Stepan Gordeev
UConn

Sudhir Singh MSU, World Bank

Sep 29, 2023

Stockman

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how does heterogeneous product choice affect aggregate misallocation cost?

DATA

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- $\boldsymbol{\cdot}$ $\,$ agriculture is perfect to explore interaction of $\,$ product choice and $\,$ misallocation
 - ▶ why
 - but mechanisms apply equally to other sectors

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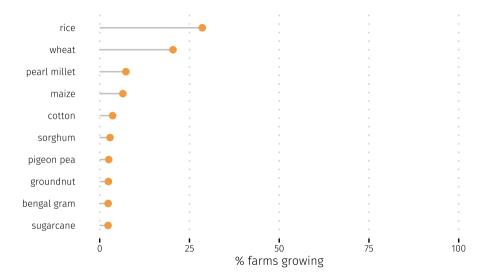
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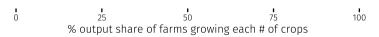
MULTI-PRODUCT FARMS IN INDIA

CROP CHOICE IS HETEROGENEOUS

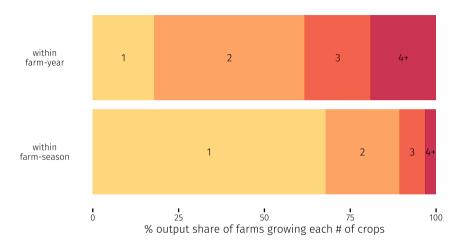


MANY FARMS GROW MULTIPLE CROPS, MAINLY ACROSS SEASONS





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

PRODUCTION FUNCTIONS

$$y_{f,i,t} = z_{f,i,t} l_{f,i,t}^{\gamma_i} x_{labor,f,i,t}^{\alpha_{labor,i}} x_{inter,f,i,t}^{\alpha_{inter,i}}$$

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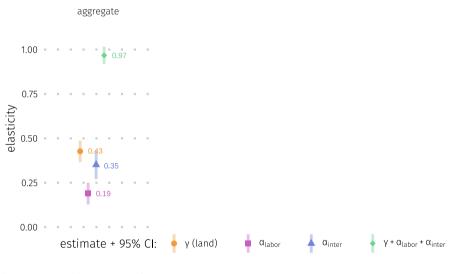
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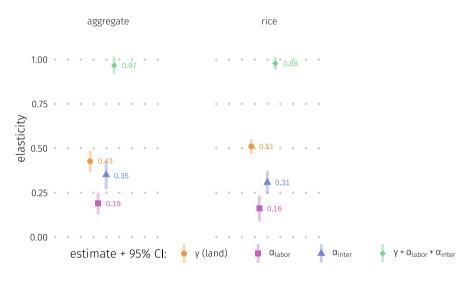
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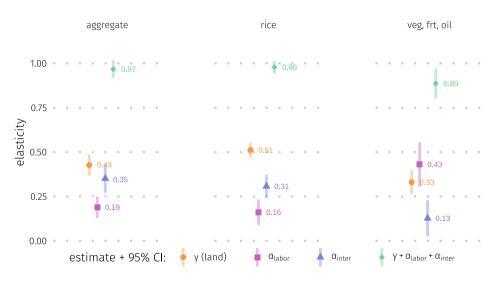
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· OBJECTIVES:

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- provide a mapping from observable outcomes to unobserved distortions

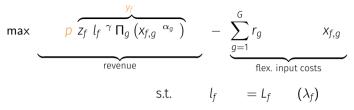
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- add multi-product firms choosing among heterogeneous crops



• profit-maximizing farm f: sells output py_f , pays for inputs

$$\max \qquad p \overbrace{Z_f \ l_f \ ^\gamma \Pi_g \left(x_{f,g} \right. ^{\alpha_g} \right)}^{y_f} - \underbrace{\sum_{g=1}^G r_g}_{\text{flex. input costs}} \\ \text{s.t.} \qquad l_f = L_f \quad (\lambda_f)$$

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- Cobb-Douglas production function with TFP z_f

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revenue $flex. input costs$

S.t. $l_f = L_f \ (\lambda_f)$

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- flexible inputs g: labor, intermediates
 - quantity $x_{f,g}$ rented at r_g

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

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$$p \ \overline{z_f \ l_f} \ {}^{\gamma} \Pi_g \left(x_{f,g} \ {}^{\alpha_g} \right) - \sum_{g=1}^G r_g \tau_{f,g} \ x_{f,g}$$
revenue $s.t. \ l_f = L_f \ (\lambda_f)$

- farm-input distortions $\tau_{f,g}$ capture misallocative frictions
 - represented with tax $(au_{f,g}>1)$ or subsidy $(au_{f,g}<1)$ idiosyncratic to farm f, input g

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- between farms: $\tau_{1,q} > \tau_{2,q} \ \forall g \rightarrow \text{farm 1 is "too small" given its TFP } z_f$
- · L_f fixed \rightarrow land is also distorted unless distributed to equalize λ_f
 - e.g. lacking property rights, communal land distribution

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

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

- \cdot farm-input distortions $au_{f,g}$ capture misallocative frictions
 - represented with tax ($au_{f,g} > 1$) or subsidy ($au_{f,g} < 1$) idiosyncratic to farm f, input g
- between inputs: $\tau_{f,labor} > \tau_{f,inter} \rightarrow \text{farm } f \text{ uses "too little" labor}$
- between farms: $au_{1,g} > au_{2,g} \; \forall g \; o \; \text{farm 1 is "too small" given its TFP } z_f$
- · $\mathit{L_f}$ fixed ightarrow land is also distorted unless distributed to equalize λ_f
 - e.g. lacking property rights, communal land distribution
- distortions extracted from observed input, output choices
 - rationalize all heterogeneity in data ► details

FARM: MULTIPLE PRODUCTS

$$\max \underbrace{\sum_{i=1}^{N} p_{i} \underbrace{Z_{f,i} l_{f,i} \gamma_{i} \Pi_{g} \left(X_{f,g,i} \alpha_{g,i} \right)}_{\text{revenue}} - \underbrace{\sum_{g=1}^{G} r_{g} \tau_{f,g} \underbrace{\sum_{i=1}^{N} \tau_{f,g,i} X_{f,g,i}}_{\text{flex. input costs}}$$

$$\text{s.t.} \underbrace{\sum_{i=1}^{N} l_{f,i} \tau_{f,l,i} = L_{f}}_{\text{flex. } (\lambda_{f})}$$

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- heterogeneous crops i = 1...N
- *l* in fixed supply $L_f \rightarrow$ interdependent crop production
 - params of crop i change $o \lambda_f$ changes o inputs and outputs of crops -i change
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- farm-input-crop distortions $au_{f,g,i}$, $au_{f,l,i}$
 - ightarrow fit observed input ratio heterogeneity across crops within a farm

FARM: FIXED COST

$$\max \sum_{i=1}^{N} \underbrace{\sum_{j=1}^{N} p_{i} \underbrace{Z_{f,i} l_{f,i} \gamma_{i} \Pi_{g} \left(X_{f,g,i} \alpha_{g,i} \right)}_{\text{revenue}} - \underbrace{\sum_{g=1}^{G} r_{g} \tau_{f,g} \sum_{i=1}^{N} \tau_{f,g,i} X_{f,g,i}}_{\text{flex. input costs}} - \underbrace{\sum_{i=1}^{N} \omega \cdot 1[y_{f,i} > 0]}_{\text{fixed cost per crop}}$$

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

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

$$\max \sum_{i=1}^{N} \left(p_{i} \sum_{f,i} l_{f,i} \gamma_{i} \Pi_{g} \left(x_{f,g,i} \alpha_{g,i} \right) \right)^{\eta} - \sum_{g=1}^{G} r_{g} \tau_{f,g} \sum_{i=1}^{N} \tau_{f,g,i} x_{f,g,i} - \sum_{i=1}^{N} \omega \cdot 1[y_{f,i} > 0]$$

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▶ solution ▶ GE

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- compare reallocation gain between multi-product model and 1-product model
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MATCH LEAST-DISTORTED STATE

- a more conservative and practical estimate
- downscale frictions s.t. their variances match those in the least-distorted state

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▶ sensitivity to concavity ▶ role of states, seasons

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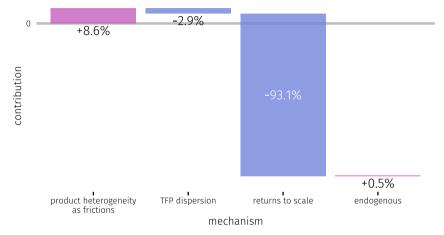
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MECHANISMS DECOMPOSITION: BENCHMARK REALLOCATION

• benchmark: single-product model understates gain by 82 pp (28%)

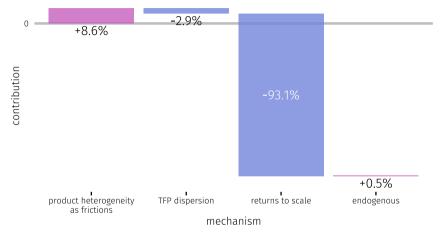
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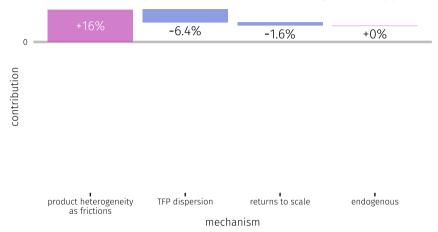
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MECHANISMS DECOMPOSITION: "LEAST-DISTORTED STATE" REALLOCATION

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

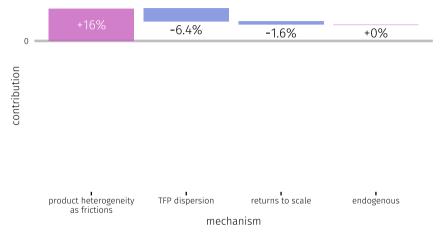
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 - no simple correction that can be applied to standard models

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 - products (crops) are ∼homogeneous across firms (farms)
- but mechanism applies to **non-agricultural** settings too
 - → relevant for *more* developed countries too



FARM SOLUTION EXPRESSIONS

$$\begin{split} \sum_{i \in l_{f}} \left(\lambda_{f}^{\frac{\eta \sum_{g} \alpha_{g,i} - 1}{1 - \eta \sum_{g} \alpha_{g,i} - \eta \gamma_{i}}} \right) \left(\left(p_{i} Z_{f,i} \right)^{\eta} \eta \left(\frac{\gamma_{i}}{\tau_{f,l,i}} \right)^{1 - \eta \sum_{g} \alpha_{g,i}} \Pi_{g} \left(\frac{\alpha_{g,i}}{r_{g} \tau_{f,g} \tau_{f,g,i}} \right)^{\eta \alpha_{g,i}} \right)^{\frac{1}{1 - \eta \sum_{g} \alpha_{g,i} - \eta \gamma_{i}}} \tau_{f,l,i} = L_{f} \\ x_{f,g,i} &= \frac{\alpha_{g,i}}{r_{g} \tau_{f,g} \tau_{f,g,i}} \left(\frac{\gamma_{i}}{\lambda_{f} \tau_{f,l,i}} \right)^{\frac{1 - \eta \sum_{g} \alpha_{g,i} - \eta \gamma_{i}}{\alpha_{g,i} - \eta \gamma_{i}}} \left(\left(p_{i} Z_{f,i} \right)^{\eta} \eta \Pi_{h} \left(\frac{\alpha_{h,i}}{r_{h} \tau_{f,h} \tau_{f,h,i}} \right)^{\eta \alpha_{h,i}} \right)^{\frac{1}{1 - \eta \sum_{h} \alpha_{h,i} - \eta \gamma_{i}}} \\ l_{f,i} &= \left(\left(p_{i} Z_{f,i} \right)^{\eta} \eta \left(\frac{\gamma_{i}}{\lambda_{f} \tau_{f,l,i}} \right)^{1 - \eta \sum_{g} \alpha_{g,i}} \Pi_{g} \left(\frac{\alpha_{g,i}}{r_{g} \tau_{f,g} \tau_{f,g,i}} \right)^{\eta \alpha_{g,i}} \right)^{\frac{1}{1 - \eta \sum_{g} \alpha_{g,i} - \eta \gamma_{i}}} \end{split}$$

LIST OF CROPS

Crop list

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

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- · output:
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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



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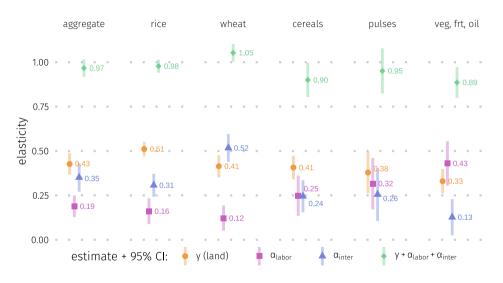
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- $\cdot \rightarrow \text{quality index} = \text{predicted price/acre}$
- quality-adjusted land = quality index × plot area



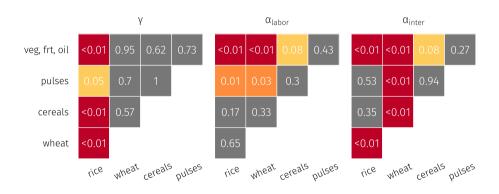
PRODUCTION FUNCTIONS: ALL CROPS



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	Υ	Υ	Υ	Υ	Υ	Υ
Season FEs	Υ	Υ	Υ	Υ	Υ	Υ
	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

PRODUCTION FUNCTIONS: PAIRWISE EQUALITY TEST P-VALUES



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- for each farm, pick profit-maximizing crop set



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 - but the appropriate way to define GE may be different



• unobserved distortions map to observed marginal revenue products:

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physical productivity implied by production fn.:

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

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physical productivity implied by production fn.:

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

distorted economy \Leftrightarrow heterog. $au_{f,g} au_{f,g,i}$ \Leftrightarrow heterog. $mrpg_{f,i}, mrpl_{f,i}$

► splitting distortions

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• split of r_g from $au_{f,g}$ imposed by GE

ESTIMATE THE ELASTICITY OF SUBSTITUTION

· from consumption FOC:

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

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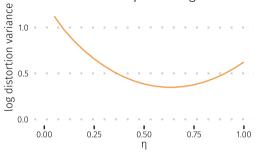
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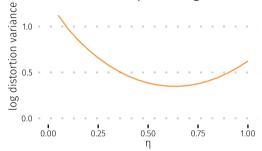
	$\log s_{h,i}$
σ	1.699
$\log p_{h,i}$	-0.699 (0.067)
Observations Kleibergen-Paap F stat	40,833 230.9

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

 \cdot τ s reproducing data need to be extreme if η is too high or too low

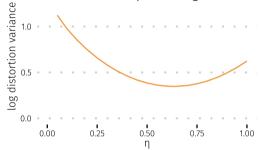


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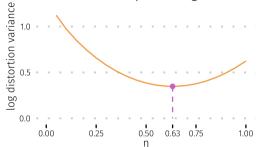
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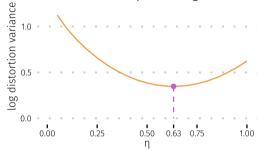
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- ▶ details

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

s.t.

$$\sum_{i} p_{i}C_{i} = \sum_{g} r_{g}X_{g}^{agg} + \Pi$$

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- ▶ profits details

· farm-crop revenue:

$$p_{i} y_{f,i} = \left(\underbrace{\left(\frac{1}{\lambda_{f} \tau_{f,m,i}}\right)^{\gamma_{i}} \Pi_{g} \left(\frac{1}{\tau_{f,g} \tau_{f,g,i}}\right)^{\alpha_{g,i}}}_{\text{composite distortion, } dist_{f,i}}\right)^{\frac{1}{1-\eta(\sum_{g} \alpha_{g,i}+\gamma_{i})}} \underbrace{\left(p_{i} Z_{f,i} \gamma_{i}^{\gamma_{i}} \eta^{\sum_{g} \alpha_{g,i}+\gamma_{i}} \Pi \left(\frac{\alpha_{g,i}}{r_{g}}\right)^{\alpha_{g,i}}\right)^{\frac{1}{1-\eta(\sum_{g} \alpha_{g,i}+\gamma_{i})}}}_{\text{"objective" factors}}$$

back

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



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 au, 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: τ s, ω s 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

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- · compare reallocation gain between multi-product model and 1-product model
 - ► reallocation exercise details

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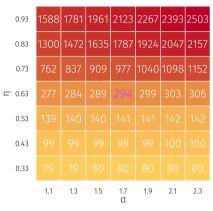
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 - ightarrow need to parameterize **unconditional** z, au distributions and calibrate to match observed **conditional** distributions

BENCHMARK EXERCISE SENSITIVITY

	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		284	289	294	299	303	306
	0.53					141		
	0.43							
	0.33							
		1.1	1.3	1.5	1.7 σ	1.9	2.1	2.3

(a) reallocation gain, %

BENCHMARK EXERCISE SENSITIVITY



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· misallocation estimates are always sensitive to calibrated concavity

BENCHMARK EXERCISE SENSITIVITY

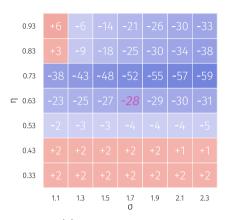


- (a) reallocation gain, %
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 - firms can expand grow more easily in reallocation ightarrow greater gain

BENCHMARK EXERCISE SENSITIVITY



(a) reallocation gain, %



(b) single-product model error, %

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



REALLOCATION: ROLE OF STATES AND SEASONS

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

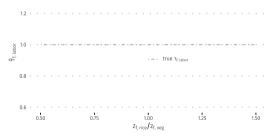
back

• 1-product model misinterprets crop heterogeneity as frictions

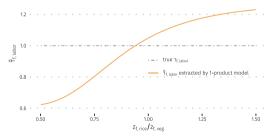
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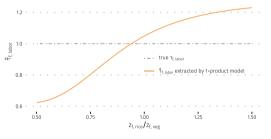
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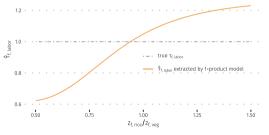
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• exercise to isolate: apply 1-product model to counterfactual reallocation data generated by multi-product model



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- exercise to isolate: treat farm-crops as separate farms for 1-product model



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- \cdot some products have higher returns to scale o some farms grow more in reallocation
- 1-product model misses their greater potential growth



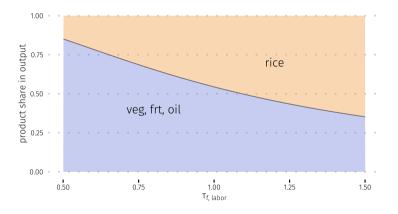
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- 1-product model misses their greater potential growth
- → 1-product model understates misallocation



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- → 1-product model understates misallocation
 - exercise to isolate: rescale input elasticities in multi-product model s.t. all crops have the same returns to scale



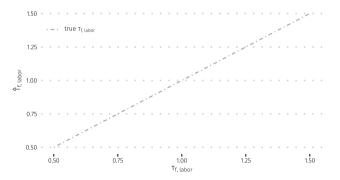
• simulated multi-product farm as labor distortion $\tau_{f,labor}$ is varied:



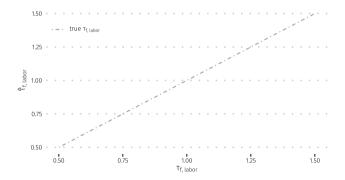
• $\tau_{f,labor}$ \uparrow \rightarrow shift from labor-intensive vegetables to land-intensive rice



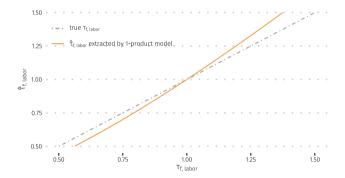
• apply **single**-product model to extract frictions from simulated **multi**-product data



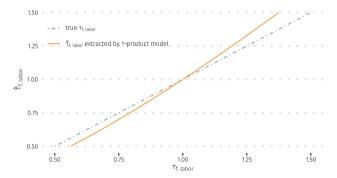
- apply single-product model to extract frictions from simulated multi-product data
- multi-product model: optimal product choice response to frictions
 - modest $\tau_{f,labor}$ increase \rightarrow shift to land-intensive rice \rightarrow hire even more land rel. to labor



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- ullet 1-product model: high input ratio dispersion ullet infer large heterogeneity in frictions
 - ightarrow 1-crop model overstates misallocation



- 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



Remove More Distortions → 1-Product Model Overstates

• 1-product error when conducting increasingly expansive reallocations:

