Misallocation in the Market for Inputs:

Enforcement and the Organization of Production

Johannes Boehm

Ezra Oberfield

Sciences Po

Princeton

LSE Workshop on Networks in Macro & Finance

June 2017

Misallocation in the Market for Inputs

• How important are distortions for income differences?

- Our focus: Distortions in use of intermediate inputs
 - Role of courts & contract enforcement
- Margins
 - Which intermediate inputs to use?
 - How much to do in-house?
- Distortions
 - Might have wrong producers doing wrong tasks
 - Accumulate in supply chains

Manufacturing Plants in India

- New facts
 - Enormous variation in materials shares
 - $\star\,$ but more variation in industries that use rel.-spec. inputs
 - In states with worse enforcement...input bundles systematically different
 - * Industries using homogeneous inputs: higher materials share
 - * Relative to those, industries using rel.-spec. inputs: lower materials shares
 - Within input bundles: shift toward homogeneous inputs
- Impact on aggregate productivity? \Rightarrow Structural model
 - Key ingredients:
 - * Firms can choose between different modes of production
 - Organization of production is endogenous
 - Key Challenge: Separate misallocation from heterogeneity
 - Preliminary results: Back out wedges on use of rel.-spec. inputs, labor
 - ★ Correlated with court congestion
 - * Reducing congestion in worst state to that of best state \Rightarrow TFP $\uparrow \approx 6\%$.
 - ★ Wedges are several times larger

Literature

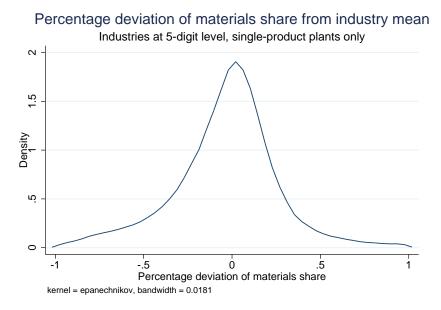
- Factor Misallocation Literature: Restuccia & Rogerson (2008), Hsieh and Klenow (2009, 2014), Midrigan and Xu (2013), Hsieh Hurst Jones Klenow (2016)
- Multi-sector models with linkages: Jones (2011a,b), Bartelme and Gorodnichenko (2016), Boehm (2016), Ciccone and Caprettini (2016), Liu (2016), Bigio and Lao (2016), Caliendo, Parro, Tsyvinski (2017), Tang and Krishna (2017)
- Firm heterogeneity and linkages in GE: Oberfield (2016), Eaton, Kortum, and Kramarz (2016), Lim (2016), Lu Mariscal Mejia (2016), Chaney (2015), Kikkawa, Mogstad, Dhyne, Tintelnot (2017)
- Aggregation properties of production functions: Houthakker (1955), Jones (2005), Lagos (2006), Mangin (2015)
- Courts and economic performance: Chemin (2012), Acemoglu and Johnson (2005), Nunn (2007), Levchenko (2007), Antras Acemoglu Helpman (2007) Laeven and Woodruff (2007), Ponticelli and Alencar (2016)

REDUCED FORM EVIDENCE

Data

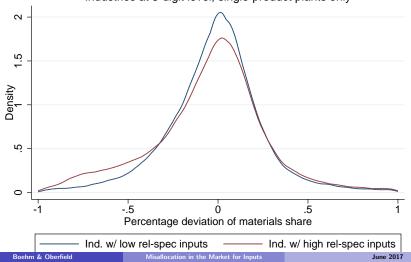
- Indian Annual Survey of Industries (ASI), 2001-2010
 - All manufacturing plants with more than 100 employees, 1/5 of plants between 20-100
 - > Drop plants without inputs, not operating, extreme materials share
 - $\blacktriangleright~\sim 25,000$ plants per year
- Standardized vs. Relationship-specific (Rauch)
 - Standardized \approx sold on an organized exchange, ref. price in trade pub.
 - Relationship-specific \approx everything else
 - ▶ Standardized: 30.1% of input products, 50.0% of spending on intermediates
- We exclude energy, services (treat those as primary inputs)
- For reduced form evidence, use single-product plants

Large Variation in Materials Shares (within industries)



Different depending on industry's reliance on relationship-specific inputs

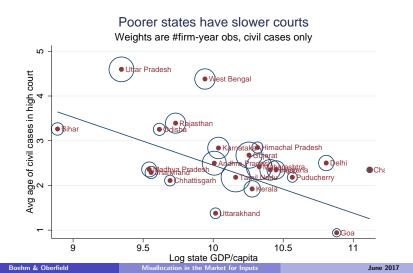
Percentage deviation of materials share from industry mean Industries at 5-digit level, single-product plants only



8 / 28

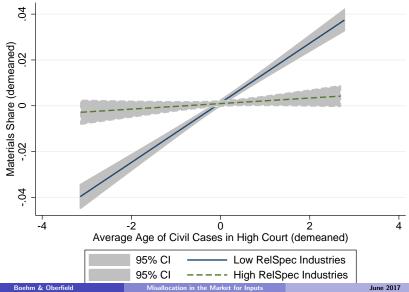
Slow Courts

- Contract disputes between buyers and sellers
- District courts can de-facto be bypassed, cases would be filed in high courts
- Court quality measure: average age of pending civil cases in high court



9 / 28

Mat Share higher in states with more congested courts – but relatively lower in relationship-specific industries



7 10 / 28

Within Industry Regression

	(1)	(2)	(3)	(4)
	MatShare	MatShare	MatShare	MatShare
Avg age of Civil HC cases	0.00715***	0.00904***	0.0135***	0.0147***
	(0.000592)	(0.000679)	(0.00131)	(0.00138)
Log district GDP/capita		0.00605***		0.00612***
Log district ODT / cupitu		(0.00129)		(0.00129)
		()		()
log Pop Density 2001		-0.00213***	-0.00109*	-0.00219***
		(0.000516)	(0.000475)	(0.000517)
AvgAgeOfCivCases * Rel. Spec.			-0.0128***	-0.0121***
6 6 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7			(0.00248)	(0.00257)
5-digit product FE	yes	yes	yes	yes
Observations	198127	183688	191004	183688
R^2	0.431	0.441	0.437	0.441
Chandrand amount in manual based and an attack land				

Standard errors in parentheses, clustered at state level

* p < 0.05, ** p < 0.01, *** p < 0.001

• Large asymmetry between industries that rely heavily on relationship-specific inputs vs industries that rely on standardized inputs

Within Industry, State Regression

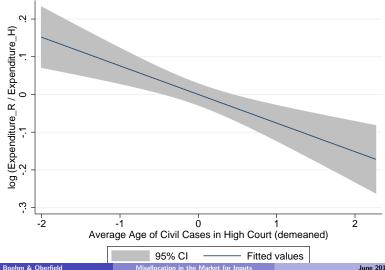
	(1)	(2)
	MatShare	MatShare
AvgAgeOfCivCases * Rel. Spec.	-0.0120***	-0.0105**
	(0.00256)	(0.00341)
Log GDP/capita * Rel. Spec.		-0.000602 (0.00714)
5-digit product FE	yes	(0.00714) yes
State FE	yes	yes
Observations	209188	200663
R^2	0.470	0.476

Standard errors in parentheses, clustered at state level

* p < 0.05, ** p < 0.01, *** p < 0.001

 Moving from avg age of 1 year to 4 years: ⇒ M-share ↓ 3.6pp more in industries that rely on relationship goods than in industries that rely on standardized inputs

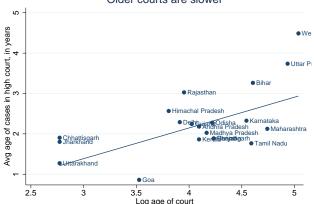
In states with slow courts, input baskets are tilted towards homogeneous inputs Within-industry relationship:



Misallocation in the Market for Inputs

Endogeneity: IV

- Since independence: # judges based on state population
- \Rightarrow backlogs have been accumulating over time
 - But: new states have been created, and therefore new high courts
 - These courts start with a clean slate



Older courts are slower

IV makes coefficient larger

	(1)	(2)	(3)
	logshareRH	logshareRH	logshareRH
Avg age of civil HC cases (instr.)	-0.0544**	-0.0438*	-0.0580*
	(0.0205)	(0.0209)	(0.0292)
log pop density		-0.0220*	-0.0113
		(0.0101)	(0.0149)
log(gdpc)		. ,	-0.0806
			(0.0503)
Recipe FE	yes	yes	yes
Observations	24387	24387	22924
R^2	0.695	0.695	0.700

Standard errors in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001

MODEL: HOW COSTLY ARE DISTORTIONS?

Goals

- Goal: Natural distribution of expenditure shares on different types of inputs
- Main identifying assumption: slow courts do not distort use of homog. inputs
 - Slow courts shift distribution
 - First moment matters! (contrast to Hsieh-Klenow)
- Things we don't want to attribute to misallocation
 - Heterogeneity in production technology across plants
 - Selection into method of production
 - Heterogeneity across locations in
 - ★ Preferences over goods
 - * Prevalence of various industries

Model

- Many industries indexed by $\omega\in\Omega$
 - Differ by suitability for consumption vs. intermediate use
 - Rubber useful as input for tires, not textiles
- Mass of measure J_{ω} of firms (varieties) in industry ω
- Household has nested CES preferences

$$U = \left[\sum_{\omega} \beta_{\omega}^{\frac{1}{\eta}} C_{\omega}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \qquad C_{\omega} = \left[\int_{0}^{J_{\omega}} c_{j}^{\frac{\varepsilon_{\omega}-1}{\varepsilon_{\omega}}} dj\right]^{\frac{\varepsilon_{\omega}}{\varepsilon_{\omega}-1}}$$

Production

- Technology: Firms draw many ways of producing, uses most cost-effective
 - Recipe $\rho \in \varrho(\omega)$: broad class, uses inputs from particular industries, $\hat{\omega}_1^{\rho}, ..., \hat{\omega}_n^{\rho}$
 - A technique is production function using
 - ★ particular suppliers $s_1, ..., s_n$

$$y_b = G_\rho \bigg(z_l l, z_{x1} x_{s_1}, ..., z_{xn} x_{s_n} \bigg),$$

 \boldsymbol{G} is CRS, inputs are complements

Production

- Technology: Firms draw many ways of producing, uses most cost-effective
 - Recipe $\rho \in \varrho(\omega)$: broad class, uses inputs from particular industries, $\hat{\omega}_1^{\rho}, ..., \hat{\omega}_n^{\rho}$
 - A technique is production function using
 - * particular suppliers $s_1, ..., s_n$
 - ★ Match-specific input-augmenting productivities $z_l, z_{x1}, ... z_{xn}$

$$y_b = G_{\rho} \bigg(z_l l, z_{x1} x_{s_1}, ..., z_{xn} x_{s_n} \bigg), \qquad G \text{ is CRS, inputs are complements}$$

- Techniques arrive randomly: Among those of type $\omega,$
 - # techniques for recipe ρ with each productivity better than $\{z_l, z_{x1}, ..., z_{xn}\}$ is \sim Poisson with mean

$$m_{\omega\rho}z_l^{-\zeta_l^{\rho}}z_{x1}^{-\zeta_{x1}^{\rho}}...z_{xn}^{-\zeta_{xn}^{\rho}}$$

- $\blacktriangleright \ \ \text{with} \ \ \zeta_l^\rho + \zeta_{x1}^\rho + \ldots + \zeta_{xn}^\rho = \gamma_\omega$
- Define normalized tail exponents

$$\alpha_l^{\rho} \equiv \frac{\zeta_l^{\rho}}{\gamma_{\omega}}, \qquad \qquad \alpha_{xi}^{\rho} \equiv \frac{\zeta_{xi}^{\rho}}{\gamma_{\omega}} \qquad \Rightarrow \qquad \alpha_l^{\rho} + \sum_i \alpha_{xi}^{\rho} = 1$$

Contract Enforcement

• Weak Enforcement: For each technique two types of wedges

```
t_l, t_{x1}, ..., t_{xn} \sim T_{\rho} (t_l, t_{x1}, ..., t_{xn})
```

- Equivalent to tax (paid with output) that is thrown in ocean Why?
- One Microfoundation Details
 - * Goods can be customized, but holdup problem
 - * Workers can steal, but stealing effort is wasteful
 - * Court quality determines size of loss before contract is enforced
- Depends on sourcing industry
 - *i* Homogeneous: $t_{xi} = 1$
 - *i* Relationship-specific: $t_{xi} \in [0, 1]$

Aggregation

Proposition: Let $q_j = \frac{w}{MC_j}$, $F_{\omega}(q)$ be CDF among firms in industry ω . Then

$$F_{\omega}(q) = e^{-(q/Q_{\omega})^{-\gamma_{\omega}}}$$

where

$$\begin{split} Q_{\omega} &= \left\{ \sum_{\rho \in \varrho(\omega)} m_{\omega\rho} \kappa_{\omega\rho} \left(t_{\omega\rho}^* \prod_i Q_{\tilde{\omega}_i^{\rho}}^{\alpha_{xi}^{\rho}} \right)^{\gamma_{\omega}} \right\}^{1/\gamma_{\omega}} \\ t_{\omega\rho}^* &= \left\{ \int \left(t_l^{\alpha_l^{\rho}} t_{x1}^{\alpha_{x1}^{\rho}} ... t_{xn}^{\alpha_{xn}^{\rho}} \right)^{\gamma_{\omega}} T\left(dt_l, dt_{x1}, ..., dt_{xn} \right) \right\}^{1/\gamma_{\omega}} \\ \kappa_{\omega\rho} &= \text{ constant} \end{split}$$

Proposition: Among firms in ω using recipe ρ , share of total exp. on:

$$\text{Labor:} \ \frac{\alpha_l^\rho \bar{t}_l^\rho}{\alpha_l^\rho \bar{t}_l^\rho + \sum_i \alpha_{xi}^\rho \bar{t}_{xi}^\rho}, \qquad \qquad \text{input} \ i: \ \frac{\alpha_{xi}^\rho \bar{t}_{ri}^\rho}{\alpha_l^\rho \bar{t}_l^\rho + \sum_i \alpha_{xi}^\rho \bar{t}_{xi}^\rho},$$

where $\bar{t}_{xi}^{\rho} \equiv \int t_{xi}\tilde{T}(dt)$, $\bar{t}_{l}^{\rho} \equiv \int t_{l}\tilde{T}(dt)$, summarize distortions

Counterfactual?

Question:

• Change wedge distribution from T to $T^\prime,$ what is impact on agg. output?

From data, need two sets of shares

- HH_{ω} : share of the household's spending on good ω
- Among those of type $\omega,$ let $R_{\omega\rho}$ be the share of total revenue of those that use recipe $\rho.$

$$\frac{U'}{U} = \left(\sum_{\omega} HH_{\omega} \left(\frac{Q'_{\omega}}{Q_{\omega}}\right)^{\eta-1}\right)^{\frac{1}{\eta-1}}$$
$$\frac{Q'_{\omega}}{Q_{\omega}} = \left\{\sum_{\rho \in \varrho(\omega)} R_{\omega\rho} \left[\frac{t^{*'}_{\omega\rho}}{t^{*}_{\omega\rho}}\prod_{i} \left(\frac{Q'_{\hat{\omega}_{i}^{\rho}}}{Q_{\hat{\omega}_{i}^{\rho}}}\right)^{\alpha_{xi}^{\rho}}\right]^{\gamma_{\omega}}\right\}^{1/\gamma_{\omega}}$$

Identification

- Same across states: Recipe technology
 - Production function (G_ρ)
 - Shape of technology draws (ζ_{ρl}, {ζ_{ρxi}})
- Different across states
 - Measure of producers of each type (J_ω)
 - Prevalence of different recipes $(m_{\omega\rho})$
 - Household Preferences (β_ω)
 - Distribution of wedges for each recipe (T_p)

• Main identifying assump.: Slow courts do not distort use of homog. inputs

- Other Assumptions
 - Plants in state d draw t_x, t_l from $T_{\rho d}(t_x, t_l)$
 - \star t_x applies to all relationship-specific inputs
 - No wedge for homogenous inputs
 - No trade across states
 - ▶ L is labor equipped with other primary inputs (capital, energy, services)

Identifying Recipes in the Data: Cluster Analysis

Use clustering algorithm to group plants that use similar input bundles.

Ward's method:

- **1** Start with the finest partition, i.e. the set of singletons $(\{j\})_{j \in J_{\omega}}$
- In each step, merge two groups to minimize the sum of within-group distances from the mean:

$$\min_{\rho_n \ge \rho_{n-1}} \sum_{\rho \in \rho_n} \sum_{j \in \rho} \sum_{\omega} (m_{j\omega} - \overline{m}_{\rho\omega})^2$$

This creates a hierarchy of partitions.

O Choose a partition (set of clusters) based on how many clusters you want.

Our implementation: cluster based on 3-digit and 5-digit input shares, pick # clusters based on # observations. Summary stats

Identifying Recipes in the Data

Cluster analysis uncovers different ways to produce a product.

Example: clot	h, bleached,	cotton ((code 63303)	
---------------	--------------	----------	--------------	--

	input value, %	Description	# firm-years
Recipe 1	95	yarn bleached, cotton	54
	2	grey cloth (bleached / unbleached)	
	2	chemical & allied substances & products, n.e.c	
	1	colour, chemicals	
Recipe 2	35	grey cloth (bleached / unbleached)	39
	13	yarn, finished / processed - cotton (knitted)	
	6	fabrics, cotton	
	5	colour, chemicals	
	5	yarn dyed, synthetic	
	35	(others)	
Recipe 3	98	yarn unbleached, cotton	22
	1	cotton raw - others (pressed)	
	1	colour, chemicals	
Recipe 4	90	yarn, grey-cotton	18
	6	dye stuff	
	2	cotton woven	
	1	maize atta/flour/maida/sooji	
	1	benders (starch)	

Moments for GMM

Proposition: Let s_{Rj}, s_{Hj}, s_{Lj} be firm j's revenue shares.

• The first moments of revenue shares among firms that use recipe ρ satisfy:

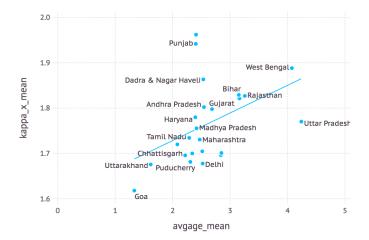
$$\begin{split} & \mathbb{E}\left[\frac{1}{\bar{t}_{x}^{\rho}}\frac{s_{Rj}}{\alpha_{R}^{\rho}}-\frac{s_{Hj}}{\alpha_{H}^{\rho}}\right] &= 0\\ & \mathbb{E}\left[\frac{1}{\bar{t}_{l}^{\rho}}\frac{s_{Lj}}{\alpha_{L}^{\rho}}-\frac{s_{Hj}}{\alpha_{H}^{\rho}}\right] &= 0 \end{split}$$

• If, in addition, G_{ρ} is CES, T_{ρ} is Pareto, the second moments of revenue shares satisfy:

$$\mathbb{E}\left[\left(\frac{2}{\overline{t}_{x}^{\rho}}-1\right)\frac{s_{Rj}^{2}}{\alpha_{R}^{\rho}\left(\alpha_{R}^{\rho}+\frac{1-\sigma_{\rho}}{\gamma_{\omega}}\right)}-\frac{s_{Hj}^{2}}{\alpha_{H}^{\rho}\left(\alpha_{H}^{\rho}+\frac{1-\sigma_{\rho}}{\gamma_{\omega}}\right)}\right] = 0$$

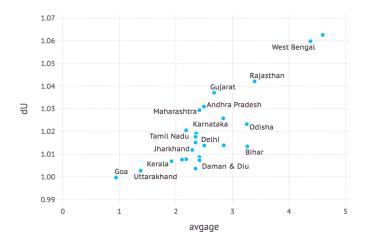
$$\mathbb{E}\left[\left(\frac{2}{\overline{t}_{l}^{\rho}}-1\right)\frac{s_{Lj}^{2}}{\alpha_{L}^{\rho}\left(\alpha_{L}^{\rho}+\frac{1-\sigma_{\rho}}{\gamma_{\omega}}\right)}-\frac{s_{Hj}^{2}}{\alpha_{H}^{\rho}\left(\alpha_{H}^{\rho}+\frac{1-\sigma_{\rho}}{\gamma_{\omega}}\right)}\right] = 0$$

Intermediate input wedges are correlated with court quality



Gains From Improving Courts

Counterfactual sets court quality to 1.



Formal definition of shocks

Simple model:

Joint CDF of shocks:

$$Z(z_l, z_x) = (z_l/\underline{z}_l)^{-\zeta_l} (z_x/\underline{z}_x)^{-\zeta_x}$$

Define

$$m = M \underline{z}_l^{\zeta_l} \underline{z}_x^{\zeta_x}$$

Holding m fixed, we then look at the limiting economy in which $\underline{z}_l,\,\underline{z}_x\to 0.$ (Back

Full model:

Joint CDF of shocks:

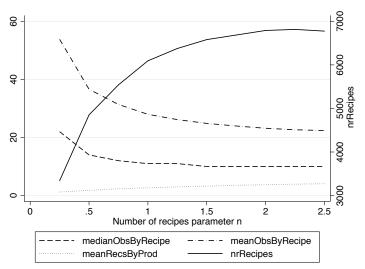
$$Z(z_{l}, z_{x1}, ... z_{xn}) = (z_{l}/\underline{z}_{l})^{-\zeta_{l}^{\rho}} (z_{x1}/\underline{z}_{x1})^{-\zeta_{x1}^{\rho}} ... (z_{xn}/\underline{z}_{xn})^{-\zeta_{xn}^{\rho}}$$

Define

$$m_{\omega}^{\rho} = M_{\omega}^{\rho} \underline{z}_{l}^{\zeta_{l}^{\rho}} \underline{z}_{x1}^{\zeta_{x1}^{\rho}} \dots \underline{z}_{xn}^{\zeta_{xn}^{\rho}}$$

Holding m_{ω}^{ρ} fixed, we then look at the limiting economy in which \underline{z}_l , $\{\underline{z}_{xn}\}\to 0$ (Back

Cluster statistics based on number of potential clusters per industry



Wedges and Enforcement

- Two ways weak enforcement might alter shares
 - Wasted resources
 - Quantity restrictions
- Common feature: Wedge between shadow values of buyer and supplier
- Prediction of quantity restriction:
 - Larger wedges imply larger "markups"
 - But we do not see this

 $\frac{\operatorname{revenue}}{\operatorname{cost}} = \underbrace{\beta}_{<0} \operatorname{Court} \operatorname{Quality} \times \operatorname{specificity} + \epsilon$

Back

Auxiliary regressions

	(1)	(2)	(3)
	MatShare	MatShare	Sales/Cost
Age	-0.000685***		
	(0.0000410)		
log(employment)		-0.0116***	
		(0.000394)	
AvgAgeHC * Rel. Spec.			-0.0449***
			(0.0116)
5-dgt Industy FE	yes	yes	yes
State FE			yes
Observations	162083	166110	164031
R^2	0.449	0.449	0.112

Standard errors in parentheses

* p < 0.05,** p < 0.01,*** p < 0.001

Wedges and Enforcement

Market wage: w wage in excess of stealing

- $\bullet\,$ If worker steals ψ^l units of output, needs to be paid $g^l(\psi^l)w$
- $\bullet\,$ If supplier customizes incompletely by ψ^x , needs to be paid $g^x(\psi^x)\lambda_s$
- Contract specifies ψ^l, ψ^l . Workers choose ψ^l , supplier chooses ψ^x

Buyer minimizes cost:

$$\min g_l(\psi_l)wl + g_x(\psi_x)\lambda_s x$$

subject to

$$G\left(z_l \min\left\{l, \frac{\tilde{y}_l}{\psi_l}\right\}, z_x \min\left\{x, \frac{\tilde{y}_x}{\psi_x}\right\}\right) - \tilde{y}_l - \tilde{y}_x \ge y_b$$

- $\bullet\,$ Weak enforcement: court only enforces claims in which damage is greater than a multiple $\tau-1$ of transaction.
- Recover functional form if $g_l(\psi_l), g_x(\psi_x) \to 1$

• Let F be the CDF of efficiency in the economy (endogenous)

• Let F be the CDF of efficiency in the economy (endogenous)

- LLN: $F(q) = \Pr(q_j \leq q)$, depends on
 - How many techniques an entrepreneur discovers

Efficiency each technique delivers



• Let F be the CDF of efficiency in the economy (endogenous)

- LLN: $F(q) = \Pr(q_j \leq q)$, depends on
 - How many techniques an entrepreneur discovers

techniques $\sim Poisson(M)$

Efficiency each technique delivers

• Let F be the CDF of efficiency in the economy (endogenous)

- LLN: $F(q) = \Pr(q_i \leq q)$, depends on
 - How many techniques an entrepreneur discovers

techniques $\sim Poisson(M)$

- Efficiency each technique delivers $\mathcal{C}(\tau_l/z_l, \tau_x/z_xq_s)^{-1}$

 - * Productivity of each technique: $z \sim Z(\cdot)$
 - **★** Efficiency of each supplier: $q_s \sim F(\cdot)$
 - ***** Wedges: $\tau \sim T(\cdot)$

Intermediate input wedges are correlated with court quality

	(1)	(2)	(3)
	logshareRH	logshareRH	logshareRH
Avg age of civil HC cases	-0.0228***	-0.0192***	-0.0391***
	(0.000458)	(0.000435)	(0.000581)
	. ,	. ,	. ,
log pop density		-0.0265***	-0.0163***
		(0.000385)	(0.000447)
log(gdpc)			-0.0592***
			(0.00120)
Recipe FE	yes	yes	yes
Observations	38430	38430	36168
R^2	0.061	0.164	0.230

Standard errors in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001