Labour productivity and firm-level TFP with technology-specific production functions

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Motivation

Focus: productivity (Y/L, TFP) differences associated to within-industry technological heterogeneity ⇒ disentangling "Technology" from "pure TFP" at the firm-level.

Early 2000 ⇒ growing attention to firms' heterogeneity:

- heterogeneity in TFP: Melitz, 2003; Melitz-Ottaviano, 2008 and subsequent;
- heterogeneity in Technology: Sampson (QJE, 2015), Perla and Tonetti (JPE, 2014), Perla, Tonetti and Waugh (2015), Benhabib, Perla, Tonetti (2015), Luttmer (QJE, 2007).

Different strands of literature: Technology Adoption, Productivity Estimation, Trade Models with Firm-Selection, Misallocation ...

Related literature

Technology Adoption/Diffusion.

- Parente and Prescott (1994): Barriers to Technology Adoption account for the great disparities in income across countries.
- Barro and Sala-i Martin (1997): imitation in technology diffusion.
- Acemoglu and Zilibotti (2001), Desmet and Rossi-Hansberg (2013): relationship between economic development and technology diffusion.
- Desmet and Parente (2010): relationship between market size and technological upgrading.

$\Rightarrow$ Aggregate perspective

Related literature (cont.)

New Trade Models with Technology Adoption. Trade Models with Heterogenous firms and Technology Adoption focus on the process of technology adoption at the firm-level $\Rightarrow$ effects of integration on aggregate productivity (and growth) through the technological upgrading.

- Sampson (QJE, 2015). Key role for ENTRANT FIRMS: trade integration $\Rightarrow$ firm-selection $\Rightarrow$ tfp distribution of incumbent firms up $\Rightarrow$ entrants draw from a better distribution $\Rightarrow$ tech diffusion. NB: heterogeneity in the tfp distribution of entrants because they do not necessarily adopt the frontier tech.
- Perla and Tonetti (JPE, 2014). Key role for the LEAST PRODUCTIVE FIRMS: diffusion of tech from the more to the less productive $\Rightarrow$ tfp distribution 'evolves' endogenously even without the introduction of new technologies.

Related literature (cont.)

New Trade Models with Technology Adoption (cont.)

- Perla, Tonetti and Waugh (2015). Firms choose whether to adopt a better tech or not. Trade integration increases the incentives to adopt better tech $\Rightarrow$ growth rate up.
- Benhabib, Perla, Tonetti (2015). Firms choose to keep producing with their existing tech, adopt a new tech, or innovate. Tech ado increases growth, but only innovation $\Rightarrow$ long run growth.
- Luttmer (QJE, 2007). The small size of entrants must indicates that imitation is difficult.
- Alvarez, Buera and Lucas (2014). Idea flows: firms get new tech by learning from the people they do business with. Trade $\Rightarrow$ more meetings $\Rightarrow$ tech diffusion $\Rightarrow$ growth rate up.
- Bloom, Draca and Van Reenen (REStat, 2015). Import competition (from low cost countries) forces firms to innovate more than otherwise (mainly because of the within-firm costly adjustment of production factors).

Related literature (cont.)

Misallocation

- Atkinson and Stiglitz (EJ, 1969): "localized" technological progress;
- Restuccia and Rogerson (Rew Econ Dynamics, 2013). Definition of misallocation: lower aggregate TFP due to distortions in the allocation of inputs across units (given firms' technology and TFP)
- Tai Hsieh - Klenow (QJE, 2009), model of misallocation with mkt distorsions (i.e. credit mkt)
- Asker, Collard-Wexler and De Loecker (JPE, 2014): dynamic input choice can explain the dispersion of static measures of K misallocation (MRPK)
- Collard-Wexler and De Loecker (2013): productivity and reallocation associated to the "minimill" technology.
- Gopinath, Kalemli-Ozcan, Karabarbounis and Villegas-Sanchez (2015): Capital Allocation and Productivity in South Europe.

Definition of terms: TFP estimation

AMBIGUITY: "TFP", "productivity" and "technology" are often used interchangeably. Actually, these concepts are not equivalent. Log

Cobb-Douglas usually assumed:

$$y_i = a_i + \beta_K k_i + \beta_L l_i + u_i$$

i=firm; $A_i = TFP$ (firm-specific); $u_i = iid$ term.

TFP usually estimated as the Solow residual

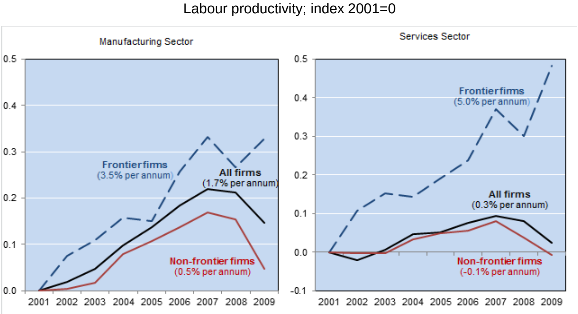
$$\hat{a}_i = y_i - \left(\hat{\beta}_K k_i + \hat{\beta}_L l_i\right)$$

$\Longrightarrow$ Technological differences across firms entirely flow into the residual

Definition of terms: TFP estimation

AMBIGUITY: Sometimes the focus is on “technology”.

- OECD (2015), *The Future of Productivity*: “the main source of the productivity slowdown is [...] a slowing of the pace at which **innovations** spread throughout the economy: a breakdown of the diffusion machine”



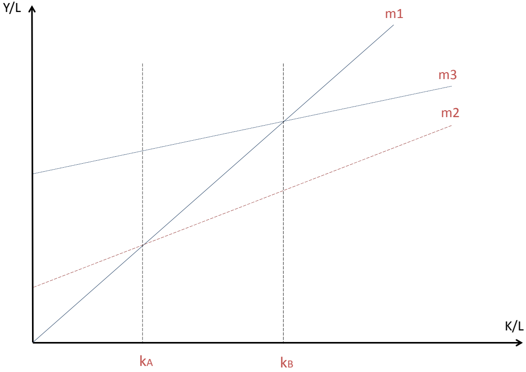
Definition of terms

In our world, the production function is *technology-specific*:

$$y_i = a_i + \alpha_m + \beta_m k_i + u_i$$

- $y_i = ln(Y_i/L_i)$ and $k_i = ln(K_i/L_i)$
- m=technology, with $m = 1, \ldots, M$
  (M = number of available technologies - exogenous)
- different production functions identify different technologies by differing in (α_m, β_m).
- several technologies are available in each sector-industry, with a number of firms using each technology.

Technology-specific production functions



$m_3 \succ m_2 \succ m_1$ for $k < kA$
$m_3 \succ m_1 \succ m_2$ for $kA < k < kB$
$m_1 \succ m_3 \succ m_2$ for $kB < k$

Technology-specific production functions (cont)

Atkinson and Stiglitz (EJ, 1969): "localized" technological progress

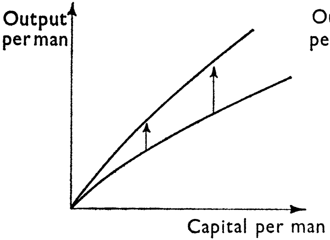


Fig. 1.

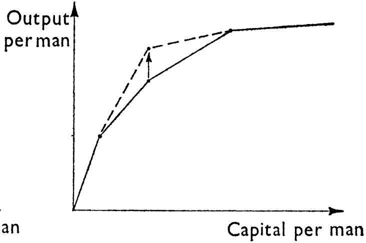


Fig. 2.

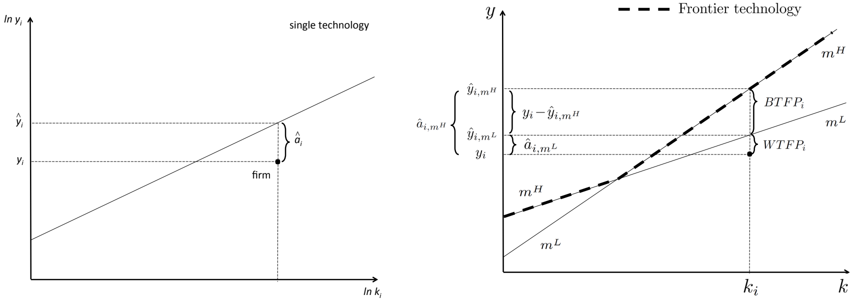
Methodological Contribution

How to use mixture models to unbundle Technology and TFP at the firm-level by estimating technology-specific production functions

- Mixture models enable us to disentangle
  - firm productivity relative to the other firms in the same technology group (i.e. **Within-technology TFP** - **WTFP**) $\Rightarrow$ a firm's ability to exploit a given technology (compared to the other firms using the same technology)
  - firm productivity relative to the labour productivity that the firm could have reached, given its capital-labour ratio, had it chosen the frontier technology (i.e. **Between-technology TFP** - **BTFP**) $\Rightarrow$ a quantification of the labour productivity gap associated with the technological choice.
- Number of technologies and (cross-firm) probability distribution of technologies observed ex-post (no ex-ante assumption);

Methodological Contribution (cont)

Figure: Definition of TFP with one technology (panel a) and two technologies (panel b).



Methodological Contribution (cont.)

...neglecting the presence of different (within-sector) technologies results in overstating the *TFP* of the firms that adopt relatively more productive technologies (due to underestimation of their input coefficient - i.e. $\beta_m > \hat{\beta}$ - and overestimation of the intercept - i.e. $\alpha_m > 0$):

$$\left.\begin{array}{r} y_i = \hat{a}_i + \hat{\alpha} + \hat{\beta} k_i \\[2em] y_i = \hat{a}_{i,m} + \hat{\alpha}_m + \hat{\beta}_m k_i \end{array}\right\} \hat{a}_i = \hat{a}_{i,m} + (\hat{\alpha}_m - \hat{\alpha}) + (\hat{\beta}_m - \hat{\beta}) k_i$$

Methodological Contribution (cont)

- Simultaneity $\Rightarrow$ "empirical model" of technology adoption;
- Technological measure (BTFP) unaffected by firm-level differences in prices and markups (difference between predicted values);
- "Misallocation":
  - In presence of technology dispersion $\Rightarrow$ not possible to attribute the whole dispersion of revenue TFP to "misallocation" (as in Hsieh and Klenow, 2009);
  - Allowing all firms to use the frontier technology does not eliminate misallocation as long as they are not free to hire the desired amount of capital and labor
- Need for internationally comparable data (to potentially capture all the available technologies);

...back to the motivation of the paper.

If one believes in such a world, the "ambiguity" is evident. For example:

- Sampson (2015): what firms draw is basically "tech" (tech diffusion), BUT selection takes place on the basis of tfp *and* technology.
- Perla and Tonetti (2014), Perla, Tonetti and Waugh(2015), Benhabib, Perla, Tonetti (2015): diffusion of tech from the more to the less productive firms. BUT it might well be the case that a firm using the frontier technology lies on the left tail of the TFP distribution because of a low "ability in using that technology" (low TFP).
- Alvarez, Buera and Lucas (2014). Idea flows. Do business contacts help firms in getting the best tech or in learning how to best exploit the tech in use (i.e. tfp)?

Empirical Contribution

Empirical Contribution: we use international firm-level data (*Orbis* database - Bureau van Dijk) $\simeq$ 35.850 worldwide distributed manufacturing firms (2015-2016) to:

- Identify, for each industry, the number M of available technologies and, for each firm, the probability of using each technology (technology clusters)
- Quantify the firm-level productivity (VA/L) gaps in terms of WTFP (not being able to fully take advantage of the technology in use) and BTFP (not using the best technology at the given K/L level)
- Look at key aggregate correlations and firm-level markers of WTFP and BTFP

Analysis: steps

- **1 - Production function(s) estimation**
  - **1.1 - Empirical model of Technology Adoption**
  - **1.2 - Mixture regressions** to identify:
    - M (# of technologies),
    - production function parameters (for each technology),
    - probability to belong to each technology group (for each firm)
- **2 - Quantification of WTFP and BTFP**
- **3 - Broad validation**
  - Correlation with Tech Balance of Payments (OECD)
  - Correlation with standard indicators of tech
  - Country coverage

Step 1 - Production function estimation

We want to estimate:

$$lnY_{i,t} = \alpha_m + lnA_{i,t} + \beta_m^K lnK_{i,t} + \beta_m^L lnL_{i,t}$$

with an endogenous finite set $\{M\}$ of available technologies indexed by m

$\Rightarrow$ OLS distorted because of "simultaneity":

- $Cov(K_{i,t}, A_{i,t}) \neq 0$ and/or $Cov(L_{i,t}, A_{i,t}) \neq 0$

In our $M > 1$ case, also potential simultaneity stemming from the technological choice:

- $Cov(K_{i,t}, m_{i,t}) \neq 0$ and/or $Cov(L_{i,t}, m_{i,t}) \neq 0$

$\Rightarrow$ An "empirical model" of Technology Adoption is needed

Step 1.1 - Empirical model of Technology Adoption

- Production function:

$$lnY_{i,t} = \alpha_m + lnA_{i,t} + \beta_m^K lnK_{i,t} + \beta_m^L lnL_{i,t}$$

- Finite set $\{M\}$ of available technologies $m = (\alpha_m, \beta_m^K, \beta_m^L)$
- One period time-to-build (i.e. the new technology is productive one period after its acquisition)
- TFP term $a_{i,t} = a_{i,t}(m_{i,t})$: evaluated wrt the other firms using technology $m \Rightarrow$ differences (not associated to K, L) in the ability to exploit the given technology
- TFP follows a first order Markov process:

$$a_{i,t} = E[a_{i,t}|a_{i,t-1}] + \xi_{m,i,t}$$

  where $\xi_{m,i,t}$ is innovation in either the adopted technology $(m_{i,t} \neq m_{i,t-1})$ or the ability to exploit it $(m_{i,t} = m_{i,t-1})$

Step 1.1 - Empirical model of Technology Adoption

Use terminology $X[t]$ to remember that variable X is chosen at time $[t]$

Timing:

- end of period t: firm chooses $K_{i,t+1}[t]$ and $m_{i,t+1}[t]$
- beginning of period $t+1$: $a_{i,t+1}$ (i.e. firm's *tfp*) and Z_{t+1} (i.e. a vector of exogenous mkt-level state vars) are observed
  $\Rightarrow$ firm adjusts L (freely) $=>$ $L_{i,t+1}[t+1]$
- end of period $t+1$: firm chooses $K_{i,t+2}[t+1]$ and $m_{i,t+2}[t+1]$ on the basis of $a_{i,t+1}$ and Z_{t+1}

Step 1.1 - Empirical model of Technology Adoption

In each period t, firm i solves:

$$\max_{(K_{i,t+1}, m_{i,t+1})} E_t \left[\sum_{j=t}^{\infty} \delta^{j-t} P_{i,j} | \Omega_{i,j} \right]$$

where the net profit $P_{i,j}$ given by

$$P_{i,j} = \underbrace{\pi_{i,j}(K_{i,j}, a_{i,j}, m_{i,j}, Z_j)}_{\text{gross profit}} - C(K_{i,j+1}, K_{i,j}, m_{i,j+1})$$

with

$$C(K_{i,j+1}, K_{i,j}, m_{i,j+1}) = \underbrace{C^I_{i,j}(I_{i,j})}_{\text{Inv. cost}} + \underbrace{C^D_{i,j}(D_{i,j})}_{\text{Disinv. cost}} + \underbrace{C^A_{i,j,m}\mathbb{I}(m_{i,j+1} \neq m_{i,j})(I_{i,j})}_{\text{tech Adjustment cost}}$$

with $D_{i,j} = \epsilon_{i,j} K_{i,j}$ and $0 \leq \epsilon_{i,j} \leq 1$

Step 1.1 - Empirical model of Technology Adoption

K accumulates according to

$$K_{i,j+1} = K_{i,j} - \delta K_{i,j} + I_{i,j} - D_{i,j}$$

Bellman equation:

$$V_{i,t}(\Omega_{i,t}) = \max_{(K_{i,t+1}, m_{i,t+1})} (P_{i,t} + \delta E_t [V_{i,t+1} | \Omega_{i,t}])$$

Step 1.1 - Empirical model of Technology Adoption

Solution $(K^*_{i,t+1}[t], m^*_{i,t+1}[t])$

- policy function for K:

$$K^*_{i,t+1}(m^*_{i,t+1}, K_{i,t}, a_{i,t}, Z_t)$$

- and the firm will choose the $m^*_{i,t+1}$ that maximizes:

$$\left[\delta E_t \left(V_{i,t+1}|\Omega_{i,t}\right) - C(K^*_{i,t+1}, K_{i,t}, m^*_{i,t+1})\right] |m = m^*_{i,t+1}$$

among all possible $m \in \{M\}$.

Step 1.2 - Production function(s) estimation

I STAGE. "Correction factors" estimation (years 2015-2016)

- estimate the K policy function $K^*_{i,t+1}(m^*_{i,t+1}, K_{i,t}, a_{i,t}, Z_{i,t})$ as

$$\ln K_{i,t}[t-1] = \rho_0 + \rho_1 \ln K_{i,t-1}[t-2] + Z_{c,t} + e^K_{i,t} + u^K_{i,t}$$

- estimate the static condition for L as

$$\ln L_{i,t}[t] = \rho_0 + \rho_1 \ln K_{i,t}[t-1] + Z_{c,t} + e^L_{i,t} + u^L_{i,t}$$

with $Z_{c,t}$ = country-year effects. Under the assumption that $u^K_{i,t}$ and $u^L_{i,t}$ are iid:

- $e^K_{i,t}$ embodies $Cov(K_{i,t}[t-1], m_{i,t}[t-1])$ and $Cov(K_{i,t}[t-1], a_{i,t-1})$
- $e^L_{i,t}$ embodies $Cov(L_{i,t}[t], a_{i,t})$

Step 1.2 - Production function(s) estimation

II STAGE: Production function estimation (year 2016)

In each 2-digits sector, we use

$$y_i = \alpha_m + \beta_m k_i^{\delta_{i,m}} + \gamma_m h_i^{\delta_{i,m}} + \varphi \hat{\Phi}_i^{\delta_{i,m}} + \psi \hat{\Psi}_i^{\delta_{i,m}} + FE_s + \varepsilon_i,$$

where FE_s are 4-digits industry fixed effects, h_i is the average wage bill within the firm (rough control for HK), and the "correction factors" $\hat{\Phi}_i = e_{i,t}^K + u_{i,t}^K$ and $\hat{\Psi}_i = e_{i,t}^L + u_{i,t}^L$ are included

$\Rightarrow$ Mixture models

Step 1.2 - Production function(s) estimation: mixture analysis

Write the (implicit) probability distribution function of $y_{i,t}$ as a weighted average of the M specific segment (technology) densities $f_m(y_{i,t}|\mu_m, \sigma_m)$, each with proper mean (μ_m) and variance (σ^2_m):

$$f(y_{i,t}|\mu, \sigma^2) = \sum_{m=1}^{M} \omega_m f_m(y_i|\mu_m, \sigma^2_m)$$

ω_m = unknown *ex-ante* probability to belong to the technology-group m. Algorithm (based on WLS regressions with weights given by ω_m): random starting points for $\omega_m \Rightarrow$ posterior probabilities through WLS $\Rightarrow$ update the regression coefficients β_m (as weights change) $\Rightarrow$ iteratively alternate WLS and probabilities until a loglikelihood convergence criterion is reached $\Rightarrow$ repeat many times to avoid local optima.

Step 1.2 - Production function(s) estimation: mixture analysis (cont)

Start with random values of $\omega_m \Rightarrow$ posterior probability $p_{i,m}$ that firm i belongs to group $m \Rightarrow$ observation weights ω_m:

$$p_{i,m} \equiv pr(i \in m) = \frac{\omega_m f_m\{y_i|\mu_m;\sigma_m^2\}}{\sum_{m=1}^{M} \omega_m f_m\{y_i|\mu_m;\sigma_m^2\}}$$

This set of probabilities is then used to update the regression coefficients by changing the weights ω_m according to

$$\omega_m = \frac{\sum_i p_{i,m}}{\sum_m \sum_i p_{i,m}}$$

with the following constraints:

$$\omega_m \geq 0 \qquad \forall m = 1, \ldots M \qquad \text{and} \qquad \sum_{m=1}^{M} \omega_m = 1.$$

Descriptive statistics (ORBIS data)

Table 2: Descriptive statistics: Sectoral distribution.

Sector description	Sector code	VA (% of tot)	K (% of total)	# firms	VA/L (avg)	K/L (avg)
Food products	Fd	4.47	3.95	4332	25.8	37.3
Beverages	Bv	3.19	6.85	583	45.6	131.8
Tobacco products	Tb	2.48	2.47	16	58.3	98.8
Textiles	TX	0.79	0.83	1435	26.0	29.3
Apparel	WA	0.92	0.54	2018	15.4	9.3
Leather and related products	LP	0.35	0.13	1151	20.8	11.4
Wood and products of wood and cork	Wo	0.35	0.26	2051	23.1	26.8
Paper and paper products	Pa	3.38	3.83	769	41.0	60.4
Printing and reproduction of recorded media	Pr	1.37	1.74	1541	30.1	29.3
Coke and refined petroleum products	PC	1.80	2.08	84	105.4	251.3
Chemicals and chemical products	Ch	7.68	9.95	1191	55.5	85.4
Basic pharmaceutical products and preparations	Ph	13.26	15.28	294	61.6	85.2
Rubber and plastic products	RP	4.37	3.04	2026	36.0	41.4
Other non-metallic mineral products	NM	6.83	10.26	2137	30.4	53.2
Basic metals	BM	6.21	7.15	710	48.1	74.6
Fabricated metal products, except machinery	MP	3.82	2.07	7060	33.3	29.6
Computer, electronic, and optical products	EP	12.51	9.86	1233	42.9	38.2
Electrical equipment	El	4.54	3.84	1309	38.3	30.9
Machinery and equipment nec	Ma	12.42	8.47	3136	45.8	36.9
Motor vehicles, trailers, and semi-trailers	MV	7.72	6.36	881	33.9	43.2
Other transport equipment	Tr	1.15	0.86	330	38.6	46.0
Furniture	Fu	0.36	0.21	1563	19.8	20.2
Total		-	-	35850	-	-

Descriptive statistics (ORBIS data)

Table 3: Descriptive statistics: Country coverage (% of total).

Country/Country Aggregate	VA	K	L	# firms
DE	27.81	23.98	17.82	4.35
ES	0.39	0.63	0.35	1.48
FR	9.31	7.47	7.69	7.20
GB	11.25	13.02	5.43	2.33
IT	5.11	4.17	4.68	25.06
PT	1.12	0.80	2.34	26.87
US	1.96	2.28	1.54	0.10
IL	0.47	1.24	0.49	0.09
OECD northern Europe	9.76	8.43	6.66	5.67
Other European OECD	1.80	1.52	1.22	0.44
Other non-European OECD	7.92	7.66	3.41	0.26
Eastern Europe	2.68	2.23	6.77	19.36
Other non-OECD	20.43	26.57	41.60	6.80

Note. OECD northern Europe includes NO, FI, SE, DK, and NL. Eastern Europe includes EE, GR, HU, LV, PL, SK, SI, CZ, RO, UA, BA, MK, HR, BG, RS, and CY. Other European OECD includes IS, IE, LU, AT, BE, and LT. Other non-European OECD includes NZ, CA, CH, AU, JP, MX, and TR. Other non-OECD includes RU, AR, SG, CL, ZA, BM, IQ, MY, KY, IN, PH, OM, BD, JO, RS, SA, UY, TZ, TN, PK, NA, LK, KE, EG, CV, BR, BH, AE, KR, CN, BW, CI, FJ, IR, KW, MA, NG, QA, TH, TT, HK, and TW.

Production function estimates (estimated βs)

Table 5: Mixture regressions: Estimated production function parameters.

Sector	# Tech	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4	α_5	β_5
Fd	4	0.190	0.121	0.767	0.379	0.000	0.147	0.000	0.180		
Bv	1	0.055	0.199								
TX	2	-0.093	0.131	0.000	0.238						
WA	3	0.326	0.120	0.000	0.267	-0.018	0.150				
LP	5	-0.251	0.101	-1.232	0.334	-0.687	0.153	0.458	0.313	0.000	0.119
Wo	3	-0.321	0.246	-0.525	0.499	0.000	0.149				
Pa	2	-0.055	0.175	0.000	0.207						
Pr	3	-0.130	0.134	-0.433	0.343	0.000	0.202				
Ch	3	-0.087	0.165	0.000	0.348	0.352	0.211				
Ph	2	1.879	0.126	-0.306	0.187						
RP	3	0.142	0.126	0.584	0.134	0.000	0.238				
NM	3	-0.076	0.155	-0.109	0.289	0.000	0.319				
BM	2	0.144	0.214	0.000	0.325						
MP	1	0.285	0.165								
EP	2	0.194	0.170	0.000	0.442						
El	3	-0.461	0.121	-0.291	0.185	0.000	0.186				
Ma	2	-0.317	0.117	0.000	0.174						
MV	3	-0.345	0.127	0.000	0.250	0.000	0.439				
Tr	1	0.350	0.217								
Fu	3	-0.100	0.189	-1.495	0.453	0.000	0.145				

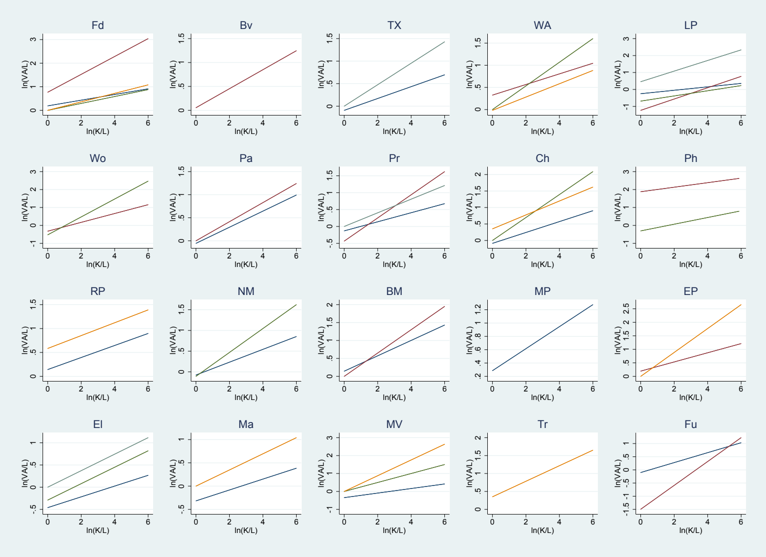
All reported β parameters are statistically significant at the 1% level. Clusters are dropped (and the corresponding coefficients are not reported) when $\beta < 0.1$ or $\beta > 0.9$. Both α and β are considered to be equal to zero when they are not statistically different from zero at the 1% level of statistical significance.

BIC values

Table 4: BIC values from the mixture analysis.

Sector	BIC_1	BIC_2	BIC_3	BIC_4	BIC_5	BIC_6	BIC_7	BIC_8	BIC_9	BIC_{10}	BIC_{min}
Fd	5010.87	3898.95	3741.37	3577.64	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	3577.64
Bv	1132.48	974.24	993.91	1010.26	1041.50	n.c.	n.c.	n.c.	n.c.	n.c.	974.24
Tb	38.49	25.05	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	25.05
TX	2170.23	1902.11	1907.00	1820.22	1781.37	n.c.	n.c.	n.c.	n.c.	n.c.	1781.37
WA	2059.63	1343.36	1272.99	1212.16	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	1212.16
LP	1189.45	814.69	755.69	711.76	701.95	656.92	n.c.	n.c.	n.c.	n.c.	656.92
Wo	2815.85	2280.44	2215.38	2143.86	2112.48	2124.15	2073.52	n.c.	n.c.	n.c.	2073.52
PC	168.49	148.46	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	148.46
Pr	2111.21	1904.85	1891.29	1907.51	1840.34	n.c.	n.c.	n.c.	n.c.	n.c.	1840.34
Pa	1060.93	971.59	983.96	987.68	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	971.59
Ch	2058.61	1905.79	1936.74	1867.89	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	1867.89
Ph	528.28	485.00	484.01	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	484.01
RP	2726.69	2357.59	2329.68	2287.84	2248.99	2242.98	n.c.	n.c.	n.c.	n.c.	2242.98
NM	3438.23	2904.53	2821.25	2767.11	2708.72	2613.42	n.c.	n.c.	n.c.	n.c.	2613.42
BM	1255.25	1171.33	1186.54	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	1171.33
MP	9011.74	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	9011.74
El	1914.06	1695.30	1691.26	1655.78	1577.49	n.c.	n.c.	n.c.	n.c.	n.c.	1577.49
EP	1984.22	1758.36	1712.58	1651.17	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	1651.17
Ma	4799.58	4137.46	4080.23	4046.61	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	4046.61
MV	1431.00	1303.53	1278.07	1231.85	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	1231.85
Tr	602.40	584.83	555.29	530.60	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	530.60
Fu	2069.80	1523.02	1472.50	1482.03	1448.46	1420.63	1396.22	n.c.	n.c.	n.c.	1396.22

Estimated Production Functions



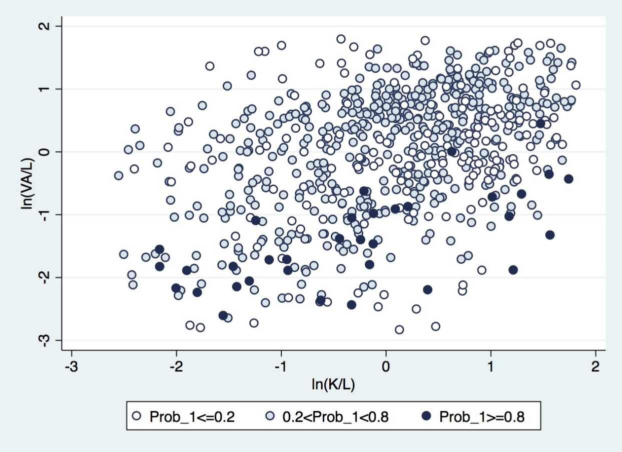
Production function estimates (Total prob by tech group)

Table 6: Mixture regressions: Total probability by technology group.

SECTOR	$prob_1$	$prob_2$	$prob_3$	$prob_4$	$prob_5$
Fd	1331	487	1525	988	-
Bv	422	-	-	-	-
TX	453	498	-	-	-
WA	70	559	905	-	-
LP	464	11	15	207	438
Wo	290	8	582	-	-
Pa	440	329	-	-	-
Pr	503	277	577	-	-
Ch	514	449	80	-	-
Ph	14	250	-	-	-
RP	831	14	789	-	-
NM	1005	26	573	-	-
BM	368	342	-	-	-
MP	7060	-	-	-	-
EP	552	139	-	-	-
El	744	26	443	-	-
Ma	1438	1371	-	-	-
MV	251	127	459	-	-
Tr	244	-	-	-	-
Fu	430	52	448	-	-

For each technology m (with $m = 1, \ldots, 5$), the reported values represent the sum, over all the firms in the sector, of the probability of using technology m.

Example of estimated probabilities of belonging to a given technology cluster: the basic metals (BM) sector



Note. Firm-level observations are plotted. Color scale reproduces the probability classes of belonging to technology cluster 1 (for BM, two clusters are obtained from the mixture analysis).

Step 2 - Quantification of WTFP and BTFP

Use m^H to refer to the *locally optimal* (i.e. "frontier") technology $y_{i,m^H}|k = k_i > y_{i,m}|k = k_i \quad \forall m \neq m^H$.

- For each firm, we are able to compute the predicted values $\hat{y}$ and $\hat{a}$ under the frontier tech (m^H) and any other tech (m):

$$\hat{y}_{i,m} = \hat{\alpha}_m + \hat{\beta}_m k_i \qquad \text{and} \qquad \hat{y}_{i,m^H} = \alpha_{m^H} + \hat{\beta}_{m^H} k_i$$

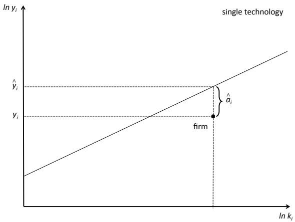
$$\hat{a}_{i,m} = y_i - \hat{y}_{i,m} \qquad \text{and} \qquad \hat{a}_{i,m^H} = y_i - \hat{y}_{i,m^H}$$

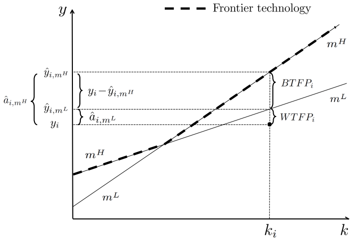
These map into the following probabilistic measures $\Longrightarrow$

Step 2 - Quantification of WTFP and BTFP

$$\text{BTFP} = \sum_{m=1}^{m^H} p_{i,m} \cdot (\hat{y}_{i,m} - \hat{y}_{i,m^H}) = \sum_{m=1}^{m^H} pr_{i,m} \cdot (\hat{a}_{i,m^H} - \hat{a}_{i,m})$$

$$\text{WTFP} = \sum_{m=1}^{m^H} p_{i,m} \cdot \hat{a}_{i,m}.$$





Step 2 - Quantification of WTFP and BTFP (cont)

- **WTFP** Labor productivity gaps due to being relatively less productive within a given technology group (a relatively low ability in exploiting the given technology, as measured by the idiosyncratic component $a_{i,m}$)

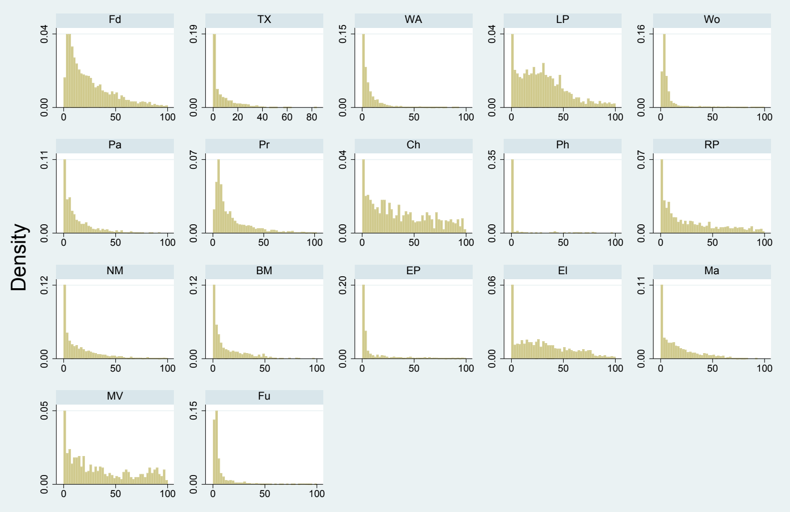
$$\text{Rescaling} \Rightarrow \overline{WTFP}_{\text{best5\%}} - \text{WTFP}_i$$

- **BTFP** Labor productivity gaps due to not choosing the frontier technology (i.e., the productivity gain each firm would enjoy by filling the gap with the highest productivity firms in the same technology group or by switching to the best available technology in the sector).

$$\text{Positive values} \Rightarrow -\text{BTFP}_i$$

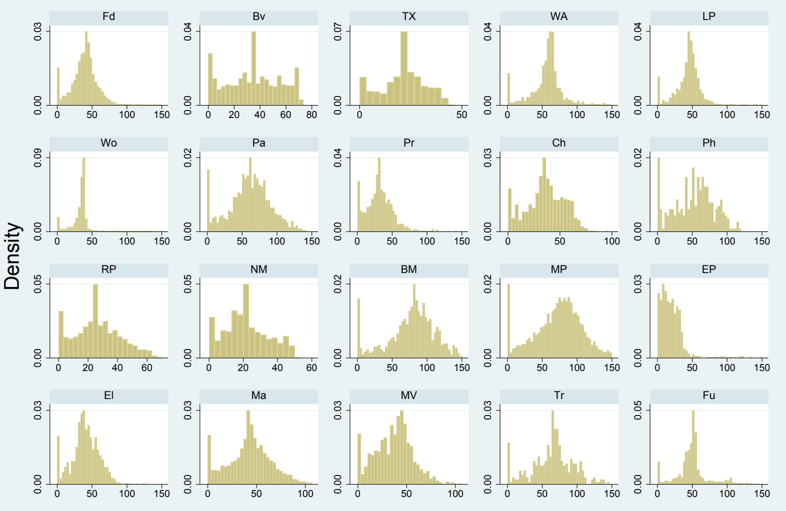
Step 2 - Sectoral distribution of BTFP gaps

Figure 6: Sectoral distribution of BTFP.



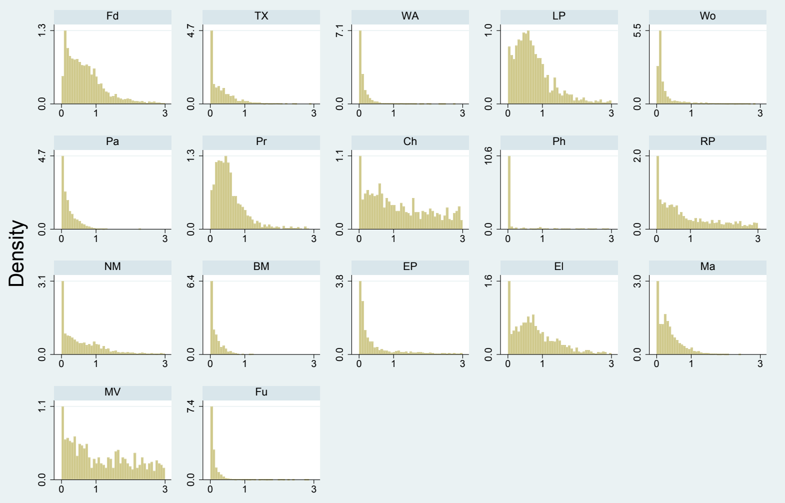
Step 2 - Sectoral distribution of WTFP gaps

Figure 5: Sectoral distribution of WTFP.



Step 2 - Sectoral distribution of the BTFP/WTFP ratio

Figure 3: Sectoral distribution of the BTFP/WTFP ratio.



Step 2 - Sectoral BTFP and WTFP estimates.

Table 7: WTFP and BTFP estimates: Sectoral averages.

	Average			Standard Deviation		
SECTOR	WTFP_i*	BTFP_i*	$\text{BTFP}_i/\text{WTFP}_i$	WTFP_i*	BTFP_i*	$\text{BTFP}_i/\text{WTFP}_i$
Fd	31.906	30.451	0.88	23.1254	29.84432	2.33
Bv	16.591	0.000	0.00	20.694	0.000	0.00
TX	17.427	6.233	0.31	10.604	10.203	0.46
WA	34.990	26.717	0.52	30.113	16.392	0.85
LP	32.180	59.749	2.67	22.695	31.852	4.78
Wo	32.757	11.851	1.21	22.008	25.793	4.39
Pa	52.357	9.740	0.20	37.872	15.933	0.36
Pr	27.059	23.949	0.99	23.592	19.273	5.59
Ch	29.539	43.144	1.32	18.365	61.048	5.88
Ph	39.361	65.329	6.47	28.887	98.280	109.29
RP	18.103	109.059	10.61	15.526	51.932	29.35
NM	20.216	44.674	2.24	12.750	22.421	8.95
BM	78.822	24.968	0.29	46.634	16.643	0.30
MP	63.469	0.000	0.00	40.706	0.000	0.00
EP	19.246	45.203	8.13	21.112	28.217	11.37
El	33.731	55.588	2.35	19.584	27.540	4.17
Ma	34.916	9.289	0.24	22.286	17.506	1.09
MV	29.334	46.874	1.73	19.409	49.955	74.14
Tr	51.144	0.000	0.00	30.365	0.000	0.00
Fu	40.039	8.845	0.38	23.968	21.641	2.31
Total	31.265	34.191	2.11	24.59	27.09	13.86

* % of frontier values.

Total average BTFP is calculated over positive sectoral averages only (1-technology sectors are omitted from the total average). Both WTFP and BTFP are weighted by the sectoral share of employees over total employees.

Step 2 - Quantification of WTFP and BTFP (cont)

- Sectoral number of technologies ranging from 1 (beverages) to 5 (leather)
- BTFP slightly larger (34%) than WTFP (31%) on average
- The relative role of WTFP and BTFP varies considerably across sectors and firms
- Even in sectors in which BTFP dominates on average, there are firms for which labor productivity gaps are mostly driven by WTFP

Step 3 - Correlation with Tech BoP and firm-level markers of WTFP and BTFP

WTFP and BTFP cross-section regressions using

- OECD Stat (2015) data from the technology Balance of Payments, measuring international technology receipts - i.e. outcoming technology flows (variable *Tech Receipts*) - and payments - i.e. incoming technology flows (variable *Tech Payments*). Data covers licence fees, patents, purchases and royalties paid, know-how, research and technical assistance.
- Firm-level characteristics (age, listed, intangibles, liquidity, MNE)

Step 3 - Correlation with Tech BoP and firm-level markers of WTFP and BTFP (cont)

Table 8: Markers of WTFP and BTFP (OLS regressions).

	$WTFP_i$	$BTFP_i$
COUNTRY-SECTOR VARIABLES		
Tech Balance	1.935*	-2.674***
	(0.566)	(0.355)
FIRM-LEVEL VARIABLES		
Firm Age	3.696***	0.070
	(0.483)	(0.350)
Listed	-2.932	15.502
	(8.391)	(11.644)
Firm Intangibles	-0.408**	-0.367***
	(0.153)	(0.125)
Liquidity Ratio	-6.836***	-2.752***
	(0.504)	(0.365)
Multinational	-2.936***	-0.475
	(0.982)	(0.751)
Labor Input	-0.709**	-0.746**
	(0.331)	(0.322)
Constant	30.222***	13.683***
	(4.180)	(4.067)
# obs.	4714	4714
Country FE	yes	yes
Sector FE	yes	yes
R^2	0.414	0.366

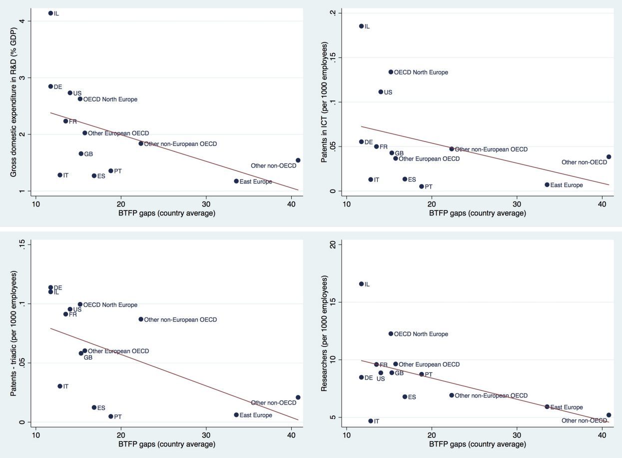
Robust standard errors are in parentheses. All variables are in logs.
Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Step 3 - Correlation with Tech BoP and firm-level markers of WTFP and BTFP (cont)

- As expected, BTFP measure strongly correlated with tech-BoP
- Country-sectors that are net exporters of tech are those in which firms' labor productivity is closer to the local frontier on average
- This might suggest that
  - net exporters, which are more likely to use advanced technologies, may benefit more from initiatives aimed at improving WTFP; viceversa (larger benefits from technology upgrades) for net importers;
- Firm-level dimension: younger and multinational firms characterized by higher WTFP $\Rightarrow$ multinational chains vehicles of 'know-how' rather than 'hard' technology.

Step 3 - Correlations with standard measures of tech

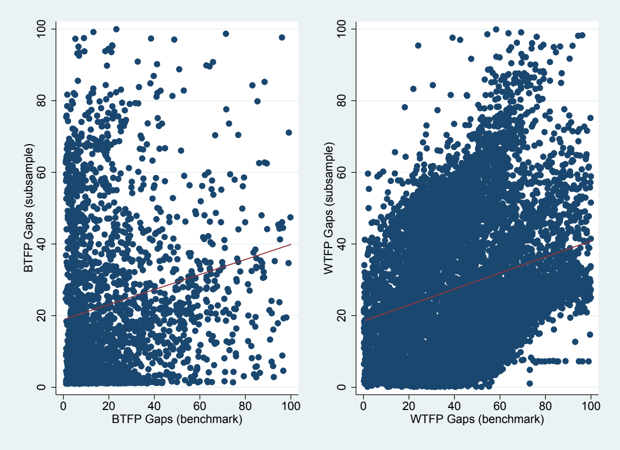
Figure 4: Country-level BTFP gaps and technological patterns.



Note. Proxies of technological patterns (vertical axis) are averaged over 2014–2016 (source: STAN database; OECD, 2018).

Step 3 - Country selection (re-estimated cluster - Bos et al., 2010 subsample)

Figure 8: Correlation between the benchmark and re-estimated (subsample) BTFP and WTFP.



Note. Subsample mixture estimations are run on firm-level data from Finland, Italy, Germany, France, the Netherlands, and Spain.

Conclusions

- Neglecting the existence of multiple technologies results into:
  - biased and more dispersed TFP estimates
  - uncorrect identification of the TFP markers and distorted policy implications.
- Mixture models can be used to estimate technology-specific production functions
  - avoiding any type of ex-ante assumption on the degree of technological sharing across firms and countries (the number of available technologies is endogenously determined by the mixture estimation algorithm $\Rightarrow$ the distribution of technologies across firms is observed ex-post)
  - controlling for simultaneity
  - price dispersion less of an issue in BTFP wrt standard TFP measures
- Availability of internationally comparable data is key

Conclusions (cont)

- The suggested methodology allows disentangling between
  - firm productivity relative to the other firms in the same technology group (i.e. **Within-technology TFP - WTFP**) $\Rightarrow$ a firm's ability to exploit a given technology (compared to the other firms using the same technology)
  - firm productivity relative to the labour productivity that the firm could have reached, given its capital-labour ratio, had it chosen the frontier technology (i.e. **Between-technology TFP - BTFP**) $\Rightarrow$ a quantification of the labour productivity gap associated with the technological choice.
- Number of technologies ranging from 1 (beverages) to 5 (leather)...3 in most cases
- BTFP gaps slightly larger than WTFP on average
- However, the relative weight of WTFP and BTFP varies considerably across sectors and firms

Conclusions (cont)

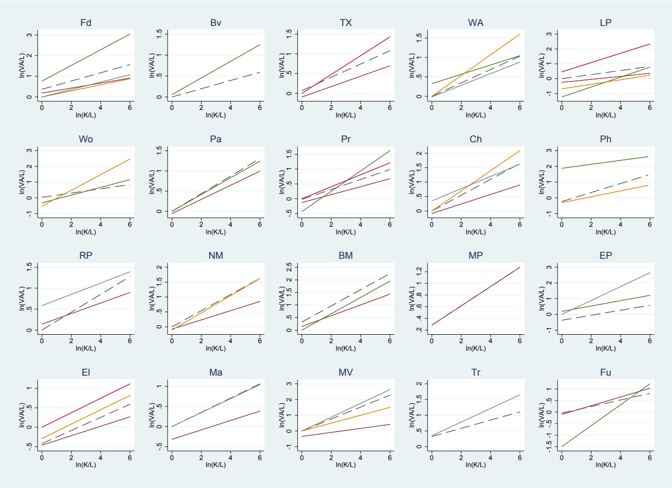
From a policy perspective:

- ...even in sectors in which BTFP dominates on average, there are firms for which labor productivity gaps are mostly driven by WTFP
  - In these cases, increasing workers' skills (e.g., lifelong learning, managerial improvements, organizational innovation) might be more effective than trying to stimulate the adoption of new production technologies $\Rightarrow$ MORE TARGETED INNOVATION POLICY
- "Misallocation": the presence of technology dispersion introduces an additional source of dispersion in revenue TFP
  - not possible to use revenue TFP dispersion to infer the presence of distortions in factor markets (as in Hsieh and Klenow, 2009);
  - allowing all firms to use the frontier technology does not eliminate misallocation as long as they are not free to hire the desired amount of capital and labor

RESERVE SLIDES

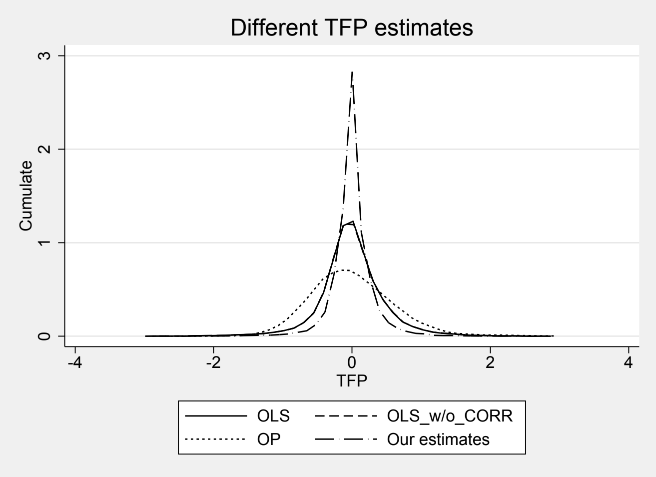
Production functions: comparison with standard OLS (dashed line)

Figure 9: Estimated production functions: Comparison with standard OLS (dashed line)



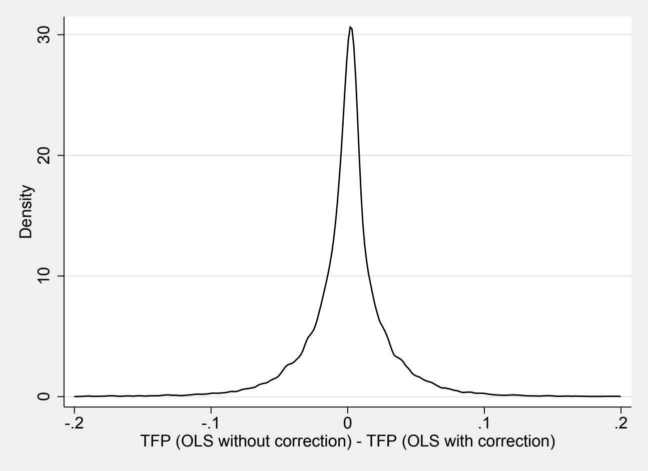
TFP densities

Figure 10: Comparison across TFP densities estimated with different methods



Difference between corrected and non corrected OLS

Figure 11: Difference between corrected and non-corrected OLS-estimated TFP



Variables description

- *Added Value*. Log of added value. Added value is defined as profit for period + depreciation + taxation + interests paid + cost of employees. This is a firm-level variable, covering years from 2012 to 2014, which we deflated using the OECD-Stan sector-country specific deflators (source: Orbis, 2015)
- *Labour Input*. Log of total number of employees included in the company's payroll. This is a firm-level variable, covering years from 2012 to 2014, which we deflated using the OECD-Stan sector-country specific deflators (source: Orbis, 2015)
- *Capital Input*. Tangible assets: buildings, machinery and all other tangible assets. This is a firm-level variable, covering years from 2012 to 2014, which we deflated using the OECD-Stan sector-country specific deflators. (source: Orbis, 2015)
- *Average Wage*. Log of the average wage bill within the firm. Firm-level variable. (source: Orbis, 2015)

Variables description (cont)

- *Firm Intangibles*. Intangible assets: formation expenses, research expenses, goodwill, development expenses. 2012-2014 (source: Orbis, 2015)
- *Firm Size*. Log of total number of employees included in the company's payroll. This is a firm-level variable, covering years from 2012 to 2014, which we deflated using the OECD-Stan sector-country specific deflators (source: Orbis (2015))
- *Firm Age*. Age of the firm (years). This is a firm-level variable, covering years from 2012 to 2014. (source: Orbis (2015))
- *Listed Firm*. Dummy variable (1 = the firm is listed in the stock market, 0 = otherwise). This is a firm-level variable, covering years from 2012 to 2014. (source: Orbis (2015))
- *Multinational*. Dummy variable (1 = the firm is part (as a controller or controlled enterprise) of multinational group. This is a firm-level variable, covering years from 2012 to 2014. (source: Orbis (2015))