Firm-Level Dispersion in Productivity - Is the Devil in the Details?[1]

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[1]Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

Background

- Important finding in empirical literature: productivity differences among establishments are large, even in narrowly defined industries (Syverson (2011), FGHW (2015)).
  - Dispersion is important as a measure of heterogeneity and because it is relevant for business dynamism and growth
- This conclusion holds for both revenue-based and quantity-based productivity measures.
  - However, micro datasets rarely contain information on prices or quantities. Most of the evidence is based on revenue productivity.
- High dispersion robust to alternative estimation methods. Estimation methods viewed as not critical for this and other core findings (Syverson (2011))
- But as we show, the alternative methods yield conceptually different measures. Moreover, this is potentially important since one specific measure has become important as an indicator of misallocation (Hsieh-Klenow (2009)).

Background

- Their insight is that dispersion in a particular revenue productivity measure reflects dispersion in distortions - under certain assumptions about production and demand.
- Widely used in analyses of misallocation [keyword search in title on ideas.repec.org returns 70 records in 2014-2015].
- This paper investigates the generality of this insight:
  - we show that the conclusions in Hsieh-Klenow (2009) don't necessarily hold under alternative assumptions about returns to scale (relevant because evidence suggests NCRS)
  - we show that alternative revenue productivity measures have different implications even under the assumptions made by Hsieh-Klenow (2009);
  - present a framework that can be used to make inferences about the properties of distortions and frictions.

TFPR conceptual measure is critical

- Conceptual measure of revenue per composite input, useful to consider (Foster-Haltiwanger-Syverson (2008), in logs):

$$tfpr_i = p_i + tfpq_i = p_i + q_i - \sum_j \alpha_j x_{ij}$$

- α_j are factor elasticities from Cobb-Douglas production function
- Insight in Hsieh-Klenow (2009):
  1. Downward sloping demand $\Rightarrow$ negative relationship between physical productivity and product prices.
  2. Add CRS technology and iso-elastic demand $\Rightarrow$ *TFPR* is equalized across plants in the absence of distortions or frictions because high-productivity plants experience an exactly offsetting price decline.
  3. The implication is that observed *TFPR*-dispersion must reflect distortions.

What do we measure?

TFPR vs. commonly used revenue productivity measures

1. Cost-share-based methods: cost min. with CRS yields factor elasticities and, by definition, *TFPR*:

$$tfpr_i^{cs} = p_i + q_i - \sum_j \widehat{\alpha}_j x_{ij}$$

$$\Rightarrow tfpr_i^{cs} = tfpr_i$$

2. Regression-based methods in general yield revenue elasticities

$$tfpr_i^{rr} = p_i + q_i - \sum_j \widehat{\beta}_j x_{ij}$$

$$\Rightarrow tfpr_i^{rr} \neq tfpr_i^{cs}$$

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Revenue elasticities will, in general, be a function of factor elasticities and demand parameters. Revenue residual will be a function of technical efficiency and demand shocks.

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  - Demand elasticity (ρ)
  - RTS (γ)
  - Dispersion in demand shocks (δ_{ξ}), TFPQ (δ_{tfpq}) and distortions (δ_{κ}).

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(Conceptual) *TFPR*

$$\delta_{tfpr} = \frac{1}{1-\rho\gamma}\left((1-\gamma)\left(\delta_{\xi} + \rho\delta_{tfpq}\right) + (1-\rho)\sum_{j}\alpha_j\delta_{\kappa_j}\right)$$

Implication: RTS is crucial for the result on dispersion.

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Conclusion: deviation from CRS yields the result that variation in *TFPR* is affected also by demand shocks and *TFPQ* shocks.

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Empirical measures

- Under the same assumptions, we also show that empirical estimates of $tfpr_i^{rr}$ depend on demand elasticity (ρ), demand shocks (ξ) and *tfpq*.

$$tfpr_i^{rr} = \rho tfpq_i + \ln \xi_i + p$$

(no distortions here, RTS free)

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- This implies we can write $tfpr_i$ as

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- Under NCRS, correlation is determined by γ and ρ.

Digging Deeper – Exploratory empirical exercise

- To implement above decompositions exactly, need to estimate factor elasticities and demand parameters.
- Absent data on prices and quantities, we follow the approach in Klette-Griliches (1996) and De Loecker (2011) to jointly identify revenue function and demand parameters. Crude approach, would be better to have data on demand.
- Under those assumptions, α_j-s can be calculated using estimates of β_j and ρ, and therefore we can estimate $tfpr_i$, its dispersion and the components of the decomposition.

Digging Deeper – Exploratory empirical exercise

1) Recover quantity elasticites (α_j) from revenue elasticities (β_j)

- Under isoelastic demand, $P_i = P(Q/Q_i)^{1-\rho}\xi_i$ where ξ_i is a demand shifter, writing out plant-level log-revenues gives the estimating equation:

$$\begin{aligned} p_i + q_i &= \rho q_i + \ln\xi_i + (1-\rho)q + p \\ &= \rho(\sum_j \alpha_j x_i^j + tfpq_i) + \ln\xi_i + (1-\rho)q + p \\ &= \sum_j (\rho\alpha_j) x_i^j + \rho tfpq_i + \ln\xi_i + (1-\rho)q + p \end{aligned}$$

- Joint estimation of rev. elasts and demand parameter helps. $\widehat{\beta}_j = \widehat{\rho\alpha_j}$: rev. elasts. We can recover demand parameter using coefficient of *aggregate* revenues $\widehat{\beta}_q = 1 - \widehat{\rho}$, and factor elasticities are determined by $\widehat{\alpha_j} = \widehat{\beta}_j / \widehat{\rho}$.

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- So we can charaterize the composite distortion term $(\frac{1-\rho}{1-\rho\gamma}\sum_j \alpha_j ln\kappa_{ij})$ and its dispersion $(\frac{1-\rho}{1-\rho\gamma}\sum_j \alpha_j \delta_{\kappa_j})$

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- Plant-level data: ASM, CM (1972-2010), 50 largest industries (see FGHW (2015) for details).

Exploratory empirical exercise - Findings

- Dispersion in $tfpr_i^{rr}$ and κ (derived estimate of distortions) are similar, on average .2-.3.
- Correlation between $tfpr_i^{rr}$ and κ is high.
- Interpretation:
  - $corr(tfpq_i, \kappa)$ and $corr(\xi, \kappa)$ positive ($\approx$ FGHW (2015) with much less structure)
  - In other words, empirical evidence suggests that *tfpq* shocks and demand shocks are more likely to hit plants with higher distortions - under HK assumptions.
  - Why?

Conclusions

- Empirical evidence suggests that *tfpq* shocks and demand shocks are more likely to hit plants with higher distortions - under HK assumptions.
- An alternative interpretation associates the derived distortion estimates with frictions. Establishments with high *tfpq* have high *tfpr* because it takes time to adjust their production factors.
- In sum, caution needs to be used interpreting dispersion in revenue productivity as reflecting distortions.
- Estimation methods matter and can be insightful in this context.
- Additional caution since alternative demand/production functions yield more wedges between tfpr and distortions.

Table: Cross-industry moments of the estimated demand parameter (ρ), returns to scale (γ), and dispersion measures: *tfpr*, $tfpr^{rr}$, $tfpr^{cs}$ and distortions.

	ρ	γ	δ_{tfpr}	$\delta_{\text{tfpr}^{rr}}$	δ_{κ}
			OP		
mean	0.95	1.09	0.53	0.29	0.27
sd	0.16	0.51	1.08	0.08	0.09
			tfpr^{cs}		
mean	.	1	0.31	.	0.31
sd	.	1	0.11	.	0.11

Table: Within-industry correlations of terms underlying dispersion measures.

Panel 1: 50 industries					
A: Cross-industry averages					
	OP				
	$tfpr^{rr}$	tfpr	dist	$tfpr^{cs}$	$tfpr_0^{rr}$
$tfpr^{rr}$	1				
tfpr	0.9	1			
dist	0.96	0.88	1		
$tfpr^{cs}$	0.88	0.81	0.92	1	
$tfpr_0^{rr}$	0.85	0.76	0.82	0.75	1

Relationship between returns to scale and the correlation between TFPR and distortions (r(tfpr,dist)).