Farm Household Misallocation

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Where does misallocation come from?

And why does it matter?

Micro: Farmers in poor countries face many market failures

- **Input markets:** Land, labor, machinery, seed, fertilizer, . . .
- **Financial markets:** Credit, insurance . . .

Macro: Misallocation is extremely costly

This Paper: Using data from rural Thailand:

- How do different market failures combine to generate misallocation?
- How does (second-best) policy depend on the *full set* of distortions?

Why we need to know the sources of misallocation

Interaction effects between distortions matter for policy

Policies targeting a single distortion depend on distortions in *all* markets (Lipsey and Lancaster 1956)

- Market failures compound or counteract each other in equilibrium
- Policies may reallocate towards HH already inefficiently large
- Considering subset of market failures in isolation can backfire

Need to characterize the full distribution of input and financial distortions

- But not separately identified from production data alone (Hsieh and Klenow 2009)

This paper: Link production and consumption problems

But farm-households are also consumers! Under imperfect markets

1. Consumption tells us how financial frictions affect investment
    - Creates distinct wedges from input frictions
2. Leverage these distortions to structurally estimate production function
    - Recover parameters from well-specified FOCs
3. Allows us to account for correlated distortions in counterfactuals
    - Also helps address concerns over measurement error

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Misallocation more than the sum of its parts

Preview of Results

Separately IDing distortions important for measurement and policy

- Aggregate TFP increases by 20-31% under the efficient allocation

- 11-16% (5-8%) TFP gains from removing financial (input) frictions in isolation

- Additional 4-7% TFP gains from addressing multiple distortions together
  - Financially constrained HH relatively *subsidized* by input markets
  - Diminishing returns to reducing single distortion

- Existing methods produce 39% larger estimates of misallocation
  - And would suggest financial reform *lowers* aggregate productivity

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Contribution

Misallocation in agriculture: Adamopolous and Restuccia (2014;2020), Shenoy (2017), Chari et al (2021) Donovan (2021), Manysheva (2021), Adampolous et al (2022a;b) Aragon et al (2022a;b), Chen et al (2022;2023),

- First to estimate *joint distribution* of input and financial distortions
- Compute counterfactuals that account for offsetting effects

Additional contributions:

- **Measurement error** in agriculture: Arthi et al (2018), Abay et al (2019;2021) and beyond Bils et al (2021), Gollin and Udry (2021), Rotermberg and White (2021)
- **Production function estimation with distorted inputs:** Asker et al (2014; 2019), De Loecker et al (2016), Shenoy (2017; 2021) Cairncross et al (2023)

Roadmap

1. Introduction
2. Data and Descriptives
3. Model
4. Estimation
   - Marginal utility of consumption and input wedges
   - Production Function Estimation
   - Productivity and Financial Distortions
5. Counterfactuals

Background: Thailand

Rural Thailand – 16 villages from 4 changwats (provinces) over 196 months from 1998 to 2014.

Markets functional but imperfect

- Microfinance and informal insurance networks have been extensively studied: e.g. (Kaboski and Townsend 2011,2012; Kinnan and Townsend 2012; Samphantharak and Townsend 2018; Kinnan et al 2023)
- Few drastic misallocative institutions (e.g. land expropriation)

May be more relevant benchmark than full efficiency for LDCs

Setting and data

Townsend Thai Data –196 months from 1998 to 2014

- Monthly input expenditures, output and consumption
- Rich data on HH assets and investments

708 of 775 HH engage in agriculture. Rice the main crop.

- Median farm sizes between 2-5 ha
- Active labor market, less active land rental market
- Fertilizer and mechanization common

Wage labor, aquaculture, other businesses common

- Average household earns $\approx 50\%$ of income off own farm

⏩ Summary Statistics

Do markets actually fail in Thailand?

Literature on financial frictions using Townsend Thai Data

- Causal effects of Million Baht Village (credit) program
- Propagation of shocks

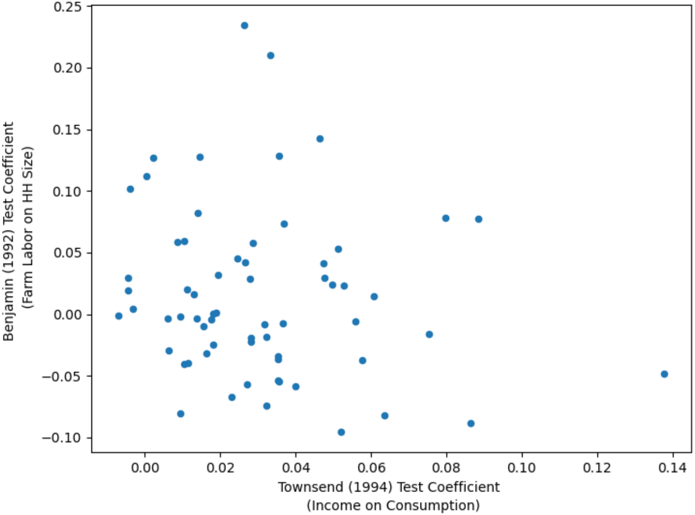
Canonical tests of complete markets reject

- Townsend (1994) test of full insurance
  - H_0 Income shocks have no effect on consumption
- Benjamin (1992) test of separability
  - H_0 Labor intensity doesn't depend on family size

Reject complete markets

	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

Test coefficients negatively correlated across villages



Suggests input and financial distortions may offset each other

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One-sector Farm Household Model

Households (j):

- Maximize discounted sum of expected utility, $\sum_{s=t}^{\infty} \mathbb{E}_t[\delta^{s-t} u(c_{js})]$
- Produce numeraire good, receive stochastic endowment income
- Can save, but may face borrowing constraints and imperfect insurance

Markets:

- K factors of production in fixed supply at the village level
- Households may face arbitrary taxes or rations on inputs
- Assume perfect markets for output and goods ⏩ Evidence

Production

Common production technology F with K (static) inputs $q_1, \ldots, q_K$

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

Timing:

- Season t: Choose inputs
- Season $t+1$: realize shock $\varphi_{jt+1} \equiv \frac{e^{\phi}_{jt+1}}{\mathsf{E}[e^{\phi}_{jt+1}]}$ before harvest

Optimization: Summarized by three FOCs

Dynamic HH problem collapses to 3 sets of FOCs

1. Equate marginal utility of expenditure across goods

$$u_i(c_{jt}) = \lambda_{jt} p_{it}$$

2. Equate marginal utility of expenditure across periods (Euler)

$$\lambda_{jt} = \delta R_{jt} \mathbb{E}_t[\lambda_{jt+1}] + \bar{\mu}_{jt}$$

3. **Not** equate expected marginal products of k to common price

$$\bar{w}_{kt} \tau_{jkt} = \delta \frac{\mathbb{E}_t \left[\lambda_{jt+1} F_k(q_{jt}, \varphi_{jt+1}) \right]}{\lambda_{jt}}$$

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3. **Not** equate expected marginal products of k to common price
   Except under perfect markets

$$\bar{w}_{kt} \tau_{jkt} = \delta \mathbb{E}_t \left[F_k(q_{jt}, \varphi_{jt+1}) \right]$$

Identifying distortions from FOCs

Marginal products weighted by IMRS equal HH $j's$ shadow price

$$\bar{w}_{kt}\tau_{jkt} = \delta\frac{\mathbb{E}_t\left[\lambda_{jt+1}F_k(q_{jt},\varphi_{jt+1})\right]}{\lambda_{jt}}$$

where $\lambda = u'(c)$

- Input frictions drive wedge τ_{jkt} btwn shadow and market price for k
- Binding credit constraints $\implies \lambda_{jt} > \delta\mathbb{E}_t[\lambda_{jt+1}]$
- Imperfect insurance $\implies c_{jt+1}$ depends on φ_{jt+1}, $cov_t(\lambda, F_k) \neq 0$

Note: Agnostic towards specific institutions that generate distortions

Production: Generalized Cobb-Douglas

Production: Following Just and Pope (1979): K factors of production $q_1, \ldots, q_k$ at time t, mean 0 production shock $\varphi \equiv e^{\phi} - \mathbb{E}[e^{\phi}]$ and output Y realized the following period.

$$Y_{t+1} = A_t \prod_k^K q_{kt}^{\alpha_k} + \varphi_{t+1} B_t \prod_k^K q_{kt}^{\beta_k}$$

- Inputs are "riskier" the higher β_k is relative to α_k
- Nests Hicks-neutral Cobb-Douglas if $\alpha = \beta$ and $B = A/\mathbb{E}[e^{\phi}]$
- $\gamma \equiv \sum_k \alpha_k < 1$: Ensures a non-degenerate efficient allocation

Input FOCs: Generalized CD

Demands for each input can be written

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

Two different financial wedges:

- Credit constraints: $\mathbb{E}_t[\lambda_{jt+1}]/\lambda_{jt}$ governed by α
- Uninsured risk: $cov_t(\lambda_{jt+1}, Y_{jt+1})/\lambda_{jt}$ governed by β
- Under full insurance β doesn't affect input demands

Nonhomothetic generalization of Hicks-neutral Cobb-Douglas (HNCD)

- But requires stronger ID assumptions
- Focus on HNCD for today but will show results from both

Input FOCs: Hicks-neutral CD

Financial frictions constant across inputs

Under Cobb-Douglas input demands simplify to

$$q_{jkt} = \alpha_k \delta \frac{\mathbb{E}_t[Y_{jt+1}]}{\bar{w}_{kvt}\tau_{jkt}} \underbrace{\frac{\mathbb{E}_t[\lambda_{jt+1}\varphi_{jt+1}]}{\lambda_{jt}}}_{\Lambda_{jt}}$$

where single financial distortion Λ_{jt} applies equally to all inputs

- Homothetic: Financial wedges Λ_{jt} only affect *scale* of production
- Only τ_{jkt} affects *composition* of production
- Obtain efficient allocation when $\tau = \Lambda = 1$ Generalized NH version

Separate Identification of Distortions

To see this divide demands for inputs k and l

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

- Financial distortions Λ_{jt} (and TFP) cancel out
- Ratios of τs are (inversely) proportional to ratios of inputs
- If input K freely traded within villages ($\tau_K = 1$), absolute τs ID'ed
  - Plausibly holds for fertilizer and seed ⏩ Evidence

What Determines Misallocation in Equilibrium?

Efficient allocation is just a function of relative TFP

Let ω_{jk} be the share of input k allocated to j (dropping time subscripts)
Under perfect markets

$$\omega_{jk} = \omega_j^* \equiv \frac{A_j^\eta}{\sum_j A_j^\eta}$$

where $\eta \equiv \frac{1}{1-\gamma}$ where $\gamma < 1$ is returns to scale.

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where $\eta \equiv \frac{1}{1-\gamma}$ where $\gamma < 1$ is returns to scale. In general: inputs allocated proportionally to

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

Can directly compute aggregate TFP with estimates of A, τ, Λ and α.

Roadmap

Empirical Approach: Roadmap

Estimate $\{A, \Lambda, \tau, \alpha\}$ as follows

1. Estimate marginal utilities λ from consumption data

 $\rightarrow \lambda$

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,  / 

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Empirical Approach: Roadmap

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    $\rightarrow \lambda$

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    / ,  /  $\rightarrow \tau_T, \tau_L$

3. Use λ and τ to estimate α from input FOCs.

    ,  ,  ,  $, \lambda, \tau \rightarrow \alpha, A, \varphi$

Empirical Approach: Roadmap

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1. Estimate marginal utilities λ from consumption data

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4. Estimate Λ from the covariance between marginal utilities (ex-post) λ and production shocks φ

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4. Estimation
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Estimating λ and τ

Standard but non-trivial

Marginal utility of expenditure: λ

- Most general case: CFE demand system (Ligon 2020)
  - Non-homothetic and unrestricted rank
  - Nests CRRA and other common function forms.
- Results similar to CRRA ($\lambda \equiv c^{-\theta}$) Details

Input wedges: τ_k Details

- Ratios of input wedges τ proportional to ratio of inputs
  - Common in the misallocation literature
- In the paper: More to address input heterogeneity and meas. error
  - Little effect on estimation results or qualitative conclusions from CFs

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Production Function Estimation

λ and τ allow identification of α from distorted input demands

Challenges:

- Endogeneity concerns especially relevant when input choices distorted
- Structural approaches that rely on profit maximization not valid

But λ and τ tell us *how* input choices distorted

- Under rational expectations α identified from household optimization
- Anticipated shocks factored into these decisions
- Holds for all HH producing — less concern over sample selection
- Estimate with linear GMM (Hansen and Singleton 1982)

Estimate α from input demand moment conditions

Rearrange the FOC and write (shadow) expenditure on input k as $x_{jkt} \equiv \bar{w}_{kv} \hat{\tau}_{jkv} q_{jkv}$

$$\delta \alpha_k \mathbb{E}_t[\lambda_{j,t+1} Y_{j,t+1}] - \lambda_{jt} x_{jkt} = 0 \tag{1}$$

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Under rational expectations, can use GMM

- All time t info reflected in choices of consumption and investment.
- Realizations and expectations only differ by mean-zero forecast errors

$$\zeta_{jt+1} \equiv \lambda_{jt+1}Y_{jt+1} - \mathbb{E}_t[\lambda_{jt+1}Y_{jt+1}] \tag{2}$$

- Implies these are uncorrelated with time t info set.
  - Provides candidate instruments to overidentify the model.

Rational expectations = realizations on average

Substitute (2) into (1) and take sample counterpart

$$g_{NT}(a) \equiv \frac{1}{NT}\sum_t \sum_j \delta a(\lambda_{j,t+1} Y_{j,t+1} - \lambda_{jt} x_{jkt}) \otimes h(z_{jt}) = 0 \qquad (3)$$

for a function $h(z_{jt})$ of variables in households' time t information sets.

- Lags of λ from before t are natural candidates for z_{jt}

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GMM estimate of α is

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

for (asymptotically efficient) weighting matrix W

Caveat: αs identified up to time-preference discount factor δ

- Use $\delta = .95$. Also compute results with Kaboski and Townsend (2011) estimate of 0.924

Details Generalized CD

Production Function Results

	α CD	α NH	β NH
Equip.	0.167	0.163	0.163
	(0.004)	(0.002)	(0.005)
Fert.	0.099	0.100	0.107
	(0.002)	(0.001)	(0.003)
Harv. Labor	0.173	0.179	0.194
	(0.009)	(0.010)	(0.017)
Land	0.208	0.138	0.288
	(0.005)	(0.011)	(0.055)
Plant. Labor	0.060	0.109	0.190
	(0.003)	(0.009)	(0.021)
Seed	0.085	0.084	0.111
	(0.001)	(0.001)	(0.003)
Weed. Labor	0.017	0.044	0.043
	(0.001)	(0.004)	(0.006)
J-stat	25.62	39.22	
p-val	0.594	0.077	
γ	0.809	0.817	
s.e.	(0.011)	(0.018)	

Bootstrapped standard errors at HH-level

Hicks-neutral CD

- Coefficients take reasonable values relative to ag. literature
- $\gamma \approx 0.81$ closer to CRS than most of the misallocation literature
- Results highly consistent across specifications
- Fail to reject overidentifying restrictions implied by lagged λs

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Bootstrapped standard errors at HH-level

Nonhomothetic CD

- Broadly similar to HNCD despite different τs
- Early-season inputs (land, planting labor, seed) appear relatively risk-augmenting
- Reject overidentifying restrictions at 10%

GMM Estimates of α: Robust across specifications

	Fert τ (Main) (1)	Seed τ (2)	CRRA (3)	Rice (4)	Plot-level (5)
Equip.	0.167	0.171	0.168	0.154	0.192
	(0.004)	(0.004)	(0.004)	(0.004)	(0.033)
Fert.	0.099	0.099	0.100	0.096	0.112
	(0.002)	(0.002)	(0.002)	(0.002)	(0.013)
Harv. Labor	0.173	0.176	0.165	0.190	0.183
	(0.009)	(0.014)	(0.009)	(0.009)	(0.017)
Land	0.208	0.215	0.205	0.205	0.233
	(0.005)	(0.005)	(0.005)	(0.004)	(0.016)
Plant. Labor	0.060	0.063	0.054	0.056	0.059
	(0.003)	(0.004)	(0.003)	(0.003)	(0.018)
Seed	0.085	0.085	0.084	0.089	0.092
	(0.001)	(0.001)	(0.001)	(0.001)	(0.013)
Weed. Labor	0.017	0.017	0.017	0.019	0.022
	(0.001)	(0.001)	(0.001)	(0.001)	(0.019)
J-stat	25.62	41.11	12.38	97.89	265.67
p-val	0.594	0.052	0.995	0.0	0.0
γ	0.809	0.826	0.791	0.81	0.893
s.e.	(0.011)	(0.016)	(0.011)	(0.011)	(0.052)

▸▸ NH results ▸▸ Single labor input

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Recovering A and φ

Productivity shocks not predictable with time t info

Main specification: Use household average realized TFP as measure of A_{jt}

- Deviations from average TFP at $t+1$ not predicted by info at t
  - Out of sample $R^2 \approx 0$ Details

Deviation from average within-HH TFP is φ_{jt+1}

Recovering Λ

Learn the conditional expectation with rich baseline info

After separating A and φ need to recover Λ_{jt}

$$\Lambda_{jt} \equiv \frac{\mathbb{E}_t[\lambda_{jt+1}\varphi_{jt+1}]}{\lambda_{jt}}$$

Λ is HH j's expectation of how next period's welfare depends on realization of consumption shock, *conditional on time t information*

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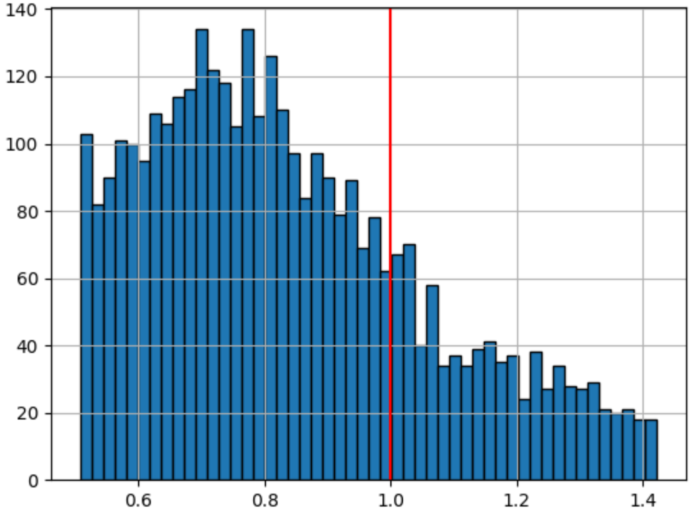
- Function of time-varying state variables (e.g. ag production, other assets, position in insurance networks etc...)
- Rational expectations still implies that subjective $\mathbb{E}_t[\lambda_{jt+1}\varphi_{jt+1}]$ equals realized $\lambda_{jt+1}\varphi_{jt+1}$ on average
- **Solution**: Use ML to learn this function, leveraging rich data on households' full balance sheets in the Thai survey.
  - Similar results using a linear predictor

Details

Histogram of Λ

$\Lambda = 1$ under perfect financial markets benchmark



Moderate financial constraints for most HH

Mean of 0.87, median 0.8.

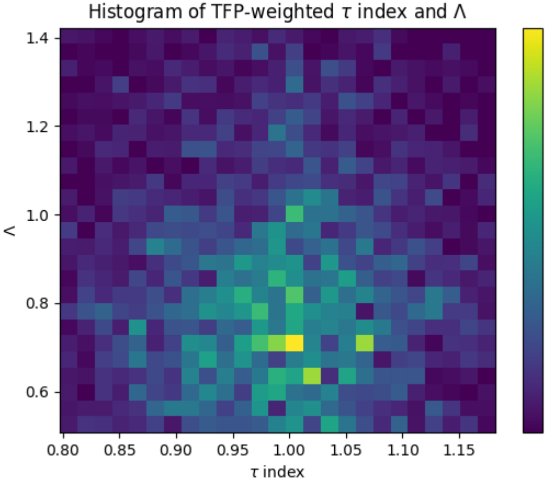
- Implies median household produces at only 47% of its desired scale
  - Elasticity of input demand w.r.t Λ is $\eta \approx 5.2$
  - Broadly consistent with other evidence (Kaboski and Townsend (2011;2012)
- $\Lambda > 1$ for 28% of households — suggests that agriculture is a hedge against other income sources (Kochar 1996).

Validation: Correlated with (untargeted) observables in the data Tables

- Less financially constrained households have higher savings, credit use and participation in risk-sharing networks.

Financially constrained HH subsidized on inputs

Policy impacts governed by TFP-weighted covariance of τ and Λ



- τ and Λ positively correlated (slope = .04 , $p =$.01)
- Consistent w/ poorer households over-supplying labor to own plots (Dillon et al 2019, Jones et al 2022)

More figures

Roadmap

1. Introduction
2. Data and Descriptives
3. Model
4. Estimation
   - Marginal utility of consumption and input wedges
   - Production Function Estimation
   - Productivity and Financial Distortions
5. Counterfactuals

Counterfactuals

We can now compute aggregate TFP under anyl values of Λ and τ

- Status quo
- Remove financial distortions, leave τs unchanged
- Remove input market distortions, leave Λ unchanged
- Remove all distortions

Note this does not capture the direct effects of τ on λ and vice versa

- Requires more explicit stance on mechanisms distortions
- However, input subsidies for poor HH suggest gains further attenuated

Counterfactuals and Measurement Error

Two ways to compute any counterfactuals

1. **TFP-based:** Compute ω^* and multiply by estimated distortions
2. **Input-based**: Take the observed allocation and divide out estimated distortions

Raw input measurement enters (2) but not (1)

- Need estimates of both Λ and τ to compute both

Counterfactuals and Measurement Error

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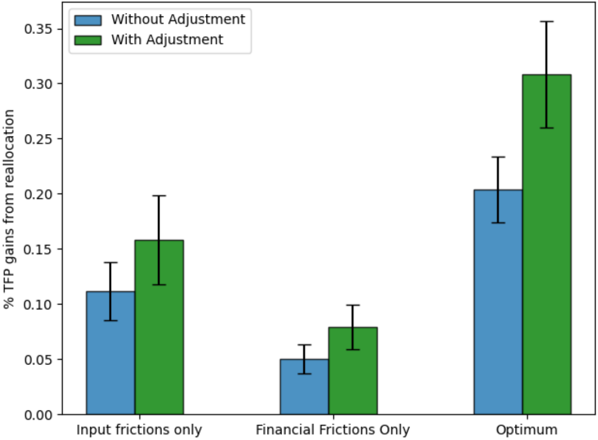
In math: Under perfect measurement efficient allocation can be written

$$\omega_j^* = \frac{A_j^\eta}{\sum_j A_j^\eta} = \frac{q_{jk}^{OBS} \tau_{jk} \Lambda_j^{-\eta} \prod_l \tau_{jl}^{\alpha_l \eta}}{\sum_{h=1}^{N_v} q_{hk}^{OBS} \tau_{hk} \Lambda_h^{-\eta} \prod_l \tau_{hl}^{\alpha_l \eta}}$$

Gains from reallocation (as % of baseline TFP)

Moderate but more than the sum of its parts



- 20-31% Gains from full reallocation
- W/ and w/o aggregate supply response of intermediates
- More than sum of gains from perfecting single market

Misallocation: More than the sum of its parts

- 11% (5%) gains from removing financial (input) distortions alone
- Why do they sum to less than 20%?
  - Financially constrained farmers relatively subsidized on inputs (labor)
  - Poor HH oversupply labor to own farm (LaFave and Thomas 2016)
- Relaxing financial constraints requires exacerbating input distortions
- Simultaneously reducing input frictions helps overcome this

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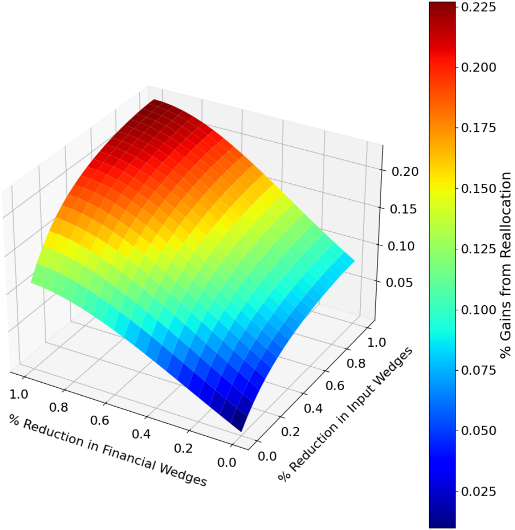
Gains from full reallocation

- Similar in magnitude to Shenoy (2017) also in Thailand
- Compare to estimates of 53% in China , 97% in Ethiopia , 259% in Malawi and 286% in Uganda from land markets alone (Adamopolous et al 2022, Chen et al 2021, Restuccia and Santaeulalia-Llopis 2017, Aragon et al 2022a, respectively)

Diminishing returns to reducing individual distortions

Can compute TFP under *any* values of Λ and τ

- Uniform reductions in each of Λ and τ
- Approximate marginal effects of policy
- Trace out planner's expansion path

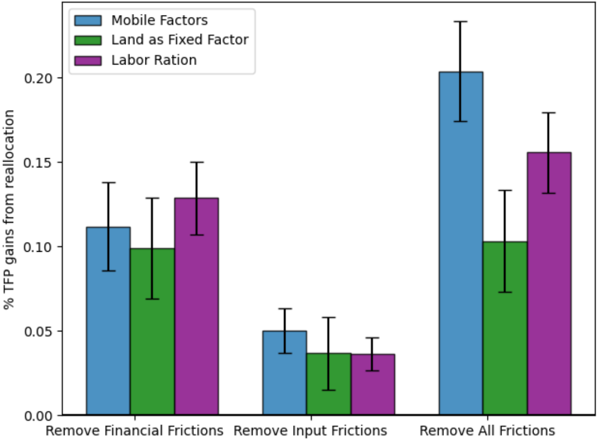


Extended graph

Results under input rations

Results above implicitly assumes τs function as a tax

- What if they act as rations?



Green bars treat land as fully fixed factor

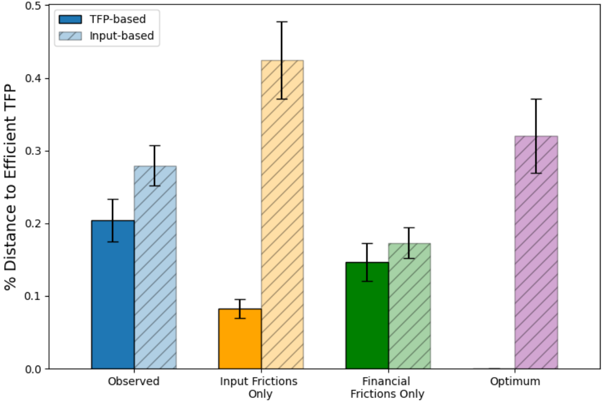
- Only about 25% of baseline TFP gains

Purple bars assume downward labor ration

- Financial reform slightly more effective

What would we conclude using input-based measure?

Introducing raw input measurement leads to:



- Up to 39% larger misallocation in the status quo
- Removing financial frictions *increases* misallocation
- Implied "optimum" worse than observed allocating

Measurement error *looks like* a spurious distortion

More Results

⏩ CRRA ⏩ Seed τ ⏩ Rice plots only ⏩ Ignore unobserved land quality

Plot level data

- Input-based measure increases, TFP-based measure similar
- Consistent with Gollin and Udry (2021) ⏩ Figure

Who gets reallocated to?

- Efficient allocation much more concentrated
- HH in the middle of the income distribution expand more ⏩ Figure

Misallocation doesn't seem to be decreasing over time

- Input misallocation stays flat
- Financial misallocation slightly increasing ⏩ Figure

Spatial heterogeneity

- Same qualitative patterns but much lower in wealthier provinces ⏩ Figure

Conclusion

- Develop a novel, theory-consistent approach to production function estimation when input choices are distorted.
- Full reallocation would only increase aggregate productivity by 20-31%.
  - About 56% of gains attainable by financial reform alone, 25% by input reform alone
- Gains from small reductions to multiple distortions outweigh those from eliminating one altogether
- Not properly accounting for measurement error in inputs could inflate estimated misallocation by up to 39%
  - Leads to incorrect conclusion that financial market reform would be productivity-decreasing

Thanks!

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Roadmap

6. Appendix

Step 1: Estimate marginal utilities from consumption data

Directly estimate this from consumption data!

- Model doesn't require any functional form assumption on preferences, but estimation does
- Simplest version: CRRA ($\lambda \equiv c^{-\theta}$)
- In the paper: Use Ligon (2022)'s approach to estimating λ from a constant Frisch elasticity demand system More
  - Nests CRRA and yields similar results
  - Estimate of relative risk aversion close to constant $\theta \approx 1.5$ Figure

Back

Step 2: Estimate τ from input ratio dispersion

Identification and measurement issues

Input ratios proportional to ratio of τs (Λ doesn't appear)

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

Identification problem: $K - 1$ ratios for K inputs.

- Assume that at least one input is freely traded within townships ($\tau_K = 1$)
- Empirically, I show this is plausible for fertilizer and seed Evidence
  - Minimal variation in reported prices within township-years (unlike for land and labor)
  - $<$ 1% of households report being unable to access fertilizer or seeds.

Back

Measurement Error and Heterogeneity in τ

A high-level overview

Measured input ratios may differ across HH due to

- True distortions τ
- Measurement error
- Heterogeneity (e.g. in land quality)

Solutions:

- Only attribute predictable variation in input ratios to τ
- Use observed transactions to value plot/worker chars.

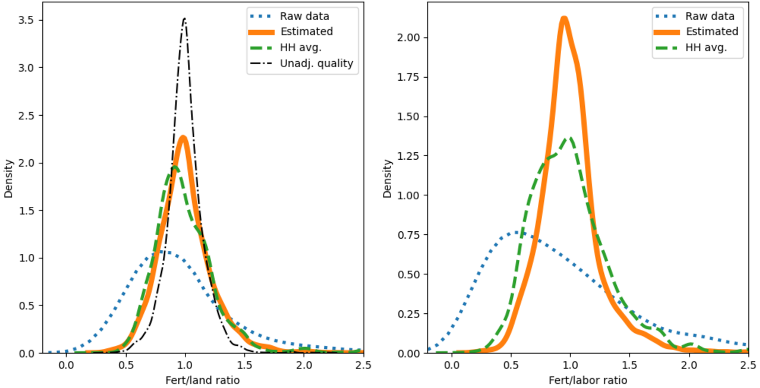
Results robust to alternative approaches

Estimating Equation | Kernel Densities | Land and labor quality | Regression tables | Back

Estimates of τ

Reduces cross-sectional variation in input ratios

Kernel density of input ratios relative to township-year average for land and labor



Regression Tables Back

Input FOCs: Generalized CD

Demands for each input can be written

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

Identical to Hicks-neutral case except β_k multiples the uncertain term rather than α_k

- Inputs with higher β relative to α “riskier"

Note that Λ_{kt} now varies by input and by scale of production Back

Generalized CD Estimation

FOC is now:

$$\mathbb{E}_t[\alpha_k \mathbb{E}_t[\lambda_{j,t+1}]\mathbb{E}_t[Y_{j,t+1}] + \beta_k cov_t(\lambda_{j,t+1}, Y_{j,t+1}) - \lambda_{jt} x_{jkt}] = 0$$

- Allows for input ratios to vary across households based on risk exposure Histograms
- Requires an estimate of households' time t expectations of λ_{t+1} and Y_{t+1}
  - Predict realizations of shocks using variables in household's time t information set Details
  - Intuition is that households should adjust consumption and investment in response to anticipated shocks

Back

Generalized CD Estimation - τ

Challenge: τs are no longer proportional to input ratios.
Borrow tricks from IO literature to estimate production functions with unobserved firm-specific prices (De Loecker et al 2016; Cairncross et al 2022).

- For land and labor obtained on the market (rather than from own endowment) – assume that τ is included in observed input expenditure
  - I.e. any distortion for traded inputs are in the form of taxes rather than rations
- Use these households to estimate PF, then use coefficients to back out τs for remaining HH.
- Analogous to De Loecker et al (2016) using single product firms to estimate product-specific PFs for multi-product firms (with control function approach to address selection)

⏩ Back

GMM Estimates of Generalized Cobb-Douglas

	α CD	α NH	β NH
Equip.	0.167	0.165	0.169
	(0.004)	(0.002)	(0.013)
Fert.	0.099	0.101	0.120
	(0.002)	(0.001)	(0.007)
Harv. Labor	0.173	0.178	0.197
	(0.009)	(0.011)	(0.025)
Land	0.208	0.144	0.171
	(0.005)	(0.017)	(0.051)
Plant. Labor	0.060	0.113	0.210
	(0.003)	(0.011)	(0.041)
Seed	0.085	0.084	0.149
	(0.001)	(0.002)	(0.012)
Weed. Labor	0.017	0.036	0.046
	(0.001)	(0.005)	(0.006)
J-stat	25.62	91.19	
p-val	0.594	0.0	
γ	0.809	0.82	
s.e.	(0.011)	(0.023)	

Back

Measurement error

To see how measurement error in inputs can lead to overstated estimates of misallocation, suppose we observe $\tilde{q}_{jk} \equiv q_{jk} \exp(\nu_{jk})$

- Expected aggregate output would then be computed as

$$\sum_j A_j \prod_k \tilde{q}_{jk}^{\alpha_k} = \sum_j \tilde{A}_j \prod_k q_{jk}^{\alpha_k}$$

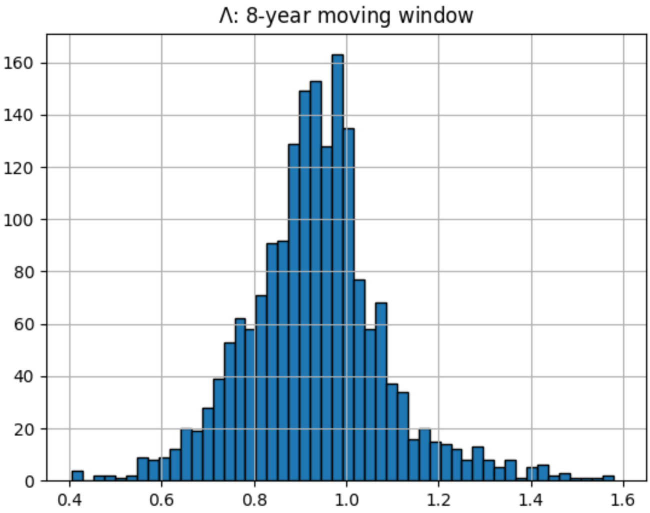
  where $\tilde{A}_j \equiv A_j \exp(\sum_k \alpha_k \nu_{jk})$.

- When computing weights, the mismeasurement term multiplying A_j also gets raised to the η (≈ 7 in my case) power.

- Can look like a big distortion if poorly measured

This can be avoided by using the TFP based measure Back

Moving Window Λ



⏩ Back

More details on A, ϕ, Λ

$$\Lambda_t \equiv \frac{\mathbb{E}_t[\lambda]\mathbb{E}_t[\exp(\phi)] + cov(\lambda, \exp(\phi))}{\lambda_t}$$

- Use PF estimate to calculate total TFP ($A_t \exp(\phi_{t+1})$).
- Divide out $\bar{A}$ as HH average.
- To distinguish between anticipated and unanticipated shocks, project remaining residual back on history of λs.
- Attribute predicted component to A_t, (log) residual to phi_{t+1}

Estimate the first term by

- Project λ_{t+1} on lags and vector of HH characteristics – obtain λ_{t+1}
- Take max of $(\hat{\lambda}_{t+1}, 1)$

Estimate the second term by taking empirical covariance of λ and $\exp(\phi)$ for each household Back

Intuition and Advantages

Can think of this as generalizing standard IO “structural approaches"

- Simple analogy with Cobb-Douglas coefficients = expenditure shares calibration.
- With knowledge of λ and τs, we can appropriately estimate coefficients using *shadow* expenditure shares.
- The key to identification is that any information available to the household but not the econometrician is captured by constrained optimal choices of inputs and consumption
- Contrast with IVs using ad-hoc specification of shocks like flood or disease (as in Shenoy (2017) and Gollin and Udry (2021)).

Back

Household Expectations

$$\mathbb{E}_t[(\alpha_k - \beta_k)\mathbb{E}_t[\lambda_{j,t+1}]\mathbb{E}_t[Y_{j,t+1}] + \beta_k \lambda_{j,t+1} Y_{j,t+1} - \lambda_{jt} x_{jkt}] = 0 \qquad (4)$$

Challenge is to separate what part of the realized λ and Y are expected by the household.

- Current approach: Project Y_{t+1} and λ_{t+1} back on variables in the time t information set
- Alternative: Households directly asked each month about expected harvest
- Can test sensitivity to different assumptions

Back

Variation in observed prices

	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

Coefficients of variation for observed prices within market-year average across years.

Back

Estimation of τ

Assume that τ_{jkt} follows an AR(1) process with input-specific persistence ρ_k and white noise ξ_{jkt}, conditional on household endowments X

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

Use dynamic panel methods (Blundell and Bond (1998)'s SysGMM) to estimate

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

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

More CFE Demands

Constant Frisch Elasticity demand system (Ligon 2022)

- Demands for all goods can be written as a log linear function of marginal utility λ with elasticity β_i, conditional on prices and HH characteristics.
- His paper shows that CFE is the only globally regular demand system in which identical HH with different budgets demands for goods differ only through a common aggregator.
- Provides flexible approach to estimating complex demands, even when not all goods are observed
- Nests CRRA (and other forms) commonly used in the literature (e.g. PIGL,PIGLog, any "generalized linear" demands as in Mullbauer 1975).

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Additional Literature

Ag Misallocation Adamopolous et al (2022a; 2022b) Adamopolous and Restuccia (2014,2020), Aragon et al (2022) Bolhuis et al (2021), Chari et al (2021)Chen et al (2017; 2021), Donovan (2021), Foster and Rosenzweig (2022) Gollin and Udry (2021), Manysheva (2021), Shenoy (2017)

Micro work on risk/credit Morduch 1990, Townsend 1994, Ligon 1998, Lehnert et al 1999, Ligon et al 2002, Dercon and Christiaensen 2006, Mobarak and Rosenzweig 2013, Karlan et al 2014, Casaburi and Willis 2018 **land** Shaban 1987, Banerjee et al 2003, Deininger et al 2011,Goldstein and Udry 2012, Ali et al 2014,de Janvry et al 2015, Burchardi et al 2018, Goldstein et al 2018, Jones et al 2022 **labor** Benjamin 1992, Breza et al 2021, Agness et al 2022 **other inputs** Emerick et al 2016, Caunedo et al 2022

Measurement in ag inputs and outputs: Abay et al 2019;2021, Arthi et al 2018, Bevis and Barrett 2020, Carletto et al 2013;2017, Desiere and Joliffe 2018 Gourlay et al 2019

PF estimation Production function estimation: De Loecker and Warzysnki (2012); Asker et al (2014; 2019) De Loecker et al (2016), Cairncross et al (2023) Back

Dynamic Panel Regressions for τ

Table: 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 (15) estimated using the Sys-GMM procedure of **?**. 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 **?** test for second-order autocorrelation and Sargan's J test of overidentifying restrictions are presented.

Back

Example of closed form subjective expectation

With RRA θ and a known distribution of ϕ,

$$\mathbb{E}_t[\lambda_{jt+1} e^{\phi_{jt+1}}] = \int_\phi \frac{\phi}{\left(A_{jt} \prod_k q_{jkt}^{\alpha_k} e^\phi + R_{jt+1}(\phi) B_{jt} + T_{jt+1}(\phi)\right)^\theta} d\phi$$

where B are other assets held by households with stochastic returns R and T are net transfers received, both of which may depend on realizations of ϕ Back

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*

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Summary Statistics — Demographics

	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

Summary Statistics — Agriculture

	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 seed	0.993	0.989	0.982	0.996	1.0
	(0.085)	(0.104)	(0.132)	(0.065)	(0.021)
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

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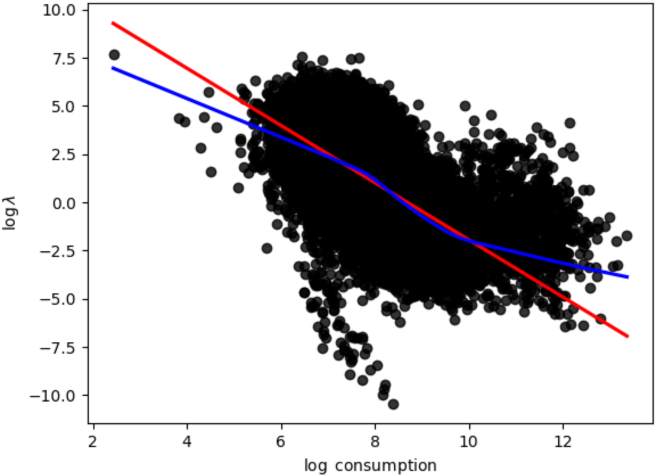
Estimates of λ

Plot CFE estimate against log consumption (Lowess, Linear)

Coefficient of relative risk aversion $-\frac{d \log \lambda}{d \log c}$ close to constant ≈ 1.48



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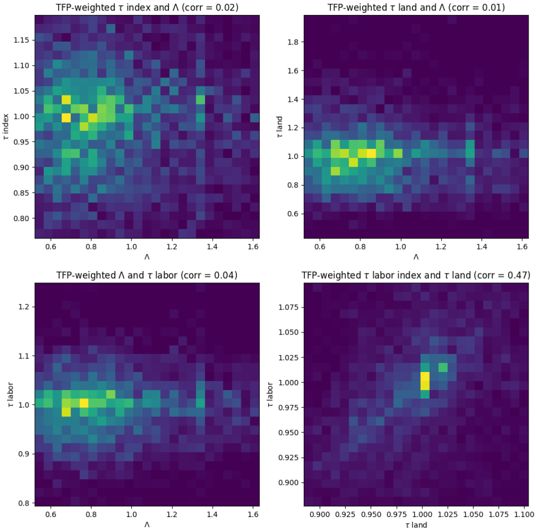
Joint distribution of τ and Λ



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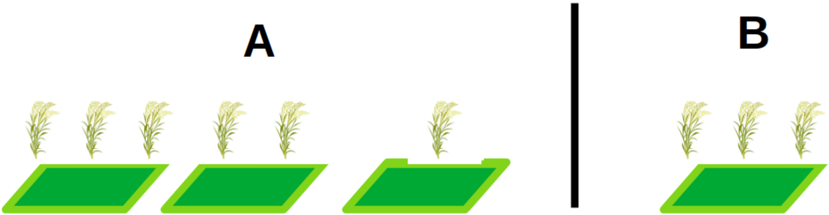
Toy Example

Two households A and B with same DRS technology: First plot yields 3, second plot yields 2 and additional plots yield 1. Suppose we observe:



- Inefficient: Can increase aggregate output by transferring A's 3rd plot to B
- Impossible to tell where the inefficiency comes from
    - Financial constraints and missing land market observationally equivalent

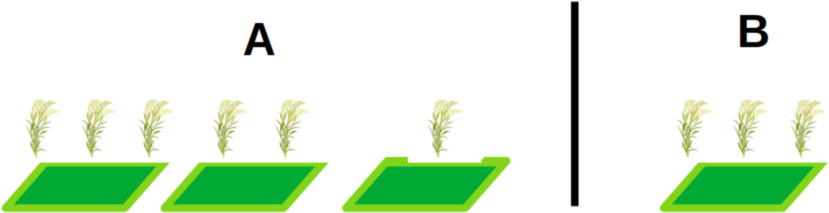
Toy Example: First-best

Suppose the true underlying friction is that B is credit-constrained and we perfect credit markets.

Achieve the efficient allocation

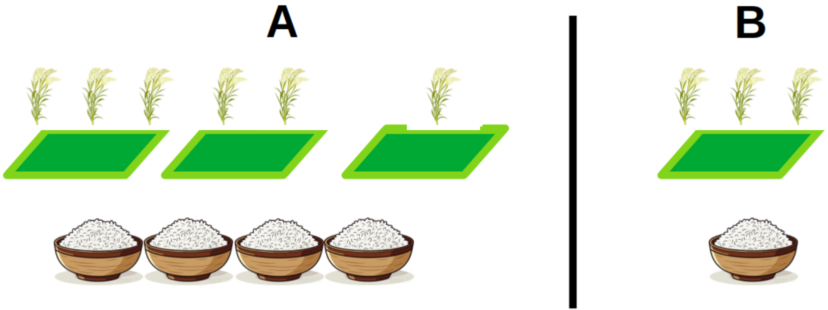
Toy Example: Wrong policy

But what if we instead intervened in land markets? Back



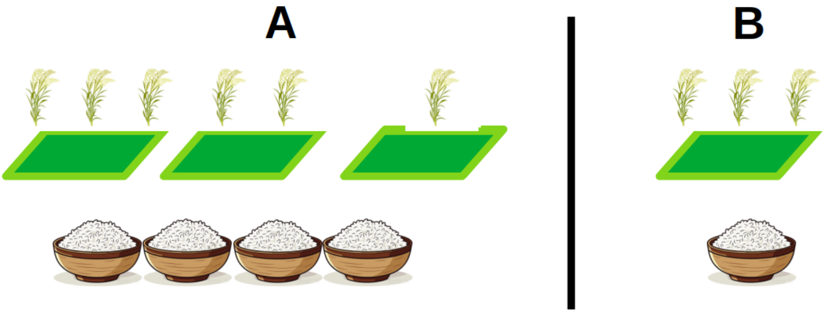
or even

Toy example: Distinguishing between distortions

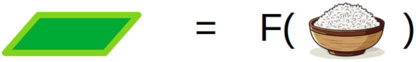


This paper: Combine production and consumption data to separate between input and financial constraints ⏩ Back

Toy example: Distinguishing between distortions



This paper: Combine production and consumption data to separate between input and financial constraints



Infer *B* is financially constrained Back

Input FOCs

Financial frictions only affect *scale* of production

Demands for each input can be written

$$q_{jkt} = \alpha_k \frac{\delta \mathbb{E}_t[Y_{jt+1}\lambda_{jt+1}]}{\bar{w}_{kvt}\tau_{jkt}\lambda_{jt}}$$
$$= \alpha_k \delta \frac{\mathbb{E}_t[Y_{jt+1}]}{\bar{w}_{kvt}\tau_{jkt}}\Lambda_{jt}$$
$$= \frac{\alpha_k}{\bar{w}_{kvt}} \left(A_{jt}\Lambda_{jt} \prod_l \left(\frac{\alpha_l}{\bar{w}_{lvt}\tau_{jlt}} \right)^{\alpha_l} \right)^{\eta}$$

where $\Lambda_{jt} \equiv \frac{\mathbb{E}_t[\lambda_{jt+1}\varphi_{jt+1}]}{\lambda_{jt}}$ (letting $\varphi_{jt+1} = \frac{e^{\phi_{jt+1}}}{\mathbb{E}_t[e^{\phi_{jt+1}}]}$)

Note that:

- Financial wedge Λ_{jt} does not vary by input
- $\tau_{jkt} \neq 1$ captures distortion in (shadow) prices
- Reduces to expected profit maximization if $\Lambda = \tau = 1$

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Land and Labor Quality

Use land and labor transactions to estimate "prices" for plot and worker attributes

- Obtain an R^2 of .58

Back

GMM Results with Single Labor Input

Back

	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

Predicting A

- Take HH average TFP (net of year FEs) (these could contain shocks but also capture secular trend in TFP growth robust to doing it the other way)
- Use XGBoost
- Features: Household's full balance sheet, HH FE, lagged λs, HH composition
- R^2 In sample .37 OOS .004

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Details

Let $\mathcal{I}_{jt}$ be observable elements of household j's information set at time t.

$$\begin{aligned} \lambda_{jt+1} e^{\phi_{jt+1}} &= \mathbb{E}_t[\lambda_{jt+1} e^{\phi_{jt+1}}] + \zeta_{jt+1} \\ &= f(\mathcal{I}_{jt}) + \varepsilon_{jt} + \zeta_{jt+1} \end{aligned}$$

Fit $f(\mathcal{I}_{jt})$ using ML (boosted trees), where $\mathcal{I}_{jt}$ contains:

- Histories of λ
- Deterministic part of production
- Disaggregated household assets/investments
- Household demographics
- Histories of state-contingent transfers.

Use $\hat{f}/\lambda_{jt}$ as estimate of Λ_{jt}. Back

Validation of Λ

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

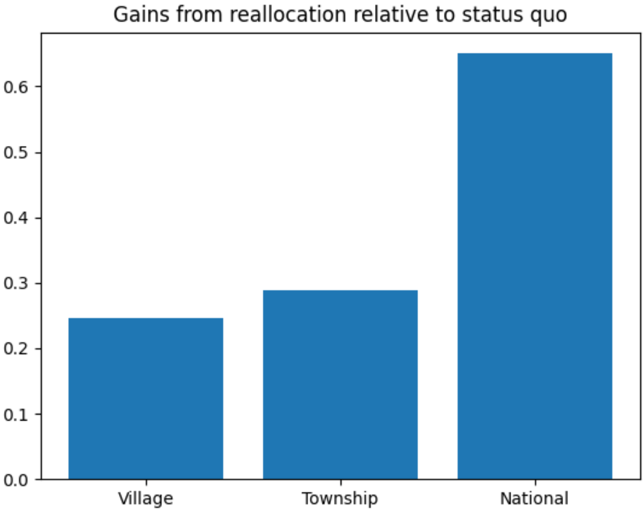
	Dependent variable:					
	Savings bal.	Debt bal	Credit bal.	Gifts made	Gifts rec'd.	N
	(1)	(2)	(3)	(4)	(5)	
log Λ	0.33^{***}	0.11^{*}	0.12	0.29^{***}	0.16^{***}	
	(0.09)	(0.07)	(0.20)	(0.10)	(0.05)	
Λ						−1
						(9
Village + Time FE	Yes	Yes	Yes	Yes	Yes	
Observations	5,442	4,951	561	4,966	5,808	
Adjusted R^2	0.17	0.20	0.19	0.03	0.27	

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

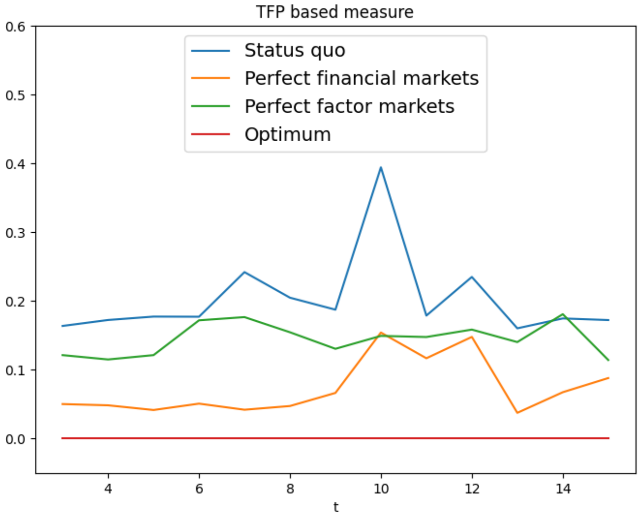
This table describes the correlation between estimated financial distortions Λ and survey measu ticipation in financial networks. The dependent variables are the logs of (self-reported) savings, c balances of loans taken, gifts made and gifts received and the level of net gifts flows in each y context, gifts can be thought of as state-contingent transfers between households (?). The resu

Different levels of aggregation

Little cross-village misallocation but nearly 3x the gains from reallocation across provinces.



Main Results by Year: TFP-based



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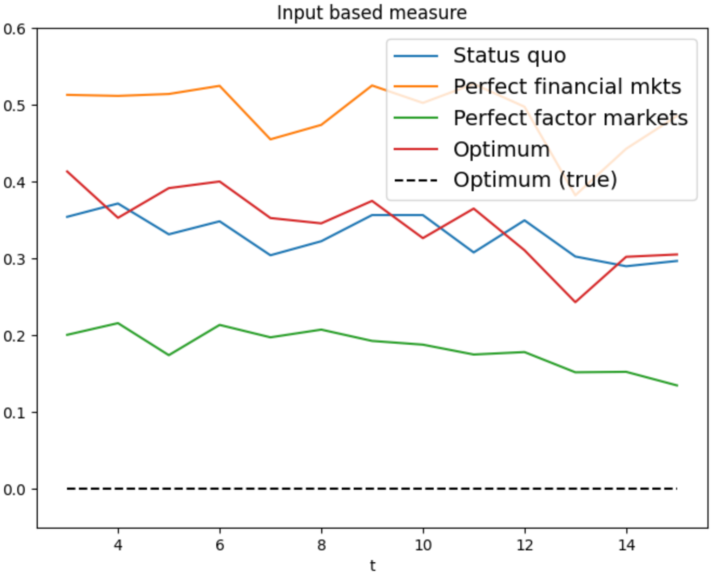
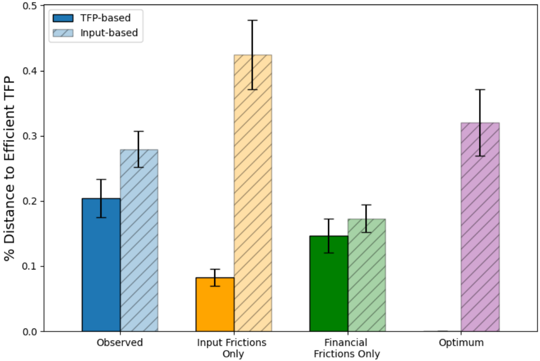
Main Results by Year: Input-based



Plot level data



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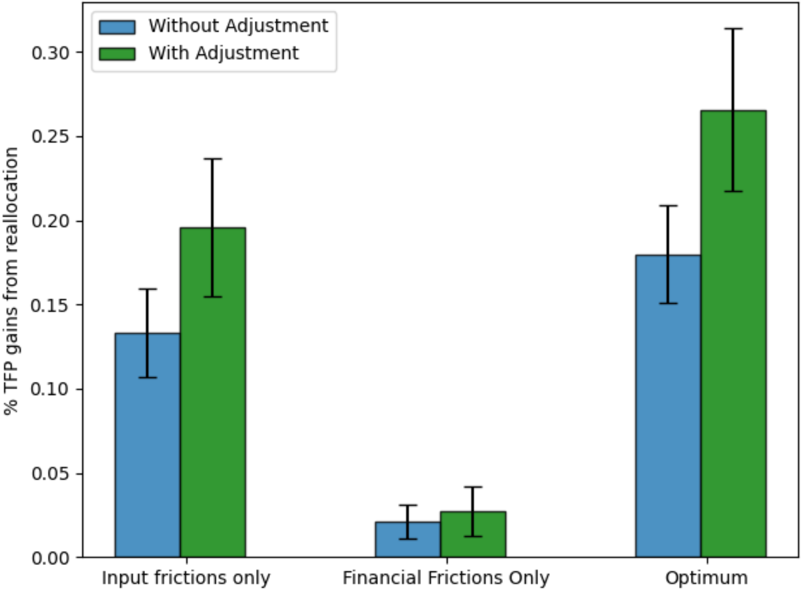
Estimated misallocation from input measure doubles

- But not TFP-based measure

If households equate marginal products across plots this shouldn't occur (Gollin and Udry 2021)

Main results with seed as normalizing input for τ



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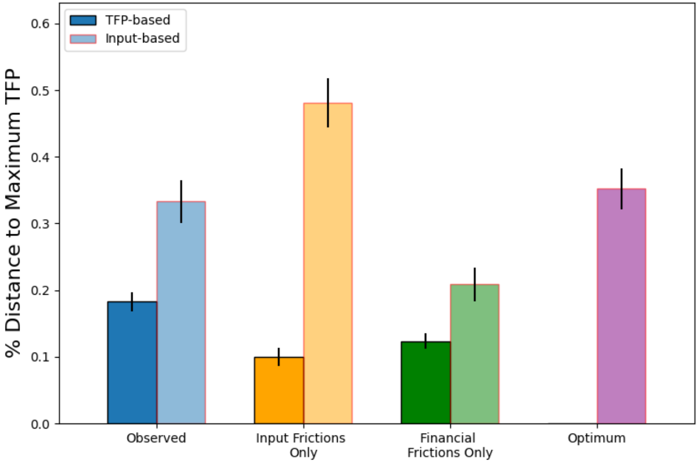
Main results with alternative τ



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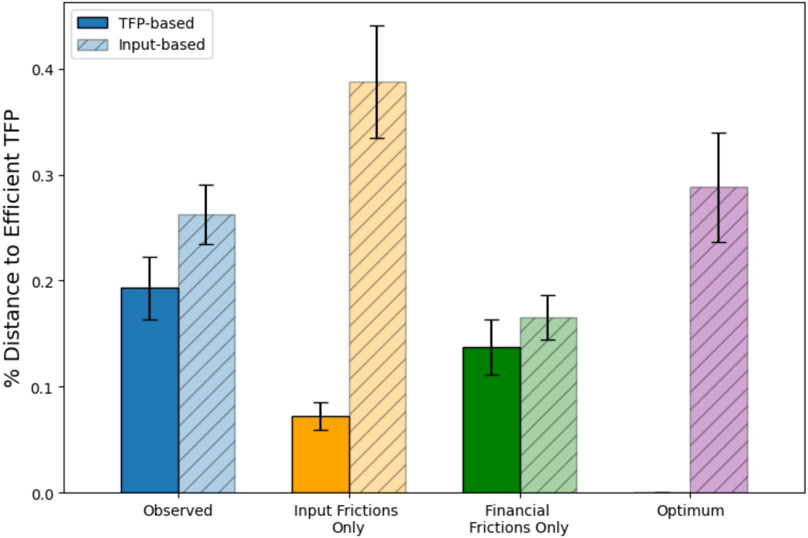
Main results with CRRA



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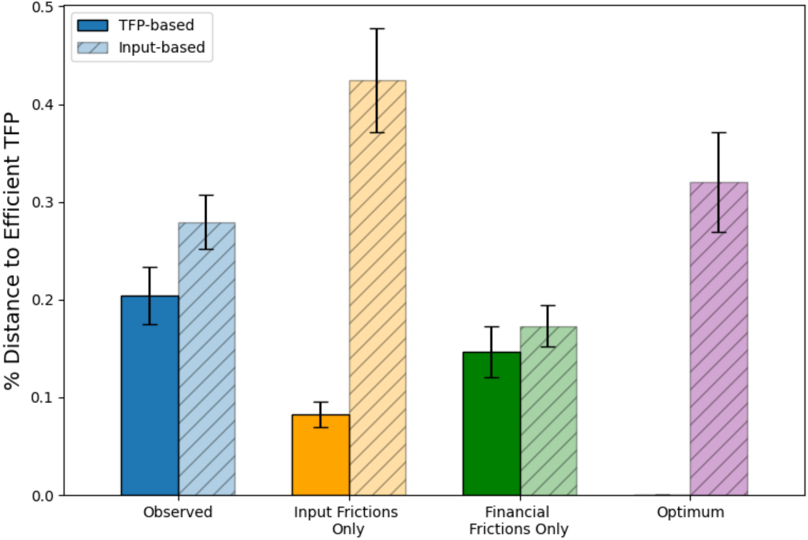
Main results restricting to rice plots



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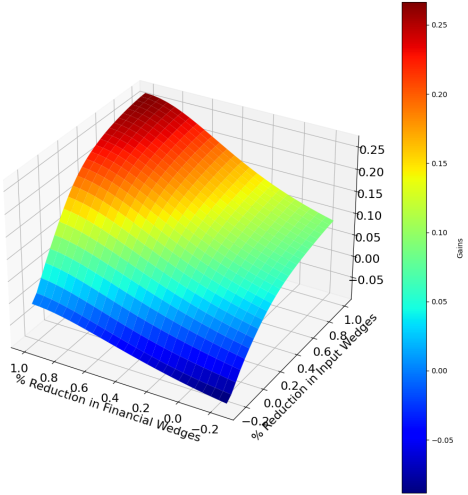
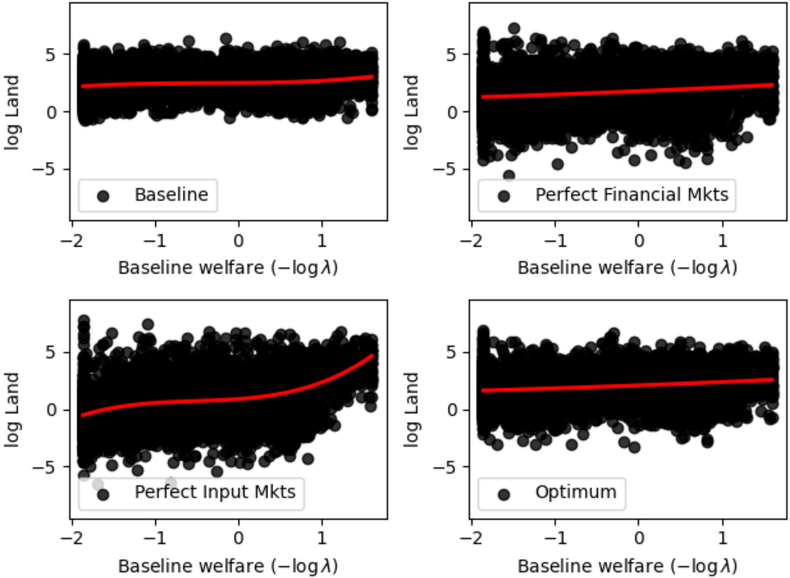
Intermediate allocations

Allowing for negatives



Land Reallocation by Baseline Welfare



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