Comments on BLS-Census Micro-Productivity Project

Mark J. Roberts

Pennsylvania State University and NBER

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Mark J. Roberts (Institute)

Micro-Productivity Project

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- One of the most important variables to help understand firm and industry performance
- Does micro data give a similar picture of industry/aggregate productivity movements
- A robust, consistently-defined measure available to RDC users would be widely used
- Stepping stone to moving beyond manufacturing to large sectors of the economy
- Excellent project that uses the expertise of BLS and Census

Growth Accounting and Index Numbers

• Developed for aggregate time-series comparisons and Tornqvist index is the basis for BLS program

$$\Delta MFP_{t} = (\ln Q_{t} - \ln Q_{t-1}) - \sum_{i} \frac{1}{2} (S_{it} + S_{it-1}) (\ln X_{it} - \ln X_{it-1})$$

In practice it captures numerous factors: shifts in production function, movements across short-run equilibria, returns to scale. Allows flexible technology and does not impose Hick's neutral technical change

• Issues when moving to micro data:

$$MFP_{ft} = \ln Q_{ft} - \sum_{i} S_{ift} \ln X_{ift}$$

- What is the reference point? Without reference point it depends on units of measure
- How are factor shares treated? If constant for all firms it imposes Cobb-Douglas form, Hicks neutral technology differences
- How to deal with entry and exit?

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Production Function:

$$\ln Q_{ft} = \beta_0 + \sum_i \beta_i \ln X_{ift} + \omega_{ft} + \varepsilon_{ft}$$

Two sources of noise: productivity ω_{ft} is observed by the firm prior to variable input choice, random shocks to ε_{ft} is not. Variable input levels are endogenous and OLS estimates of β_i are biased upward Productivity Evolution:

$$\omega_{ft} = g(\omega_{ft-1}) + \nu_{ft}$$

Estimation relies on the presence of an additional variable that is correlated with ω that can be used to control for ω in production function (investment, materials, labor) Productivity is (generally) constructed as:

$$\hat{w}_{ft} = \ln Q_{ft} - \beta_0 - \sum_i \beta_i \ln X_{ift} + 1$$

Strengths

- ullet Sensible model of firm choice, observe a serially correlated ω
- Gives estimates of productivity for each observation firm/time
- Can separate productivity from returns to scale

Weaknesses

- Large degree of arbitrariness about control variable.
- Decision depends on (unverifiable) assumptions about timing of variable input choice
- Productivity estimates depend on this assumption
- Cobb-Douglas function implies constant output elasticities/factor shares across observations
- New year of data reestimate the production function?
- Assumes Hick's neutral technology differences across observations

Problematic assumption in cross-section firm data.

How to explain the large variation in K/L and M/L ratios for firms of different sizes?

Factor price differences are too small - need enormous elasticities of substitution

Labor saving technology bias is a possible explanation.

Production Models with Biased Technology Differences - utilize information on the variation in input cost shares to estimate non-neutral or factor-augmenting technologies.

Gandhi, Navarro, and Rivers (2009), Doreszelski and Jaumandreu (2014), Zhang (2014).

This further complicates production function estimation.

Across firm	n variation	in	input	shares	is	substantial	in	micro	data

	P10	P50	P90	(P90-P10)/P50
log L	1.10	2.49	4.25	1.27
SI	.089	.198	.374	1.44
log M	7.04	8.84	11.23	0.47
Sm	.367	.564	.751	0.68
log K	8.03	9.26	11.42	0.36
Sk	.080	.192	.344	1.37
log Q	7.90	9.57	11.85	0.41

Taiwan electronics industry, 8003 firms in 1991

Cross sectional dispersion in each input's revenue share $> {\rm dispersion}$ in log input level

Multilateral Index Numbers

$$MFP_{ft} = (\ln Q_{ft} - \ln Q_t^R) - \sum_{i} \frac{1}{2} (S_{ift} + S_{it}^R) (\ln X_{ift} - \ln X_{it}^R)$$

 $\ln Q_t^R$, $\ln X_{it}^R$, S_{it}^R correspond to a reference point (hypothetical firm) with mean log input/output and mean factor shares.

- Recognizes firm variation in output, inputs, and revenue shares
- Does not assume Hick's neutral differences across firms
- Every firm is compared to reference point, transitive comparisons among firms, unit free
- The firm shares are smoothed by averaging with S_{it}^R
- Reference points can be chain-linked over time, allows time-series comparisons of reference firm
- Additional years do not disturb the historical series
- Can use firm's with one year of data
- Problem with unreasonable shares trimming necessary

Other Issues: Imputation and Reporting

- Constructing the reference point in each year
 - Use firms without imputed data, together with sampling weights to construct input, output, share means
 - Compare changes over time with aggregate BLS stats
- Data avalible in RDCs
 - Can construct *MFP_{ft}* for each observation flags indicating what data is imputed
- Reporting for public use
 - Picture of the Cross-section Distribution of *MFP_{ft}* Percentiles, Robust Measures of Dispersion
 - For industries -revenue share-weighted sum: $WMFP_t = \sum_f wr_{ft}MFP_{ft}$,

contribution of separate inputs to output

not the opinion of the Census Bureau, BLS or......

Very valuable project with many potential uses.

Avoid production function estimation - not appropriate for robust statistical products

Pursue multilateral index numbers - matches well with BLS program Focus on reconciling reference point in micro data with industry aggregates.

Interpretation of MFP_{ft} as a measure of resource allocation, not shift in production function, is fine

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