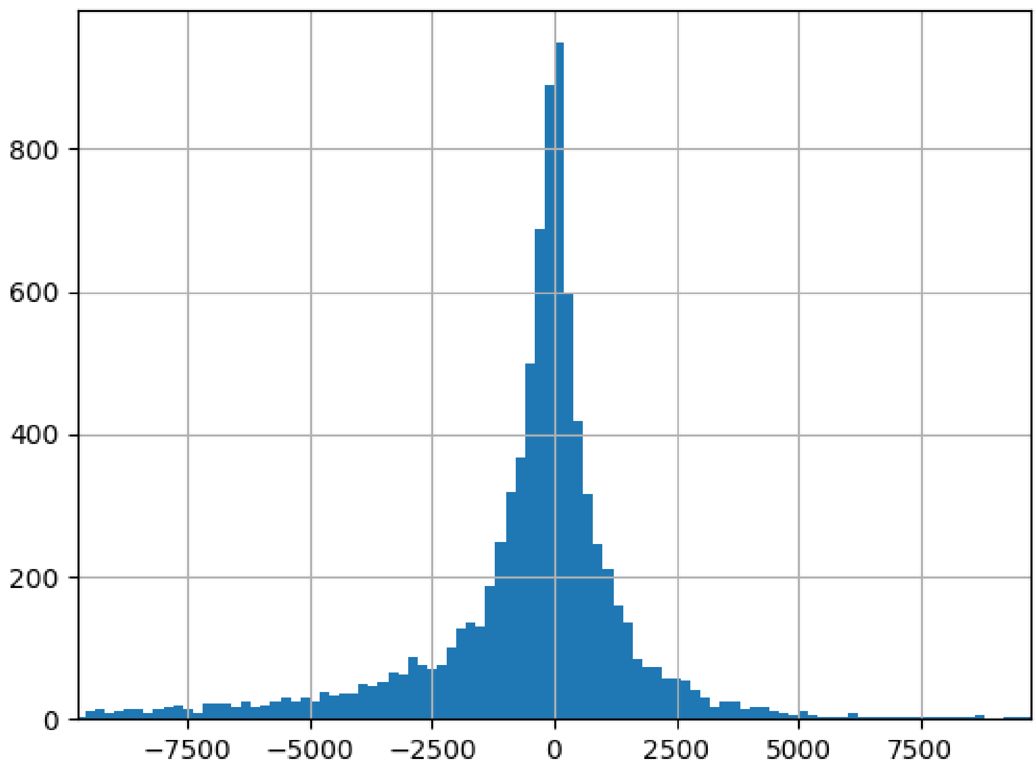
This figure shows the distribution of land under the baseline and main counterfactuals as a function of baseline welfare, which is the negative of the log MUE. The scatter plots are shown with a lowess fit. This is shown for the closed economy case, using fertilizer as the normalizing input, CFE demands, and restricting the sample to rice crops at the farm level.

Figure C9: Histogram of Λ



This figure plots the distribution of the estimated Λ_{jt} as described in Section 4.4. Perfect financial markets would imply a value of 1 for all households, while lower values reduce demand for risky inputs. Values above 1 suggest that agriculture is a hedge against some other income stream. Values are trimmed at the 5% upper and lower tails.

Figure C10: Household Forecast Errors



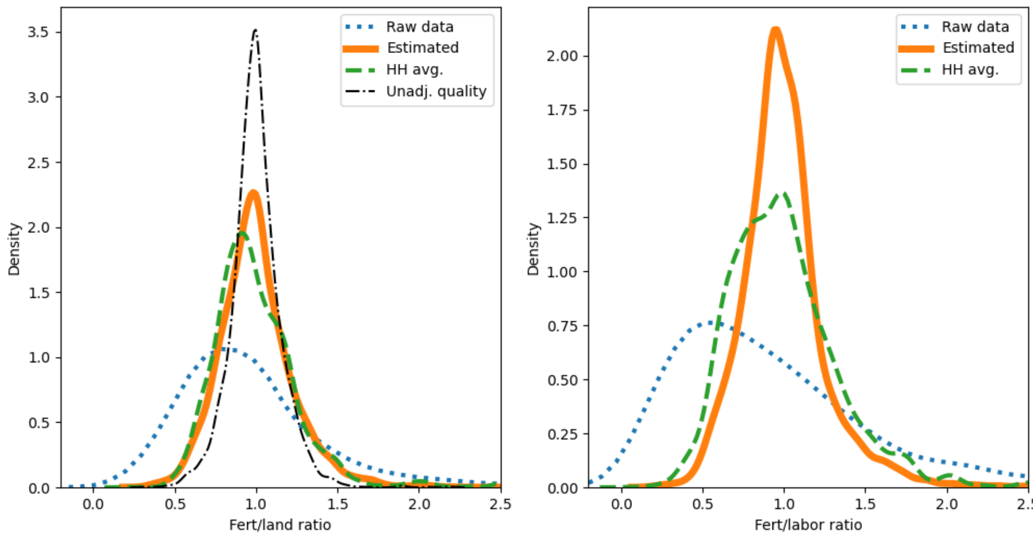
This figure shows the difference between realized rice harvests and elicited predictions at planting in kilograms. The figure is truncated at +/− 10,000 kg for appearance. The mean forecast error is -691kg, relative to an average harvest of 4,500kg, which is driven by households underpredicting (or overreporting) large harvests. In logs, the average household underpredicts harvest quantity by about 6%.

Table C8: Production function results with labor as single input

	α
Equip.	0.163
	(0.011)
Fert.	0.098
	(0.011)
Labor	0.27
	(0.018)
Land	0.272
	(0.01)
Seed	0.082
	(0.011)
J-stat	69.45
p-val	0.0
γ	0.8852
Instruments	5 lags of λ
Clustered wt. matrix	False

This table presents production function estimation results aggregating planting, weeding, and harvest labor into a single input. An annual discount factor of $\delta = .95$ is assumed. Results are computed using farm-level data, fertilizer as the normalizing input for τ, CFE demands, and both rice and non-rice crops. All specifications use tambon dummies and lags of λ_{jt} from the 5 months before input k is first applied. The J-statistic and p-values reported are from a test of the model with the full instrument set against one with only tambon dummies and a single lag of λ_{jt}. γ is the returns to scale parameter implied by the sum of the production coefficients. Standard errors are computed from 128 bootstraps of the full estimation procedure at the household level.

Figure C11: Kernel density estimation of τ by input (fertilizer)



This figure plots kernel density estimates of τ for land and each labor input using fertilizer as the normalizing input. The blue lines show the density of raw input ratios relative to the township-year mean, the green lines show the density of household average input ratio relative to the township means and the orange lines show the estimated τs following (25). The black line in the left panel shows the density for τ_{LAND} when not adjusting for land quality. An Epanechnikov kernel is used.

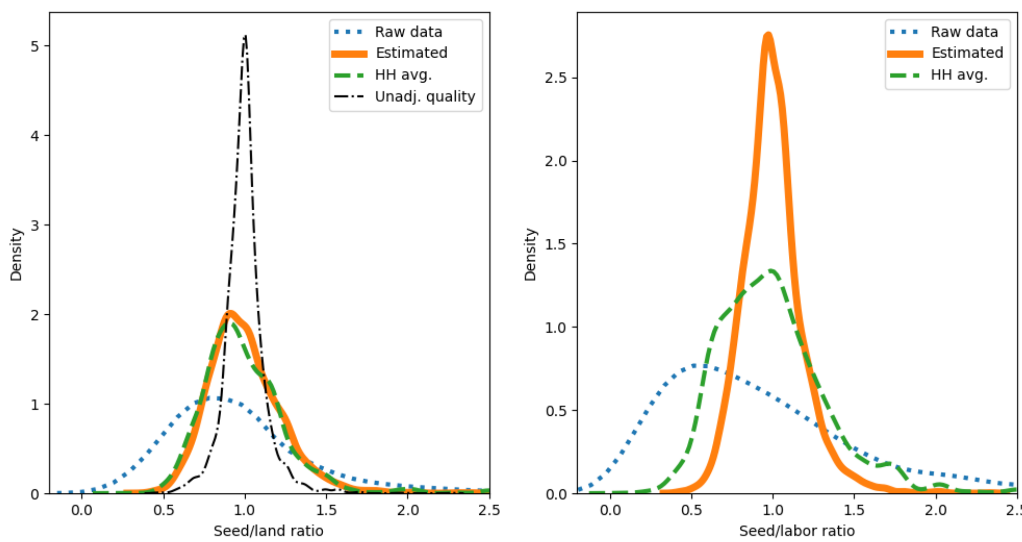
Table C9: Correlation between estimated financial distortions and household access to finance

	Dependent variable:					
	Savings bal.	Debt bal	Credit bal.	Gifts made	Gifts rec'd.	Net gifts
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \Lambda$	0.33***	0.11*	0.12	0.29***	0.16***	
	(0.09)	(0.07)	(0.20)	(0.10)	(0.05)	
Λ						−10,425.33
						(9,330.07)
Village + Time FE	Yes	Yes	Yes	Yes	Yes	
Observations	5,442	4,951	561	4,966	5,808	5,830
Adjusted R^2	0.17	0.20	0.19	0.03	0.27	0.02

*p<0.1; **p<0.05; ***p<0.01

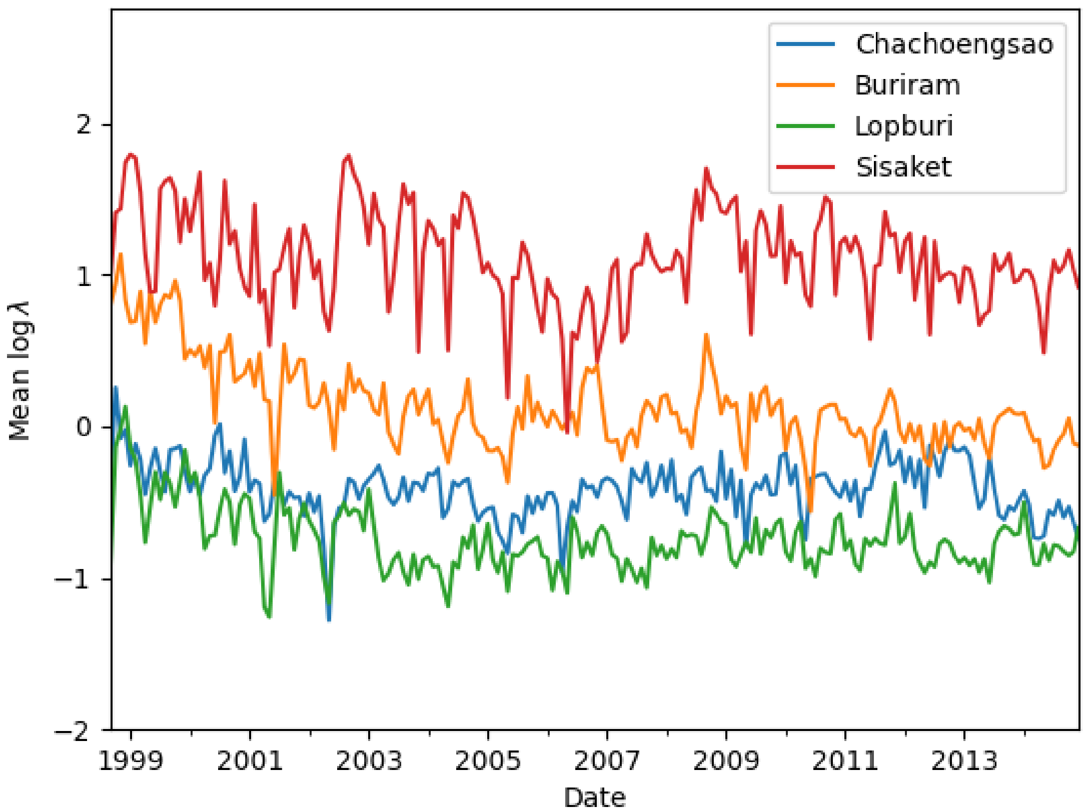
This table describes the correlation between estimated financial distortions Λ and survey measures of participation in financial networks. The dependent variables are the logs of (self-reported) savings, outstanding balances of loans taken, gifts made and gifts received and the level of net gifts flows in each year. In this context, gifts can be thought of as state-contingent transfers between households (Kinnan and Townsend, 2012). The results indicate that households that are less financially constrained (higher Λ) on average have more savings, larger loans, and greater participation in mutual insurance networks. Results include village and year fixed effects and standard errors are clustered at the household level.

Figure C12: Kernel density estimation of τ by input (seed)



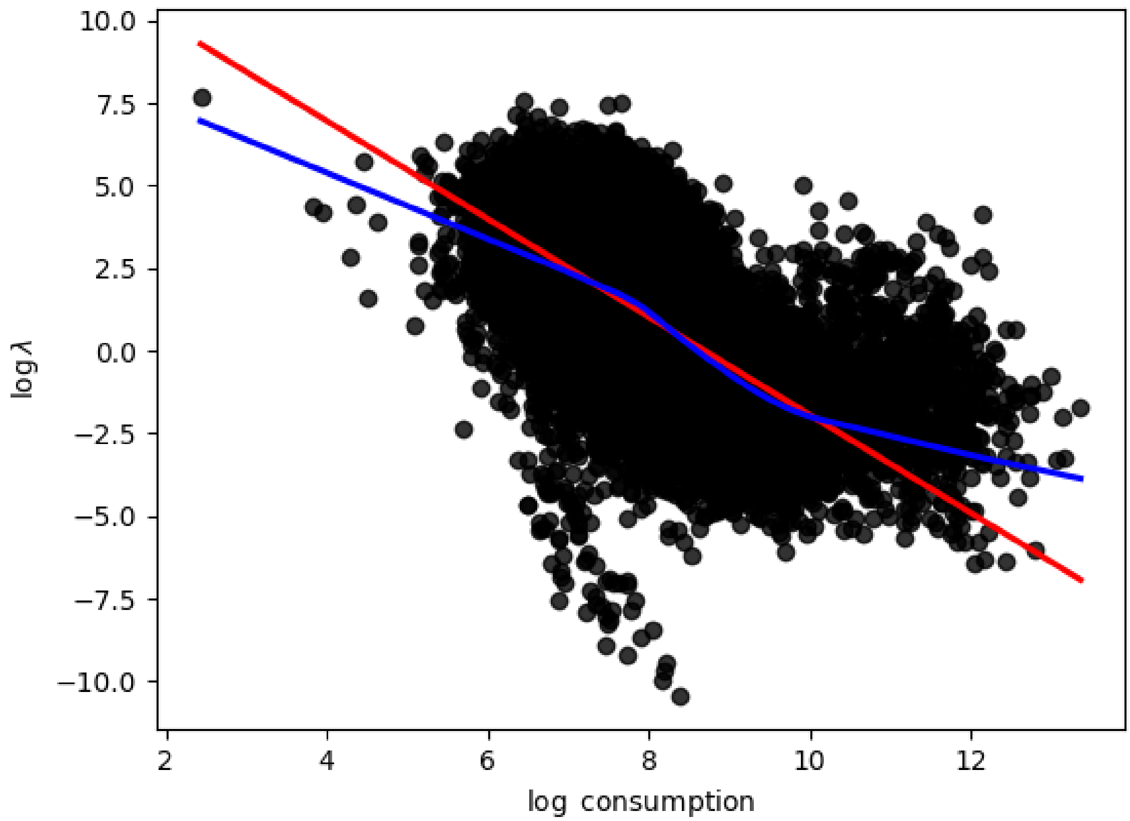
This figure plots kernel density estimates of τ for land and total labor input using seed as the normalizing input. The blue lines show the density of raw input ratios relative to the township-year mean, the green lines show the density of household average input ratio relative to the township means and the orange lines show the estimated τs following (25). The black line in the left panel shows the density for τ_{LAND} when not adjusting for land quality. An Epanechnikov kernel is used.

Figure C13: Time series plots of log λ by tambon



This figure plots the time series of the mean log λ, estimated from the CFE demand system of Ligon (2020) over the 196-month sample period in each tambon (township).

Figure C14: Relative risk aversion under CFE demands



The figure plots estimated log λs against the log of consumption after partialing out month fixed-effects. The slope of the graph at any point is (minus) the coefficient of relative risk aversion under von Neumann-Morgenstern preferences. The red line is the estimate of relative risk aversion when imposing CRRA preferences, while the blue line is a Lowess fit of the relative risk aversion implied by CFE demands.

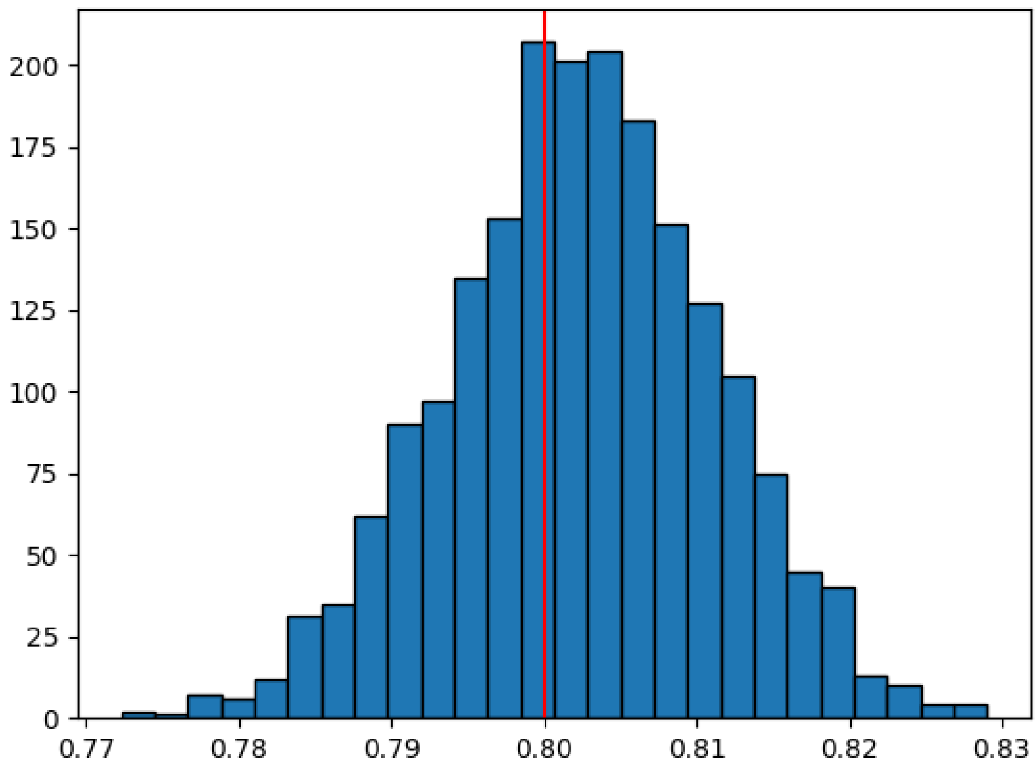
Table C10: Production shocks' effect on interhousehold transfers

	Dependent variable:				
	Gifts made	log gifts made	Gifts recieved	log gifts recieved	Net gifts
	(1)	(2)	(3)	(4)	(5)
Shock (s.d)	4,032.94*		−219.65***		−4,252.59**
	(2,154.06)		(81.81)		(2,159.53)
log shock		0.11*		−0.10***	
		(0.06)		(0.03)	
Village + Time FE	Yes	Yes	Yes	Yes	Yes
Observations	4,398	4,110	4,398	4,381	4,398
Adjusted R^2	0.02	0.15	0.16	0.29	0.02

*p<0.1; **p<0.05; ***p<0.01

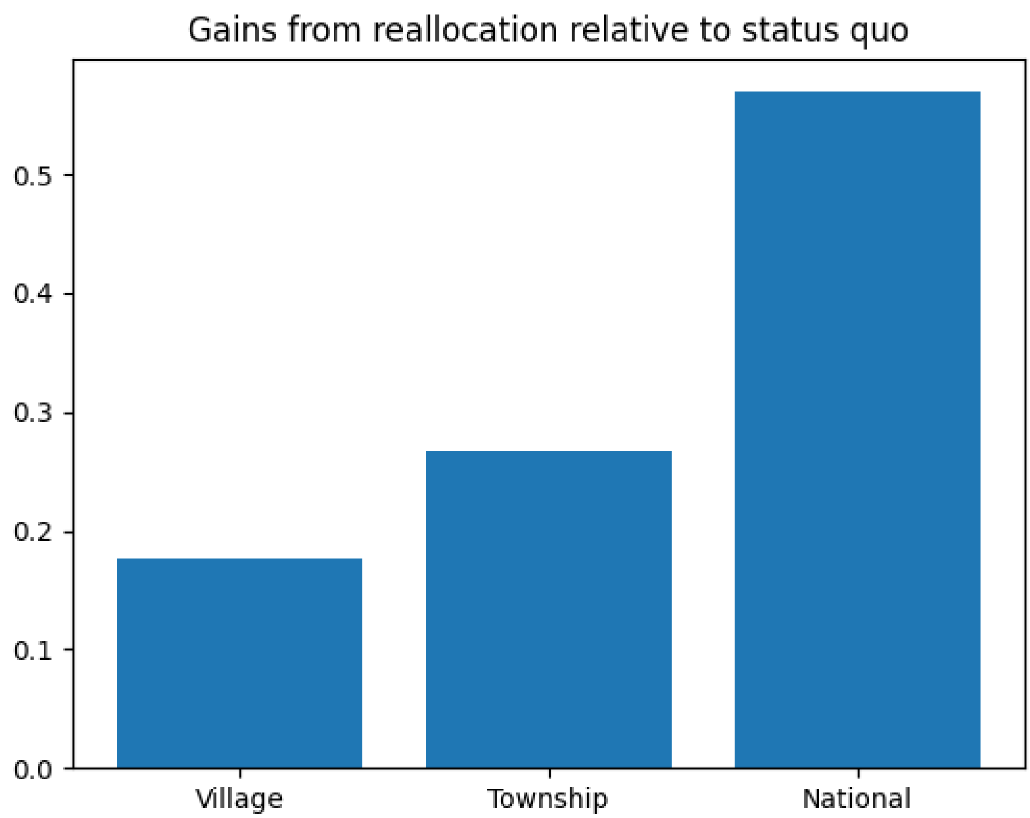
This table describes the correlation between estimated production shocks φ and survey measures of participation in gift exchange networks. In this context, gifts can be thought of as state-contingent transfers between households (Kinnan and Townsend, 2012). Odd-numbered columns are estimated in levels and even-numbered columns are estimated in logs. The results indicate that households make significantly larger outgoing transfers and receive significantly smaller transfers when they experience positive production shocks. Results include village and year fixed effects and standard errors are clustered at the household level.

Figure C15: Monte Carlo Simulations of Estimation with Aggregate Shocks



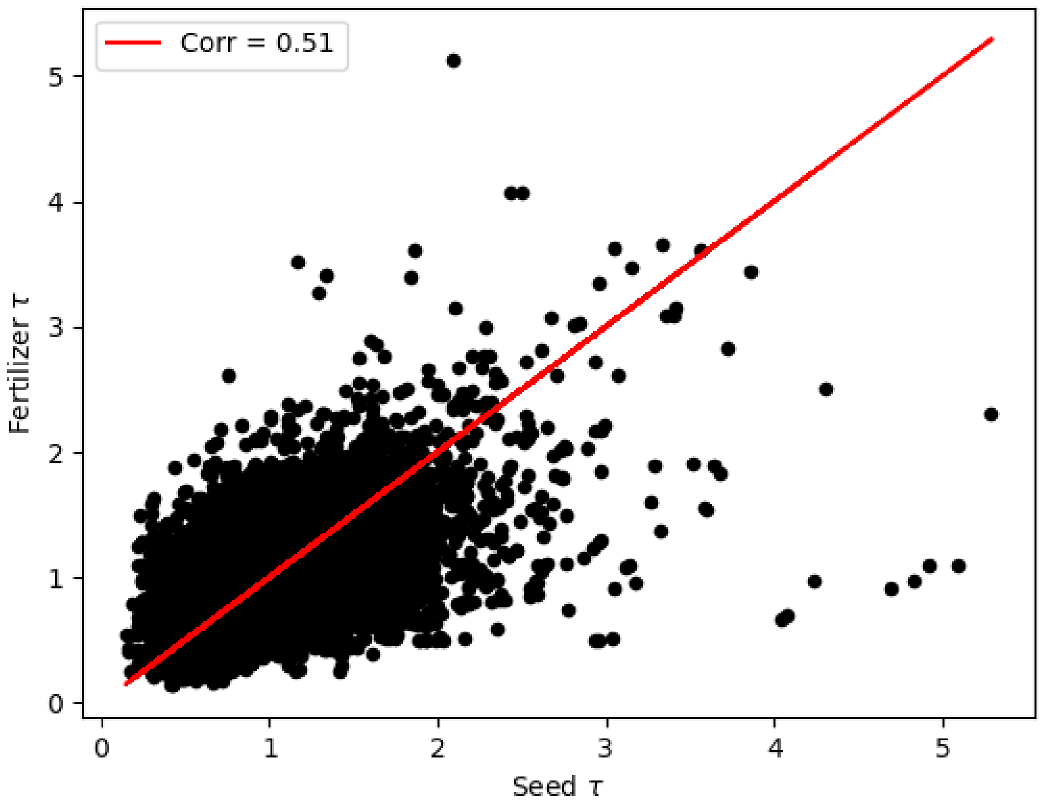
This figure presents a histogram of the regression coefficients of 1,000 Monte Carlo simulations of the GMM estimator. I develop a simulated data-generating process under a single-input production function with $\alpha = 0.8$ and CRRA preferences with $\theta = 1.5$. I simulate an $N = 1,000$ by $T = 16$ year panel. For each t, I draw $\phi_{jt} \sim \mathcal{N}(\mu_t, \sigma)$ where the μ_t's themselves are drawn from a $\mathcal{N}(0, \sigma)$ distribution. In the main simulations, I choose $\sigma = 0.4$ (to match the variance of the residuals in Section 4.3.1). I then apply the GMM estimator to each simulated dataset. The distribution of coefficients is centered near the true value of 0.8 (indicated by the red line in the figure) with a mean of 0.8024 standard error of 0.0087.

Figure C16: Potential gains from full reallocation



This figure shows the total gains from the efficient allocation as a percent of status quo aggregate TFP when aggregating at the village, township, and national levels.

Figure C17: Comparison of τs estimated with fertilizer and seed as normalizing input



The figure plots τs using seed as the normalizing input on the x-axis and with fertilizer as the normalizing input on the y-axis. The τs are pooled across all inputs. The 45° line is plotted in red and the correlation coefficient between both sets of τs is 0.51.

D More on CFE Demands

I provide additional details on the CFE demand system of Ligon (2020) used for the main results. CFE demands satisfy the condition that $\log p_i c_i = a_i(p) + b_i(z) - \beta_i \log \lambda$, where expenditures on good i depend on functions of the price vector p and household characteristics z and are log-linear in λ. β_i is the eponymous constant elasticity, which imposes that the elasticity of expenditure on good i with respect to the marginal utility of expenditure (as opposed to total expenditure) is a constant. This allows for highly non-linear Engel curves and an unrestricted rank of the demand system. Ligon (2020) shows that CFE is the only globally regular demand system in which identical households with different budgets' demands for goods differ only through a common aggregator. The paper also derives an estimator for the MUE that uses disaggregated consumption data. The key assumption for estimation is that observed 0 expenditures can essentially be treated as a missing data problem. While this may appear strong, the assumption essentially requires that welfare can be inferred from observed expenditures and the Frisch elasticities of those goods. See Ligon (2020) for more detail.

What matters for the model in Section 4 is the curvature of utility. The elasticity of λ with respect to total consumption is (minus) the coefficient of relative risk aversion. If this elasticity is constant, then CFE reduces to the nested CRRA case. The slope of Figure C14 shows that while there does appear to be some curvature in relative risk aversion, there is not a huge difference from CRRA. Accordingly, the results in Table C2 are similar across specifications.