Measuring the Bias of Technological Change

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Motivation

Most production function estimation in IO uses Cobb-Douglas functional form

- Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015)

Cobb-Douglas restricts CES=1 and technology to be Hicks-neutral

- This is OK if your question requires studying productivity in a broad sense
- Example: What are the productivity gains from deregulating an industry?

But many questions, especially outside of IO, are about factor-biased technology

- Example: How much can skill-biased technological change account for secular trends such as rising income inequality or the decline in the labor share?
- With Cobb-Douglas the answer is 0 by assumption
    - Factor-biased technology just isn't there and factor shares are constant[1]

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[1] This was originally seen as a feature, not a bug, since it matched Kaldor's facts

This paper

Provides a framework for estimating CES production functions with both Hicks neutral and factor-augmenting productivity

The economic question: How much of technological change is biased vs. neutral?

The challenge: hard enough to recover productivity, even more so to separate between neutral and factor-biased components

The estimation strategy is a control function approach

- Input scale provides information about factor-neutral technology
- Input mix provides information about factor-biased technology

Background on production function estimation

Based on Aguirregabiria (2019)

The canonical Cobb-Douglas setup

$$y_{it} = \alpha_L l_{it} + \alpha_K k_{it} + \omega_{it} + e_{it}$$

where ω_{it} is factor-neutral TFP and e_{it} is measurement error (both unobservable)

If firms observe ω_{it} before choosing inputs, input choices are endogenous

Panel approaches

Fixed effects

Impose a variance-components structure

$$\omega_{it} = \eta_i + \delta_t + u_{it}$$

where u_{it} isn't serially correlated (A1) and is realized after firms choose inputs (A2)

These two assumptions imply regressors satisfy strict exogeneity

$$cov(x_{it}, e_{is}) = cov(x_{it}, u_{is}) = 0 \quad \forall s \neq t$$

Once fixed effects are added, input choices no longer correlated with unobservables

A2 plausible for agriculture (think weather shocks), less so for manufacturing

Panel approaches

Dynamic panel (Arellano and Bond, 1991)

Allow firms to choose inputs after observing u_{it}, and assume choices are dynamic

$$
\begin{aligned}
l_{it} &= f_L(l_{it-1}, k_{it-1}, \omega_{it}) \\
k_{it} &= f_K(l_{it-1}, k_{it-1}, \omega_{it})
\end{aligned}
$$

Consider the first-difference of the regression equation

$$\Delta y_{it} = \alpha_L \Delta l_{it} + \alpha_K \Delta k_{it} + \Delta \delta_t + \Delta u_{it} + \Delta e_{it}$$

Under these assumptions $\{l_{it-j}, k_{it-j} \quad j \geq 2\}$ are valid instruments for $\Delta l_{it}, \Delta k_{it}$

But the absence of serial correlation in u_{it} remains a heroic assumption: it can be tested and is in fact frequently rejected

Control function approach

Olley and Pakes (1996)

Use the restrictions imposed by economic theory to control for unobservables

- Allow for serial correlation, but restrict it to be first order Markov

$$Pr(\omega_{it}|\omega_{it-1}, \omega_{it-2}, ..., \omega_{i0}) = Pr(\omega_{it}|\omega_{it-1})$$

- Capital takes time to build, while labor is a static decision

$$k_{it+1} = (1-\delta)k_{it} + i_{it}$$

- $i_{it} = f_K(l_{it-1}, k_{it}, \omega_{it}, r_{it})$ and it is invertible in ω_{it}
- No cross sectional variation in input prices, i.e., $r_{it} = r_t \; \forall i$

Step 1: estimate α_L and ϕ_t

$$y_{it} = \alpha_L l_{it} + \underbrace{\alpha_K k_{it} + f_K^{-1}(l_{it-1}, k_{it}, i_{it}, r_t)}_{\equiv \phi_t(l_{it-1}, k_{it}, i_{it})} + e_{it}$$

Step 2: estimate α_K using $\hat{\phi}_{it} = y_{it} - \hat{\alpha_L} l_{it}$ from step 1

$$\begin{aligned}
\hat{\phi}_t(l_{it-1}, k_{it}, i_{it}) &\equiv \alpha_K k_{it} + \omega_{it} + \xi_{it} \quad \text{where } \omega_{it} \equiv h(\omega_{it-1}) + \xi_{it} \\
&= \alpha_K k_{it} + h(\hat{\phi}_{t-1}(\cdot) - \alpha_K k_{it-1}) + \xi_{it}
\end{aligned}$$

Recursive estimation: Guess α_K^G, construct $\hat{\phi}_{t-1}(\cdot) - \alpha_K^G k_{it-1}$, then estimate the equation above to get $\hat{\alpha_K}$, which becomes the new guess. Iterate until $|\hat{\alpha_K} - \alpha_K^G| < \epsilon$

Limitations of the method

- Investment is lumpy: we see $i_{it} = 0$ often
- At $i_{it} = 0$ invertibility fails, so we need to drop observations with $i_{it} = 0$
- Levinsohn and Petrin (2003) use materials instead to invert for productivity

Final goal is to obtain $\hat{\omega}_{it} = \hat{\phi}_t - \hat{\alpha}_K k_{it}$

Some of the findings

- Plants which eventually exit have lower TFP growth
- Surviving entrants have higher TFP growth than incumbents

This paper: Incorporating factor-biased technology

CES production function

$$Y_{jt} = \left\{ \beta_K K_{jt}^{-\frac{1-\sigma}{\sigma}} + [\exp(\omega_{Ljt}) L_{jt}]^{-\frac{1-\sigma}{\sigma}} + \beta_M M_{jt}^{-\frac{1-\sigma}{\sigma}} \right\}^{-\frac{\nu\sigma}{1-\sigma}} \exp(\omega_{Hjt}) \exp(e_{jt})$$

- Combining FOC wrt M and L gets rid of Hicks neutral productivity ω_{Hjt}
- Optimal input mix is a function of factor-biased ω_{Ljt} and relative prices

$$m_{jt} - l_{jt} = \sigma \ln \beta_M - \sigma(p_{Mjt} - w_{jt}) + (1-\sigma)\omega_{Ljt} \qquad \text{(FOC ML)}$$

Sketch for separately recovering ω_{Ljt} and ω_{HLjt}

1. estimate σ from FOC ML, then recover ω_{Ljt} residually
2. given $\omega_{Ljt}, \omega_{Hjt}$ can be recovered from FOC L

In step 1, OLS on FOC ML leads to upward bias since $Cov(w_{jt} - p_{Mjt}, \omega_{Ljt}) > 0$

Step 1: Controlling for factor-biased productivity

- Assume both productivity types are Markov and capital takes 1 period to build
- From FOC ML one can invert for $\tilde{\omega}_{Ljt} \equiv (1-\sigma)\omega_{Ljt}$

$$\tilde{\omega}_{Ljt} = \underbrace{\tilde{\gamma}_L + m_{jt} - l_{jt} + \sigma(p_{Mjt} - w_{jt})}_{\tilde{h}_L(m_{jt}-l_{jt}, p_{Mjt}-w_{jt})}$$

- Control for $\tilde{\omega}_{Ljt}$ using the Markov structure, i.e., $\omega_{Ljt} = E_t[\omega_{Ljt}|\omega_{Ljt-1}] + \xi_{Ljt}$

$$\begin{aligned} m_{jt} - l_{jt} &= -\sigma(p_{Mjt} - w_{jt}) + \overbrace{E_t[\tilde{\omega}_{Ljt}|\tilde{\omega}_{Ljt-1}]}^{\equiv \tilde{g}_{Lt-1}(\tilde{\omega}_{Ljt-1})} + \tilde{\xi}_{Ljt} \\ &= -\sigma(p_{Mjt} - w_{jt}) + \tilde{g}_{Lt-1}(\tilde{h}_L(m_{jt-1} - l_{jt-1}, p_{Mjt-1} - w_{jt-1})) + \tilde{\xi}_{Ljt} \end{aligned}$$

where the $\tilde{g}_{Lt-1}$ part is estimated non-parametrically.

Instruments

$$m_{jt} - l_{jt} = -\sigma(p_{Mjt} - w_{jt}) + \tilde{g}_{Lt-1}(\tilde{h}_L(m_{jt-1} - l_{jt-1}, p_{Mjt-1} - w_{jt-1})) + \tilde{\xi}_{Ljt}$$

- OLS will be biased because $Cov(w_{jt} - p_{Mjt}, \xi_{Ljt}) > 0$
- IV must be uncorrelated with the innovation, rather than productivity itself
- Since $\tilde{\xi}_{Ljt}$ unknown to the firm at $t-1$, past decisions m_{jt-1}, l_{jt-1} are uncorrelated with it, although correlated with $\tilde{\omega}_{Ljt}$ due to serial correlation
- Estimation is GMM IV, where the moment condition is

$$E\left[A_{Ljt}(z_{jt})\tilde{\xi}_{Ljt}\right] = 0$$

and $A_{Ljt}(z_{jt})$ is a vector of functions of instruments z_{jt}

Step 2: Controlling for factor-neutral productivity

From FOC M we can invert for ω_{Hjt}

$$\omega_{Hjt} = \underbrace{\gamma_H + \frac{1}{\sigma} m_{jt} + p_{Mjt} - p_{jt} + \left(1 + \frac{\nu\sigma}{1-\sigma}\right) x_{jt} - \ln\left(1 - \frac{1}{\eta(p_{jt}, D_{jt})}\right)}_{\equiv h_H(k_{jt}, m_{jt}, p_{jt}, p_{Mjt})}$$

Take logs on the production function[2],

$$\begin{aligned} y_{jt} &= -\frac{\nu\sigma}{1-\sigma} x_{jt} + \omega_{Hjt} + e_{jt} \quad \text{(now we use that } \omega_{Hjt} \text{ is Markov)} \\ &= -\frac{\nu\sigma}{1-\sigma} x_{jt} + g_{Ht-1}\left(h_H(k_{jt-1}, m_{jt-1}, p_{jt-1}, p_{Mjt-1})\right) + \xi_{Hjt} + e_{jt} \end{aligned}$$

Again, lagged variables are used as instruments and estimation is GMM-IV

$$E\left[A_{Hjt}(z_{jt})(\tilde{\xi}_{Hjt} + e_{jt})\right] = 0$$

[2] X_{jt} is defined such that $Y_{jt} = X_{jt}^{-\frac{\nu\sigma}{1-\sigma}} \exp(\omega_{Hjt}) \exp(e_{jt})$

Recovering productivity

Factor-biased

- $\hat{\sigma} \in [0.45, 0.85]$ with the variation being across industries and instruments
- From FOC ML we can recover ω_{Ljt}

$$\hat{\omega}_{Ljt} = \frac{1}{1-\hat{\sigma}}\left[\hat{\hat{\gamma}}_L + m_{jt} - l_{jt} + \hat{\sigma}(p_{Mjt} - w_{jt})\right]$$

Factor-neutral

- $\hat{\beta}_K \in [0.07, 0.31]$, $\hat{\nu} \approx 1$ and $\hat{\eta} \in [1.79, 9.11]$

$$\hat{\omega}_{Hjt} = \hat{\gamma}_H + \frac{1}{\hat{\sigma}} m_{jt} + p_{Mjt} - p_{jt} + \left(1 + \frac{\hat{\nu}\hat{\sigma}}{1-\hat{\sigma}}\right) x_{jt} - \ln\left(1 - \frac{1}{\hat{\eta}(p_{jt}, D_{jt})}\right)$$

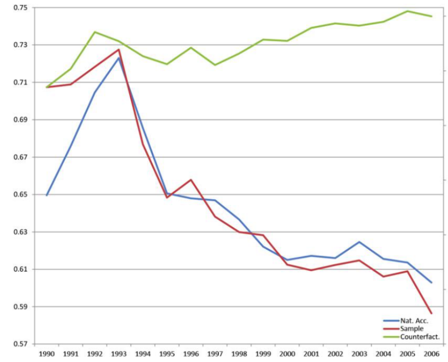

FIG. 2.—Aggregate share of labor in value added in National Accounts (left axis) and aggregate share of labor in variable cost in sample and counterfactual (right axis). The latter indices cumulate year-to-year changes using level in 1990 as base and average over industries using their share of total value added in column 4 of table B1 as weight.

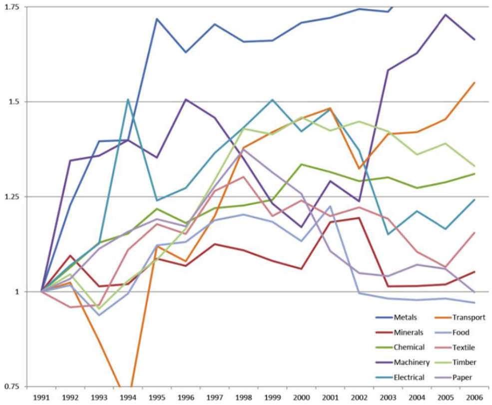

FIG. 3.—Hicks-neutral technological change. Index normalized to one in 1991.

Conclusions

Estimating production functions requires making assumptions about

- timing of input choices
- serial correlation of productivity

Economic theory provides a link between observable input choices and unobservable productivity that can be exploited in estimation

- in some cases this can be used to control for productivity (invertibility)
- FOC of a given input can be used to invert for Hicks neutral productivity
- FOC between two inputs can be used to invert for factor-biased productivity, since Hicks neutral productivity drops out

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