Misallocation and Product Choice

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how does heterogeneous product choice affect
aggregate misallocation cost?

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  - 1-product model: understate total cost of misallocation by **30%** ($3\times$ vs $4\times$ gain)

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  - → understate total cost of misallocation

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  - firm-product (farm-crop) inputs and outputs are feasible to measure
- but mechanisms apply to **non-agricultural** settings too
  - $\rightarrow$ relevant for *more* developed countries too

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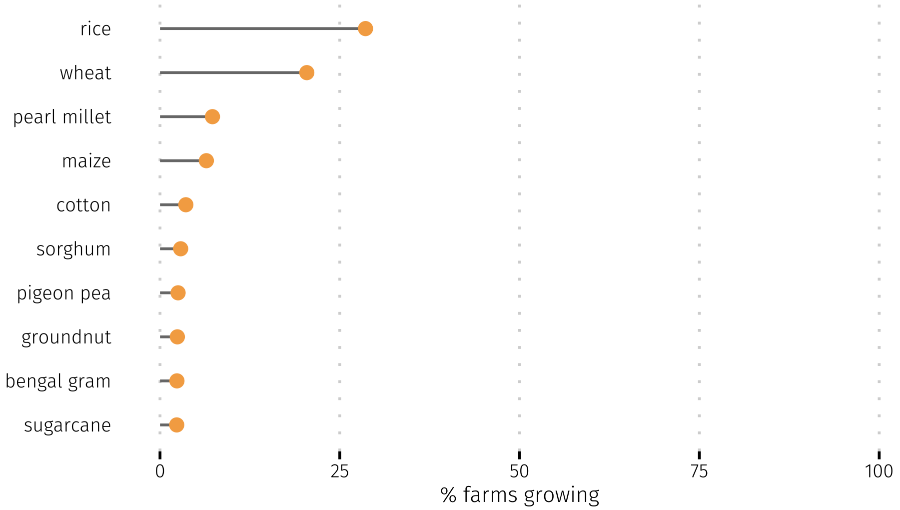
Heterogeneous Product Choice in India

Crop Choice is Heterogeneous



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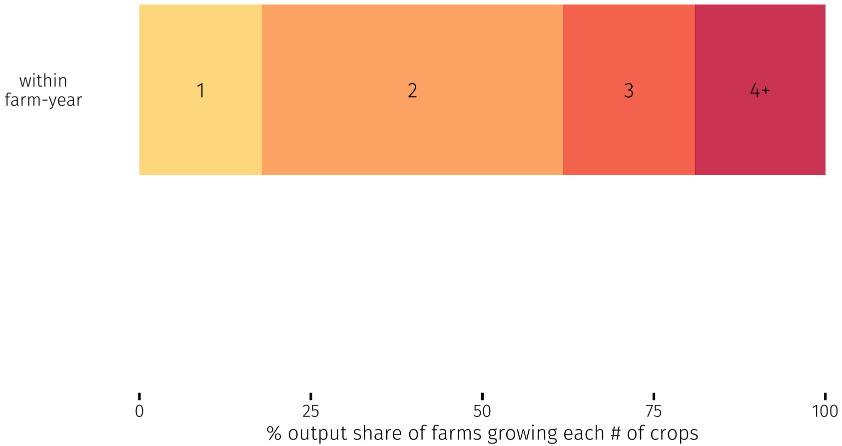

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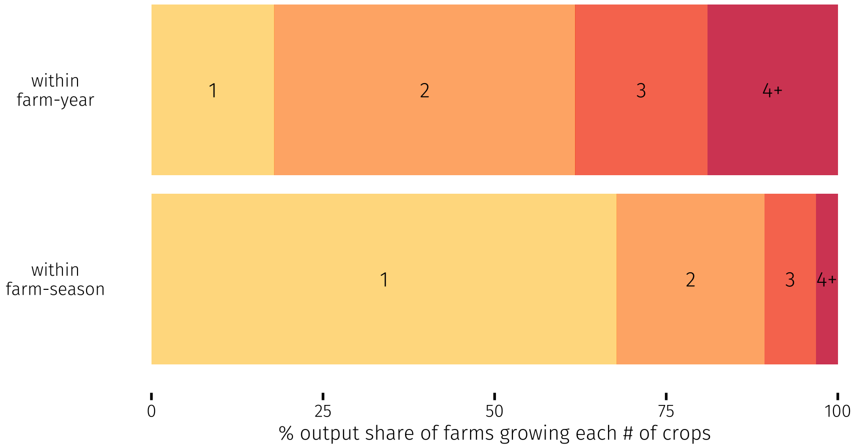

- 3 agricultural seasons: Kharif (monsoon), Rabi (winter/spring), Zaid (summer/dry)

Production Functions

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- production function:

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    - ▶ *inputs, output*
- merge crops into **5 groups**:
  - rice
  - wheat
  - other cereals
  - pulses
  - vegetables, fruits, oilseeds
    - ▶ *list of crops*

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- quality-adjusted land = quality index $\times$ plot area

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- **idea**: shocks to farm f's plots $k \neq j$ change shadow price of inputs on f's plot j

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- **production function simultaneity bias**: inputs are correlated with productivity
- **solution**: 2SLS using instruments for inputs adapting *Gollin, Udry (2021)*'s method
- **idea**: shocks to farm f's plots $k \neq j$ change shadow price of inputs on f's plot j

  $\rightarrow$ serve as instruments for inputs on j

Instrumental Variables

- specification:

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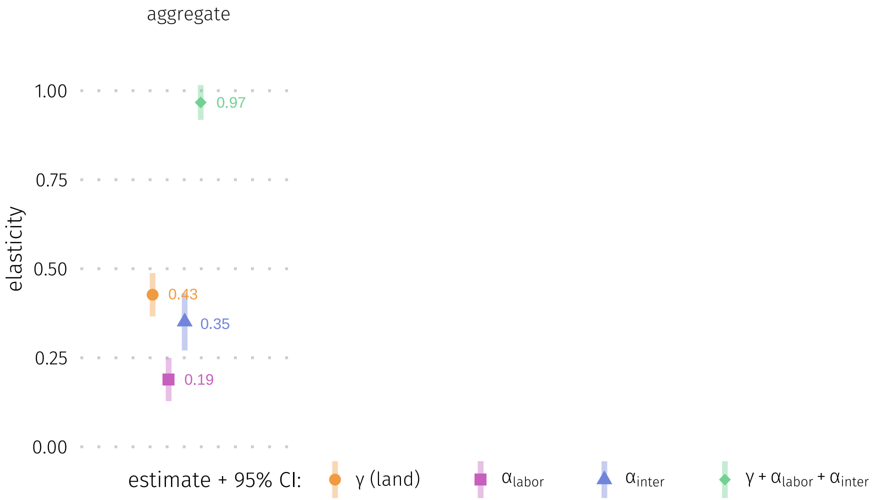
▶ *details*

Production Functions are Heterogeneous across Crops



▶ *all crops* ▶ *table* ▶ *equality tests*

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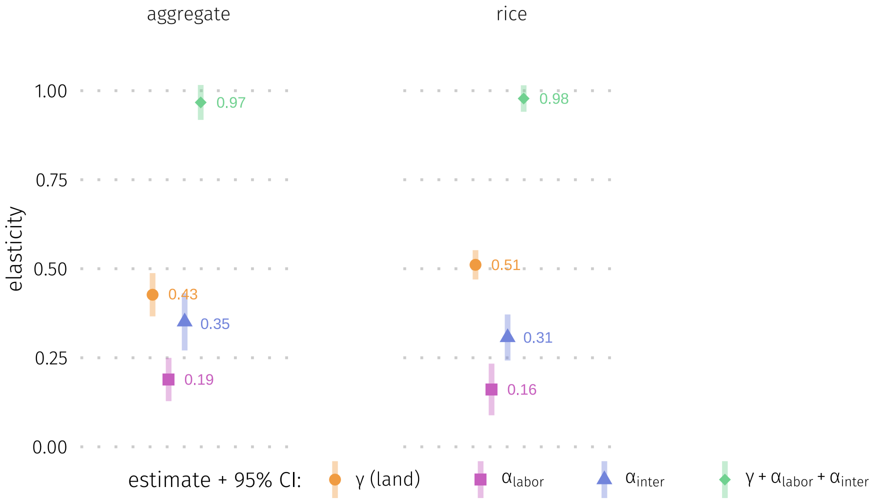

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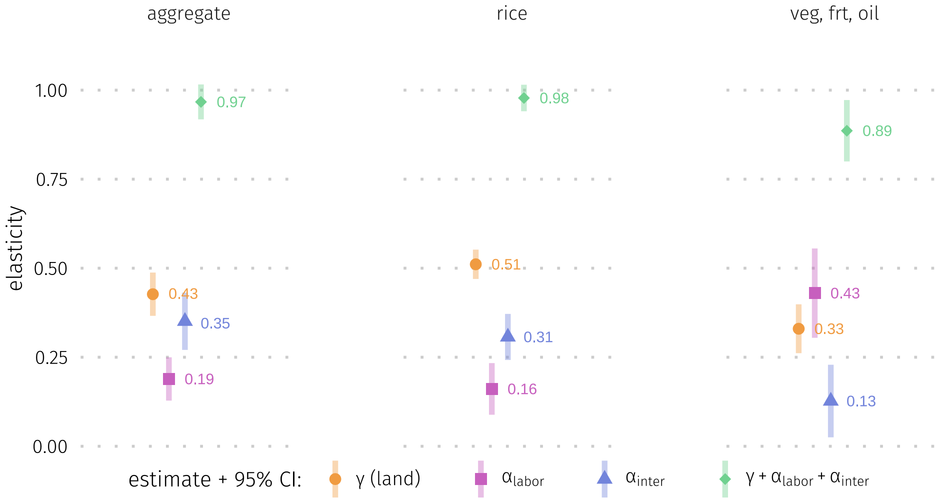

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Model

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- add multi-product farms choosing among heterogeneous products

Farm: Production

$$\max \quad \underbrace{p \; \overbrace{z_f \; l_f{}^{\gamma} \, \Pi_g \left(x_{f,g}{}^{\alpha_g} \right)}^{y_f}}_{\text{revenue}} - \underbrace{\sum_{g=1}^{G} r_g \; x_{f,g}}_{\text{flex. input costs}}$$

$$\text{s.t.} \qquad l_f = L_f \qquad (\lambda_f)$$

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- land input l is in fixed supply L_f
  - almost no land market in India

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  - e.g. market power, gov't subsidies, corruption
- L_f fixed $\rightarrow$ land is also distorted unless distributed to equalize λ_f
  - e.g. lacking property rights, communal land distribution

Farm: Multiple Products

$$\max \underbrace{\sum_{i=1}^{N} p_i \overbrace{z_{f,i} {l_{f,i}}^{\gamma_i} \Pi_g \left({x_{f,g,i}}^{\alpha_{g,i}}\right)}^{y_{f,i}}}_{\text{revenue}} - \underbrace{\sum_{g=1}^{G} r_g \tau_{f,g} \sum_{i=1}^{N} \tau_{f,g,i} x_{f,g,i}}_{\text{flex. input costs}}$$

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- heterogeneous crops $i = 1 \ldots N$
- l in fixed supply $L_f \rightarrow$ interdependent crop production
  - params of crop i change $\rightarrow \lambda_f$ changes $\rightarrow$ inputs and outputs of crops $-i$ change
  - *Just, Zilberman, and Hochman (1983)*, *Shumway, Pope, Nash (1984)*
  - justifies *Gollin, Udry (2021)* prod. fn. identification

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- farm-input-crop distortions $\tau_{f,g,i}$, $\tau_{f,l,i}$

  $\rightarrow$ fit observed input ratio heterogeneity across crops within a farm

Farm: Fixed Cost

$$\max \underbrace{\sum_{i=1}^{N} p_i \overbrace{z_{f,i} {l_{f,i}}^{\gamma_i} \Pi_g \left({x_{f,g,i}}^{\alpha_{g,i}}\right)}^{y_{f,i}}}_{\text{revenue}} - \underbrace{\sum_{g=1}^{G} r_g \tau_{f,g} \sum_{i=1}^{N} \tau_{f,g,i} x_{f,g,i}}_{\text{flex. input costs}} - \underbrace{\sum_{i=1}^{N} \omega \cdot 1[y_{f,i} > 0]}_{\text{fixed cost per crop}}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} l_{f,i} \tau_{f,l,i} = L_f \qquad (\lambda_f)$$

- fixed cost ω per produced crop
  - → farms choose **crop set** in addition to **crop mix**
  - – farms don't all produce everything
  - → fit observed heterogeneity in crop sets

Farm: Concavity

$$\max \underbrace{\sum_{i=1}^{N}\Big(p_i \overbrace{z_{f,i} {l_{f,i}}^{\gamma_i} \Pi_g \left({x_{f,g,i}}^{\alpha_{g,i}}\right)}^{y_{f,i}}\Big)^{\eta}}_{\text{revenue}} - \underbrace{\sum_{g=1}^{G} r_g \tau_{f,g} \sum_{i=1}^{N} \tau_{f,g,i} x_{f,g,i}}_{\text{flex. input costs}} - \underbrace{\sum_{i=1}^{N} \omega \cdot 1[y_{f,i} > 0]}_{\text{fixed cost per crop}}$$

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▶ *solution*

- representative consumer buys crops, sells inputs, receives profit from owned farms

$$\max_{\{C_i\}_{i=1}^N} \left(\sum_i \varphi_i C_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

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$$\sum_i p_i C_i = \sum_g r_g X_g^{agg} + \Pi$$

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▶ *profits details*

Extracting Distortions

- unobserved **distortions** map to observed **marginal revenue products**:

$$r_g \tau_{f,g} \tau_{f,g,i} = \frac{\alpha_{g,i} \eta \left(p_i y_{f,i}\right)^{\eta}}{x_{f,g,i}} = mrpg_{f,i}$$

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$$z_{f,i} = \frac{y_{f,i}}{l_{f,i}^{\gamma_i} \Pi_g \left(x_{f,g,i}^{\alpha_{g,i}}\right)}$$

- $\rightarrow$ extracted fundamentals rationalize observed dispersion b/w farms

  frictionless economy $\quad \Leftrightarrow \quad \tau_{f,g} \tau_{f,g,i} = 1 \quad \Leftrightarrow \quad mrpg_{f,i} = \overline{mrpg}_i, \; mrpl_{f,i} = \overline{mrpl}_i$

Extracting Distortions

- unobserved **distortions** map to observed **marginal revenue products**:

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distorted economy

EXTRACTING DISTORTIONS

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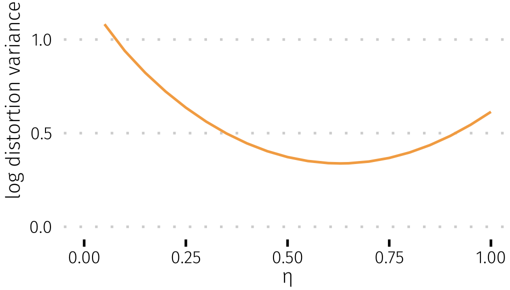
▶ *splitting distortions*

Choose η That Minimizes Implied Dispersion

- τs reproducing data need to be extreme if η is too high or too low



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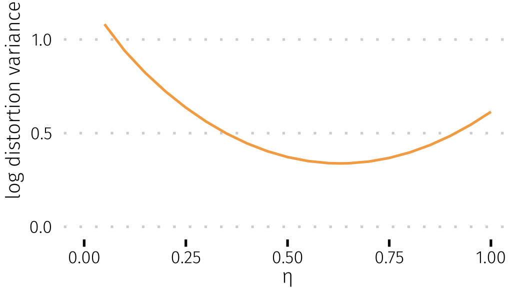

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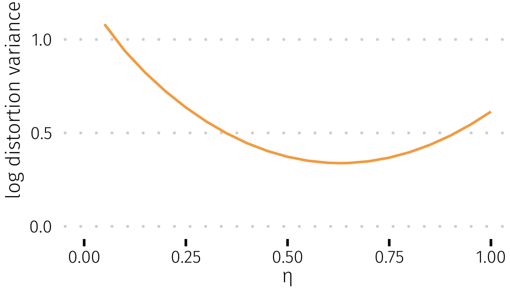

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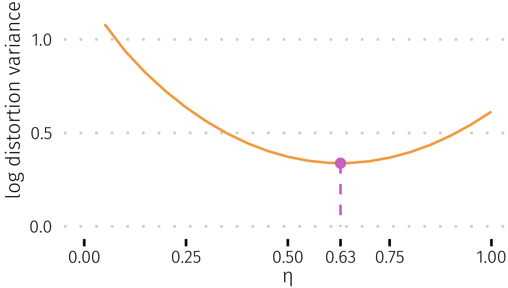

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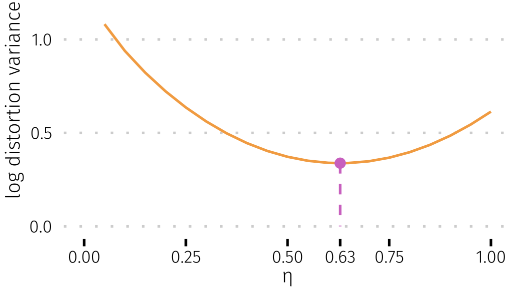

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▶ *details*

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  - aggregate inputs are fixed $\rightarrow$ aggregate output $\uparrow$ reflects aggregate TFP $\uparrow$
  - farm-level TFPs are fixed $\rightarrow$ aggregate TFP $\uparrow$ reflects pure **reallocation gain** or **misallocation cost**

▶ *reallocation exercise details*

Exercises

Benchmark Exercise

reallocation gain

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multi-product:	294%	
1-product:	212%	(28% $\downarrow$)

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Match Least-Distorted State

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- more conservative and practical

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1-product: 45% (26% ↑)

▶ *sensitivity to concavity* ▶ *role of states, seasons*

Mechanisms Contributing to 1-Product Model Error

Mechanism I: Product Heterogeneity as Frictions

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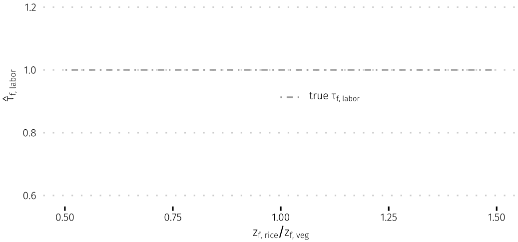
  - assume no frictions $\rightarrow \frac{\alpha_{g,rice}\eta(p_{rice}y_1)^\eta}{x_{1,g}} = \frac{\alpha_{labor,veg}\eta(p_{veg}y_2)^\eta}{x_{2,labor}}$ in multi-crop model



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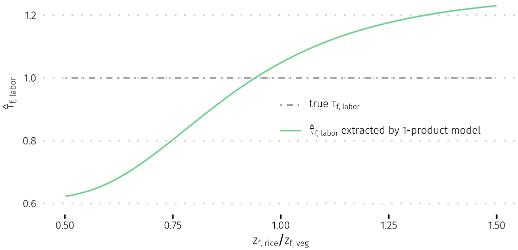
  - 1-product model: $\frac{\alpha_{labor,agg}\eta(p_{agg}y_1)^\eta}{x_{1,labor}} \neq \frac{\alpha_{labor,agg}\eta(p_{agg}y_2)^\eta}{x_{2,labor}} \rightarrow$ imputes frictions



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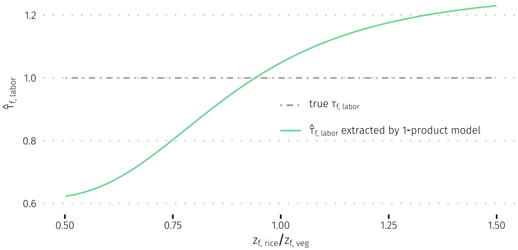

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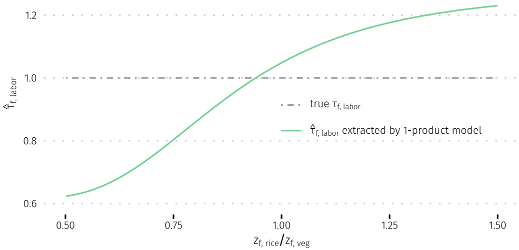
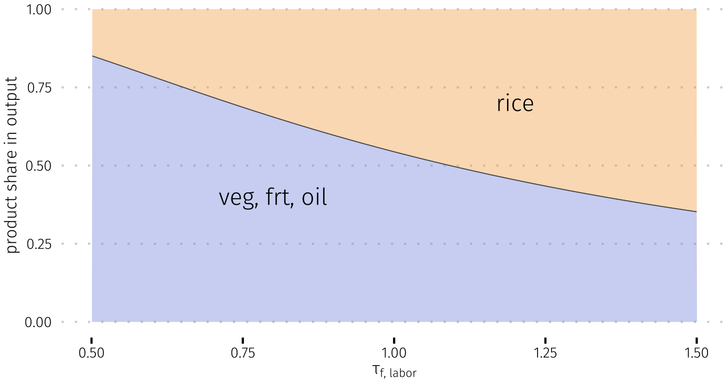
- **exercise to isolate**: apply 1-product model to counterfactual reallocation data generated by multi-product model



Mechanism II: Endogenous Product Choice

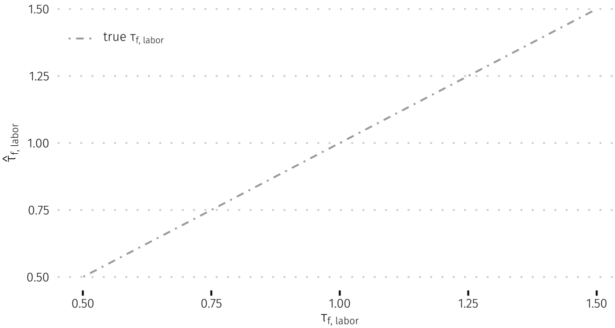
- simulated multi-product farm as labor distortion $\tau_{f,labor}$ is varied:



- $\tau_{f,labor} \uparrow \quad \rightarrow$ shift from labor-intensive vegetables to land-intensive rice

Mechanism II: Endogenous Product Choice

- apply single-product model to extract frictions from simulated multi-product data



Mechanism II: Endogenous Product Choice

- apply single-product model to extract frictions from simulated multi-product data
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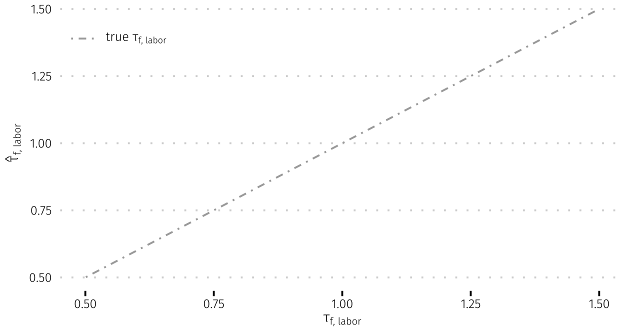

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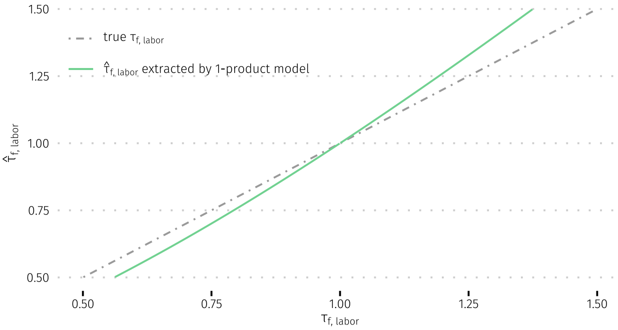

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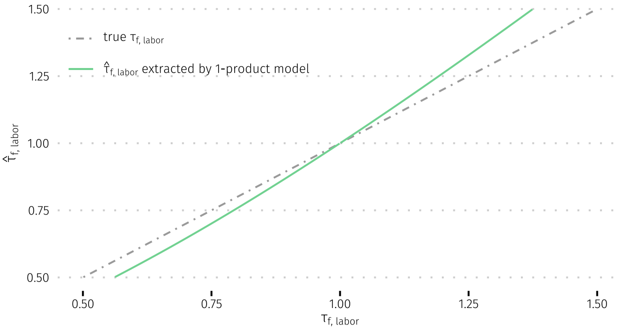

Mechanism II: Endogenous Product Choice

- **exercise to isolate**: prohibit farms in multi-product model to change product choice in counterfactuals
  - keep product sets fixed
  - keep input allocation across crops fixed: farm can choose $\sum_i x_{f,g,i}$ but $x_{f,g,i}$ gets a fixed share of total

Mechanism III: TFP Dispersion

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  - 1-product model: remove frictions $\rightarrow$ avg TFP still z_M

  $\rightarrow$ 1-product model understates **misallocation**

Mechanism III: TFP Dispersion

- 1-product model understates TFP dispersion
  - a farm has z_L in rice, z_H in vegetables
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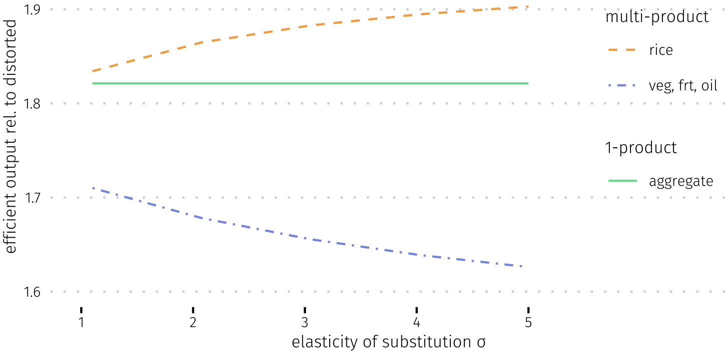
- **exercise to isolate**: treat farm-crops as separate farms for 1-product model

Mechanism IV: Returns to Scale

- some products have higher returns to scale → some farms grow more in reallocation



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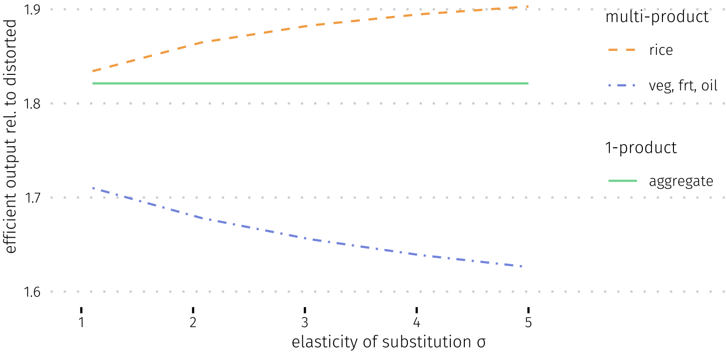

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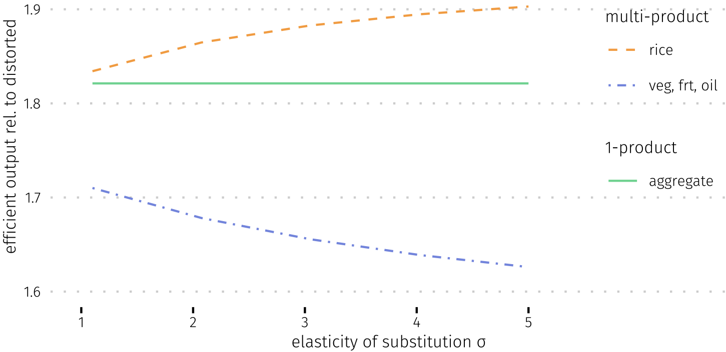

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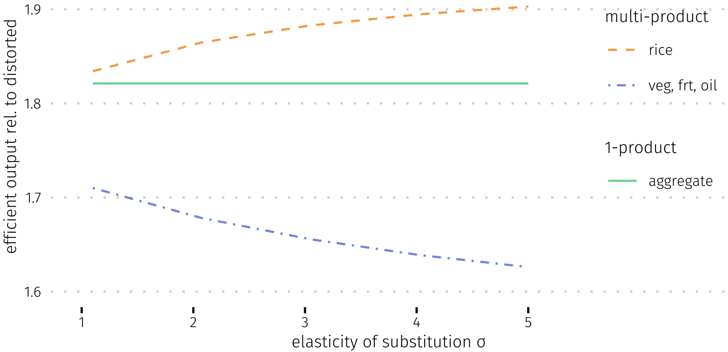

Mechanisms Decomposition: Benchmark Reallocation

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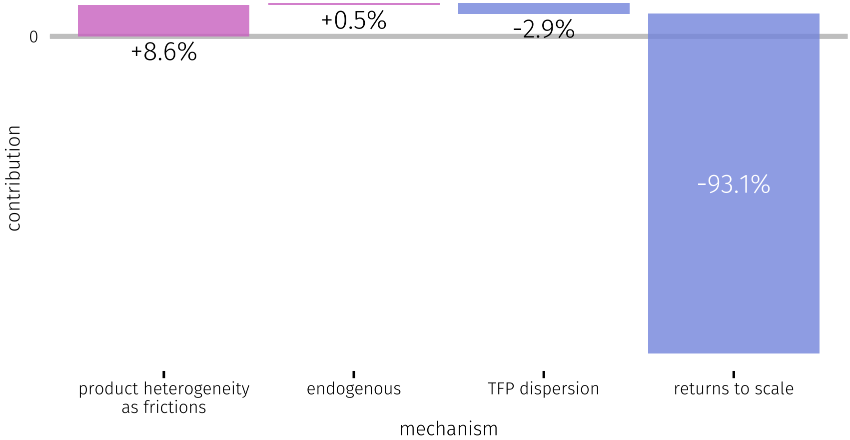

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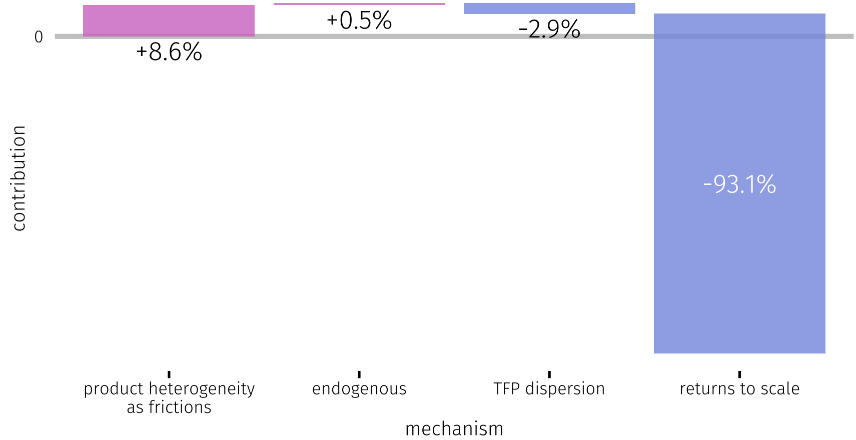

- assess total drag of misallocation → farms' ability to expand matters most
  → single-product model understates **misallocation**

Mechanisms Decomposition: "Least-Distorted State" Reallocation

- **"least-distorted state"**: single-product model overstates gain by **10 pp** (26%)

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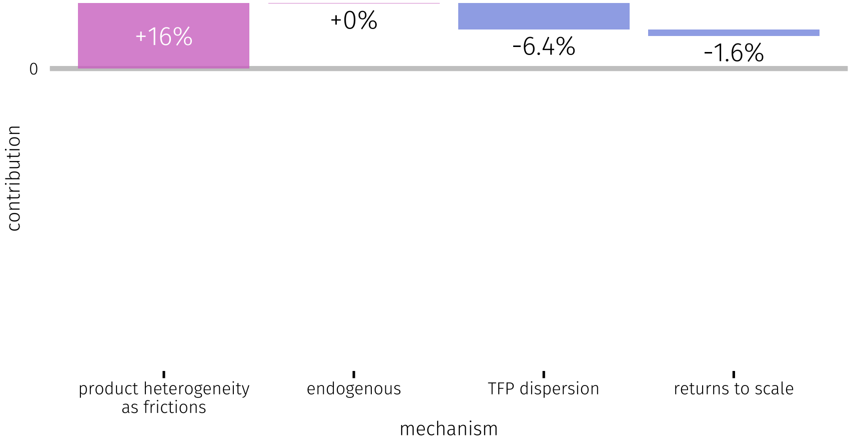

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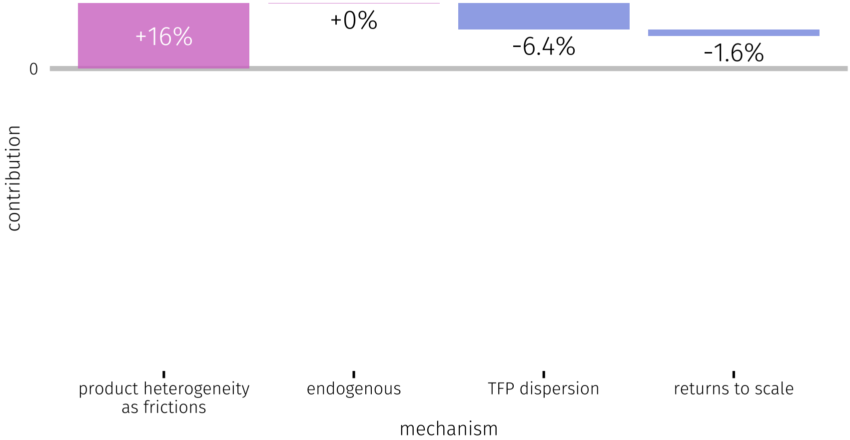

- consider partial reallocations → estimation of frictions matters most
  → single-product model overstates **misallocation** ▶ *details*

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  $\rightarrow$ input choices may appear inefficient statically but be optimal dynamically

Farm Solution Expressions

$$\sum_{i\in I_f}\left(\lambda_f^{\frac{\eta\sum_g \alpha_{g,i}-1}{1-\eta\sum_g \alpha_{g,i}-\eta\gamma_i}}\right)\left(\left(p_i z_{f,i}\right)^{\eta}\eta\left(\frac{\gamma_i}{\tau_{f,l,i}}\right)^{1-\eta\sum_g \alpha_{g,i}}\Pi_g\left(\frac{\alpha_{g,i}}{r_g\tau_{f,g}\tau_{f,g,i}}\right)^{\eta\alpha_{g,i}}\right)^{\frac{1}{1-\eta\sum_g \alpha_{g,i}-\eta\gamma_i}}\tau_{f,l,i}=L_f$$

$$x_{f,g,i}=\frac{\alpha_{g,i}}{r_g\tau_{f,g}\tau_{f,g,i}}\left(\frac{\gamma_i}{\lambda_f\tau_{f,l,i}}\right)^{\frac{\eta\gamma_i}{1-\eta\sum_g \alpha_{g,i}-\eta\gamma_i}}\left(\left(p_i z_{f,i}\right)^{\eta}\eta\Pi_h\left(\frac{\alpha_{h,i}}{r_h\tau_{f,h}\tau_{f,h,i}}\right)^{\eta\alpha_{h,i}}\right)^{\frac{1}{1-\eta\sum_h \alpha_{h,i}-\eta\gamma_i}}$$

$$l_{f,i}=\left(\left(p_i z_{f,i}\right)^{\eta}\eta\left(\frac{\gamma_i}{\lambda_f\tau_{f,l,i}}\right)^{1-\eta\sum_g \alpha_{g,i}}\Pi_g\left(\frac{\alpha_{g,i}}{r_g\tau_{f,g}\tau_{f,g,i}}\right)^{\eta\alpha_{g,i}}\right)^{\frac{1}{1-\eta\sum_g \alpha_{g,i}-\eta\gamma_i}}$$

back

List of crops

Crop list

Rice	Wheat	Other Cereals	Pulses	Oilseeds, Fruits and Vegetables		
				Oilseeds	**Vegetables**	**Fruits /Condiments**
		Barley	Black gram	Sesame	Ash gourd	Mango
		Maize	Green peas	Groundnut	Beet root	Papaya
		Sorghum	Pigeon peas	Castor	Bitter gourd	Grapes
		Pearl millet	Horse gram	Sunflower	Bottle gourd	Plum
		Finger millet	Cowpea	Niger	Eggplant	Cardamom
		Others	Kidney bean	Soybean	Board bean	Chilli
			Lentil	Safflower	Cabbage	Cumin
			Chickpeas	Rapseed	Cauliflower	Dill seed
			Others	Linseed	Carrot	Indian mustard
				Others	Potato	Other
					Cucumber	
					Peas	

back

Inputs, Outputs

- **labor**:
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back

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back

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- **2SLS first stage**:

$$M_{j,i,t} = Z_{k \neq j,i,t} + \mu_{j,i,t}$$

  - M = land, labor, intermediates
  - $Z_{k \neq j,i,t}$: instruments **from other plots within farm**
    - > agricultural shocks interacted with plot characteristics
    - > household, community characteristics & shocks interacted with plot characteristics

back

Inputs: Quality-Adjusted Land

- procedure

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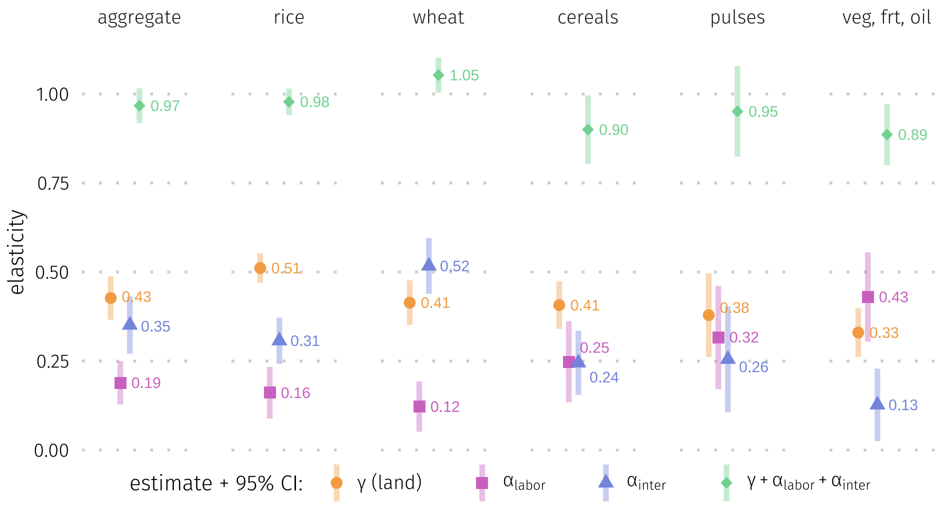
- results

	OLS	RF
MSE	0.61	0.49
R^2	0.39	0.51

back

Production Functions: All Crops



back

Production Functions: Table

	Aggregate	Rice	Wheat	Other Cereals	Pulses	Veg, Frt, Oil
Land	0.427	0.511	0.414	0.407	0.379	0.330
	(0.031)	(0.021)	(0.032)	(0.034)	(0.060)	(0.035)
Labor	0.189	0.161	0.122	0.248	0.316	0.430
	(0.031)	(0.037)	(0.036)	(0.058)	(0.074)	(0.064)
Intermediates	0.351	0.307	0.517	0.245	0.255	0.127
	(0.041)	(0.033)	(0.040)	(0.046)	(0.076)	(0.052)
Observations	14,705	4,807	3,566	2,779	1,128	2,338
R^2	0.624	0.742	0.713	0.590	0.417	0.572
Village FEs	Y	Y	Y	Y	Y	Y
Season FEs	Y	Y	Y	Y	Y	Y
			First Stage: F statistics			
Land	77.0	62.0	40.3	37.8	15.7	19.3
Labor	49.3	34.7	17.7	25.2	12.9	14.8
Intermediates	35.8	31.7	21.5	19.9	8.9	11.8
K-Paap Wald F statistic	51.1	40.4	16.0	30.8	12.4	12.7

back

Production Functions: Pairwise Equality Test P-Values

γ

	rice	wheat	cereals	pulses
veg, frt, oil	<0.01	0.95	0.62	0.73
pulses	0.05	0.7	1	
cereals	<0.01	0.57		
wheat	<0.01			

α_{labor}

	rice	wheat	cereals	pulses
veg, frt, oil	<0.01	<0.01	0.08	0.43
pulses	0.01	0.03	0.3	
cereals	0.17	0.33		
wheat	0.65			

α_{inter}

	rice	wheat	cereals	pulses
veg, frt, oil	<0.01	<0.01	0.08	0.27
pulses	0.53	<0.01	0.94	
cereals	0.35	<0.01		
wheat	<0.01			

back

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     - ▶ *expressions*
- for each farm, pick profit-maximizing crop set

back

Potential Sources of Concavity

- subsistence farmer with love of variety

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  - but the appropriate way to define GE may be different

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back

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- split of r_g from $\tau_{f,g}$ imposed by GE

back

Estimate the Elasticity of Substitution

- from consumption FOC:

$$\log\left(\frac{p_i C_i}{\sum_j p_j C_j}\right) = -\log\left(\sum_j \varphi_j^{\sigma} p_j^{1-\sigma}\right) + (1-\sigma)\log p_i + \sigma \log \varphi_i$$

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	$\log s_{h,i}$
σ	1.699
$\log p_{h,i}$	-0.699
	(0.067)
Observations	40,833
Kleibergen-Paap F stat	230.9

Village-level instruments: Elevation × rain, ruggedness × rain, pucca roads availability

back

Choose η That Minimizes Implied Dispersion

- farm-crop revenue:

$$p_i y_{f,i} = \underbrace{\left(\left(\frac{1}{\lambda_f \tau_{f,m,i}}\right)^{\gamma_i} \Pi_g \left(\frac{1}{\tau_{f,g}\tau_{f,g,i}}\right)^{\alpha_{g,i}} \right)}_{\text{composite distortion, } dist_{f,i}}^{\frac{1}{1-\eta(\sum_g \alpha_{g,i}+\gamma_i)}} \underbrace{\left(p_i z_{f,i} \gamma_i^{\gamma_i} \eta^{\sum_g \alpha_{g,i}+\gamma_i} \Pi \left(\frac{\alpha_{g,i}}{r_g}\right)^{\alpha_{g,i}} \right)^{\frac{1}{1-\eta(\sum_g \alpha_{g,i}+\gamma_i)}}}_{\text{"objective" factors}}$$

back

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- $Var(\log dist_{f,i})$ needed to match observed output dispersion depends on chosen η

back

GE Profits

$$\Pi = \sum_f \left[\sum_{i=1}^{N} p_i y_{f,i} - \sum_{g=1}^{G} r_g \sum_{i=1}^{N} x_{f,g,i} \right]$$

- distortions τ, fixed costs ω, concavity η are not reflected in dividends sent to consumer
  - farmers act *as if* frictions they face had monetary representations
  - but these are non-monetary and not added/subtracted from dividends
- equivalent formulation: τs, ωs are monetary taxes/subsidies, administered by consumer
  - show up in dividends and consumer's BC as government revenue/expense
- choice is arbitrary: both formulations (or any mixture) produce identical equilibrium conditions

back

Reallocation Exercise Details

- **benchmark**: equalize land and labor distortions

back

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- **least-distorted state**:

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  - Tamil Nadu has the lowest variance of the composite distortion

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  - compute variances of each type of distortion in Tamil Nadu

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- **least-distorted state**:
  - Tamil Nadu has the lowest variance of the composite distortion
  - compute variances of each type of distortion in Tamil Nadu
  - downscale each Indian farm's frictions s.t. aggregate variances match Tamil Nadu variances

back

Benchmark Exercise Sensitivity

η \ σ	1.1	1.3	1.5	1.7	1.9	2.1	2.3
0.93	1588	1781	1961	2123	2267	2393	2503
0.83	1300	1472	1635	1787	1924	2047	2157
0.73	762	837	909	977	1040	1098	1152
0.63	277	284	289	*294*	299	303	306
0.53	139	140	140	141	141	142	142
0.43	99	99	99	99	99	100	100
0.33	79	79	80	80	80	80	80

(a) reallocation gain, %

back

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(a) reallocation gain, %

η \ σ	1.1	1.3	1.5	1.7	1.9	2.1	2.3
0.93	+6	-6	-14	-21	-26	-30	-33
0.83	+3	-9	-18	-25	-30	-34	-38
0.73	-38	-43	-48	-52	-55	-57	-59
0.63	-23	-25	-27	-28	-29	-30	-31
0.53	-2	-3	-3	-4	-4	-4	-5
0.43	+2	+2	+2	+2	+2	+1	+1
0.33	+2	+2	+2	+2	+2	+2	+2

(b) single-product model error, %

- misallocation estimates are always sensitive to calibrated concavity
  - firms can expand grow more easily in reallocation → greater gain
- sign and magnitude of single-product model's error also depends on calibration

back

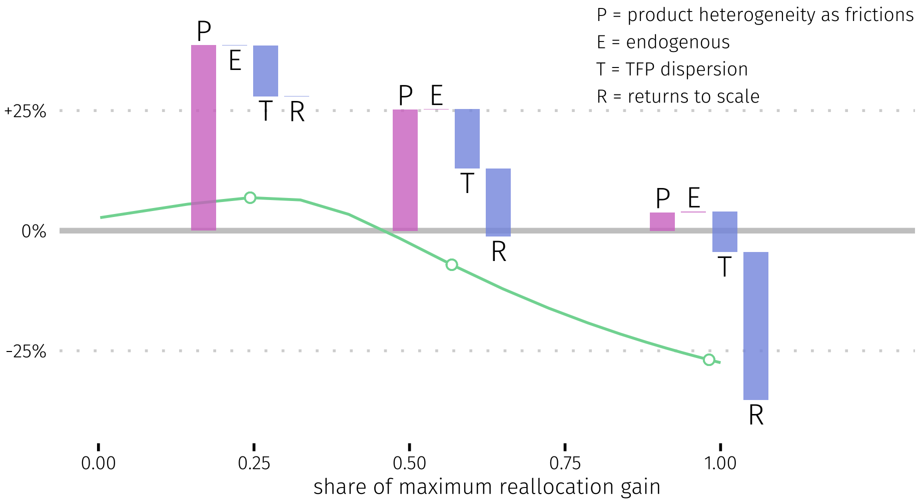
Reallocation: Role of States and Seasons

	main	within state	no split by season
multi-product:	294%	107%	314%
1-product:	212%	124%	260%

back

Remove More Distortions → 1-Product Model Overstates

- 1-product error when conducting increasingly expansive reallocations:



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