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TECHNOLOGY-SPECIFIC PRODUCTION FUNCTIONS

Michele Battisti
Filippo Belloc
Massimo Del Gatto

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CRENoS – CAGLIARI
VIA SAN GIORGIO 12, I-09100 CAGLIARI, ITALIA
TEL. +39-070-6756406; FAX +39-070- 6756402

CRENoS - SASSARI
VIA MURONI 23, I-07100 SASSARI, ITALIA
TEL. +39-079-213511

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Tel. e Fax +39070271573

Technology-specific Production Functions

Michele Battisti
University of Palermo
CeLEG LUISS Guido Carli and RCEA

Filippo Belloc
'G.d'Annunzio' University

Massimo Del Gatto[1]
'G.d'Annunzio' University
and
CRENoS

Abstract

We rely on mixture models to estimate technology-specific production functions avoiding any type of ex-ante assumption on the degree of technological sharing across firms and leaving the number of available technologies unconstrained. Internationally comparable firm-level data are used, to potentially capture all possible technologies available worldwide. Differently from conventional TFP estimates, where the terms "TFP", "productivity" and "technology" are often used interchangeably, our approach enables us to isolate the contribution to labour productivity stemming from technology (i.e. between-technology TFP) from the contribution associated to idiosyncratic productivity shocks not related to technology (i.e. within-technology TFP). While we find the former to be much larger than the latter in most sectors, the relative role of these two dimensions varies considerably across firms, being often reversed. We also find that the firm-level gaps are non-linearly correlated with the international flows of technology, as measured by the OECD country-sector technology payments and receipts. In particular, we show higher incoming (outcoming) flows of technology to be associated to higher (lower) average and dispersion of the between-technology TFP gaps. This stresses the growing importance of the availability of internationally comparable data in dealing with the technological dimension of firm-level productivity.

Keywords: TFP, technology adoption, production function estimation, mixture models.
J.E.L. Classification: D24, 033, C29.

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[1] Corresponding author: Massimo Del Gatto, `G.d'Annunzio' University, Department of Economics (DEc), Viale Pindaro 42, 65127 - Pescara (Italy). massimo.delgatto@unich.it

1 Introduction

Measured as the Solow residual of an aggregate production function, Total Factor Productivity (henceforth TFP) is usually found to be as important as capital accumulation in explaining the cross-country disparities in income and labour productivity (Kumar and Russell, 2002; Caselli, 2005; Hsieh and Klenow; 2009,2010; Battisti *et al.*, 2017). Since, as known, TFP is a wide notion encompassing a number of hard to measure factors (i.e. "all the rest", respect to capital accumulation), this means that empirical analysis is able to explain no more than 50% of the productivity differentials (even trying to take into account the human capital differences). This notwithstanding, and despite the potential impact in terms of policy implications, the literature dealing with different theoretical conceptions of TFP is scant, both at the aggregate and the firm level, and it is still true that "economists should devote more effort toward modeling and quantifying TFP" (Easterly and Levine, 2003).

In this paper, we aim at giving a sense of magnitude of how much of a firm's labour productivity can be attributed to its technological choices and, at the same time, providing with a TFP measure which is net of this "technological" component (taking into account the composite nature of such TFP notion).

The way in which firm-level differences in TFP reflect on aggregate productivity is currently receiving increasing attention. Among others, Alfaro *et. al.* (2008), Banerjee and Duflo (2005), Bartelsman *et al.* (2009), Hsieh and Klenow (2009,2010), Jones (2011) and Restuccia and Rogerson (2008) study the relationship between aggregate TFP and differences in the within-industry productivity dispersion across firms. A key word in this literature is "misallocation": lower aggregate TFP due to distortions in the allocation of inputs across units (Restuccia and Rogerson, 2013).

We deal with firm heterogeneity from a different point of view: instead of focusing on the dispersion of a wide measure of TFP (i.e. misallocation), we focus on firm-level technology adoption as a determinant of labour productivity differences among firms.

Indeed, among the many factors commonly included in the standard TFP figures, a growing body of literature concentrates on "technology", both in terms of creation of new technologies and adoption/diffusion of already available technologies. From a theoretical point of view, the relationship between technology adoption/diffusion and diffusion of development dates back to Gerschenkron (1962), Nelson and Phelps (1966), Barro and Sala-i-Martin (1992) and Howitt (2000). Within this branch of literature, Parente and Prescott (1994) show that differences in barriers to technology adoption, which vary across countries and time, account for the great disparities in income across countries. Acemoglu and Zilibotti (2001), Gancia and Zilibotti (2009), Gancia *et al.* (2010) focus on the idea of "directed technical change". Other works stress the spatial dimension of the process of technology adoption and diffusion. Desmet and Parente (2010) model the relationship between market size and technological upgrading. Desmet and Rossi-Hansberg (2014) suggest a model in which technology diffusion affects economic development because technology diffuses spatially and firms in each location produce using the best technology they have access to. Comin *et al.* (2012) propose a theory in which technology diffuses slower to locations that are farther away from adoption leaders.[2] Our approach can also be of interest to the debate on embodied versus disembodied technological progress. Differently from the latter (Solow, 1960), in which capital equipments equally participate in technical change (see Hercowitz, 1998), our multiple technology framework allows capital equipments to differ in terms of returns (see Zeira, 1998; Acemoglu, 2010; Battisti *et al.*, 2017), as far as technology is embedded in the capital stock.

Other papers specifically point out the importance of the firm-level dimension of productivity growth (i.e. changes in the productivity distribution). Gabler and Poschke (2013) and Da Rocha *et al.* (2017) introduce endogenous establishment-level productivity in the study of the evolution of aggregate productivity. A similar approach is adopted by a number of papers in which aggregate growth is fostered by the evolution of the firm-level TFP distribution, as induced by trade integration (see Grossman and Helpman (2015) for an early review). This literature explicitly focuses on the role of technological heterogeneity. Sampson (2016) stresses the role of the technological choice of the entrant firms. Perla and Tonetti (2014) focus on the diffusion of technology from the more to the less productive firms, which allows the TFP distribution to "evolve" endogenously even without the introduction of new technologies. In Perla *et al.* (2015), firms choose whether to adopt a better technology or not and trade integration, by increasing the incentives to adopt the better technologies, fosters aggregate growth. In Benhabib *et al.* (2017), firms choose whether to keep producing with their existing technology, adopt a new technology or innovate, but only innovation fosters growth in the long run. Luttmer (2007) focuses on imitation, highlighting that the small size of entrants *de facto* indicates that imitation is difficult. In Alvarez *et al.* (2014), the flow of new ideas is the engine of growth: firms get new technologies by learning from the people they do business with, so that trade, by implying more meeting opportunities, helps technology diffusion and aggregate growth. Bloom *et al.* (2015) highlight how import competition from low cost countries forces firms to innovate more than otherwise.

In these frameworks, the focus is on "technology" but the terms "TFP", "productivity" and "technology" are used as synonymous. The reason of this ambiguity is presently explained.

Anticipating the formal description, let us write firm i's production function as

$$y_i = a_{i,m} + \alpha_m + \beta_m k_i \tag{1}$$

[2] Another line of research studies more in detail the process of technology diffusion using data on specific technologies. In particular, it is worth citing the Cross-country Historical Adoption of Technology (CHAT) dataset, described in Comin and Hobijn (2009), which includes long-run information on the extensive (whether a specific technology is present or not in a given country at a moment in time) and intensive (the intensity with which producers or consumers employ a technology, at a given moment in time, scaled by the size of the economy) margins of technology adoption at the country-level on a number of technologies (e.g. tractors, fertilizer, portable cell phones). The CHAT dataset enables, among others, Comin and Hobijn (2010) to explain the very different speeds at which countries recovered after wars, Cervellati *et al.* (2014) to study the effect of trade liberalization and democratization on technology adoption, Comin and Mestieri (2013) to explore the general patterns characterizing the diffusion of technologies, how they changed over time, and the key drivers of technology.

with $y_i = ln(Y_i/L_i)$ and $k_i = ln(K_i/L_i)$. Index m is introduced to refer to a specific "technology", with $m = 1,\dots,M$ and M denoting the number of available technologies. Here, α_m and β_m capture the technological dimension by identifying different technologies in each sector-industry, with a number of firms using each technology, while $a_{i,m}$ encapsulates the idiosyncratic productivity differences among the firms using the same technology and can be thought of as the firm's ability to exploit the given technology m (say "pure" TFP). To highlight the importance of disentangling between these two dimensions, and the role that technology can play in the evolution of output, Bernard and Jones (1996a,1996b) use the expression "total technological productivity".

Since estimating (1) with standard econometrics is not possible without an ex-ante assumption on the technology used by each firm, in the standard approach to production function estimation, the information captured by $a_{i,m}$, α_m and β_m entirely flows into the TFP index (computed as the Solow residual $y_i - \hat{y}_i$), often referred to as "technology" or "productivity" interchangeably. Arguably, the TFP estimated in this way conflates technological effects and "pure" TFP effects. Common sense tends to always attribute most of this TFP variation to technology, even when the analysis points to particular aspects, such as managerial ability in Bhattacharya *et al.* (2013).[3]

To shed light on this aspect, we suggest a novel approach to production function estimation that enables us to relate the labour productivity differences among firms to their technological choices. This results into a quantification of the part of a firm's labour productivity that can be traced back to producing at a given capital-labour ratio using a given technology, instead of a different one (among the technologies used by the other firms). Relying on mixture models, we estimate technology-specific production functions avoiding any type of ex-ante assumption on the degree of technological sharing across firms and leaving the number of available technologies (i.e. technology groups) unconstrained. In doing this, we improve on the two-technology setting experimented in Battisti *et al.* (2015), where mixture models are implemented to measure the effects of intangible assets on firms' technological choices.

Recently, the importance of isolating the technological component of firms' productivity has been highlighted by Collard-Wexler and De Loecker (2015) with reference to the steel industry, documenting important productivity increases at the industry level associated to the the adoption of a particular technology (the "minimill" technology).[4] However, to the best of our knowledge, no attempts have been made in order to generalize the identification of firm-level technologies.

[3] In this case, the most intuitive interpretation points to different managerial ability in adopting the best technologies.

[4] According to Collard-Wexler and De Loecker (2015), a third of the industry's productivity increase can be traced back to the mere displacement of the older technology, with the rest associated to indirect effects occurring through increased competition.

We use balance sheet data on about 73.000 worldwide distributed manufacturing firms observed over 2013-2014, drawn from the Orbis database, provided by Bureau van Dijk, to estimate as many production function parameters (a_m , β_m) as the number of technologies suggested by our algorithm at the sectoral-level. This enables us to express a firm's productivity (i.e. TFP) relative to the other firms in the same technology group (i.e. Within-technology TFP, or "pure" TFP: hereafter WTFP) or 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: hereafter BTFP). While the former can be thought of as the firm's ability to exploit a given technology (compared to the other firms using the same technology), the latter is a quantification of the labour productivity gap associated with the technological choice.

The large international covarage offered by the Orbis database, ranging from OECD to low-income and emerging countries, is key in order to allow our algorithm to potentially capture all the technologies available worldwide. Our estimates point to a sectoral number of technologies ranging from one to five, depending on the industry.

We then focus on the labour productivity gaps associated with either being relatively less productive within a given technology group (WTFP gap) or not choosing the frontier technology (BTFP gap). This analysis reveals that the average WTFP contribution to labour productivity differences is much smaller than the BTFP contribution in most industries: when aggregated at the sectoral level, the WTFP of the top 5% firms (in terms of WTFP) is on average 90% higher than the other firms, while having all firms at the technological frontier (i.e. eliminating the within-sector BTFP dispersion) would increase the aggregate labour productivity of firms by 5.3 times. This notwithstanding, the relative contribution to labour productivity of these two dimensions varies substantially across firms, even within the same industry, with WTFP gap dominating the BTFP gap in many cases.

To help with the interpretation of the documented WTFP and BTFP gaps, we also consider their relationship with the country-sector international flows of knowledge and technology, as measured by the OECD country-sector technology payments and receipts, in a very simple cross-sectional regression analysis. Whilst not establishing causality, we show higher incoming (outcoming) flows of technology to be associated to higher (lower) average and dispersion of the BTFP gaps. These statistically significant correlations might support our emphasis on the opportunity to isolate the technological component of the labour productivity differentials by using international data in which all the available technologies in a given industry are potentially observed.

The exposition proceeds as follows. In Section 2, we develop a theoretical framework modeling technology adoption at the firm-level. In Section 3, we present the mixture model. In Section 4, we describe the within and between decomposition. In Section 5, we quantify the labour productivity gaps associated with the within and between dimensions. Section 6 concludes. In appendix 8 we discuss the analogies and differences with standard TFP measures.

2 Modeling Technology Adoption

Our first step in the analysis consists of recovering, for each technology m, the parameters α_m and β_m from the estimation of Equation (1).

As highlighted by the literature (see Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg *et al.*, 2006; Wooldridge, 2009; and Doraszelski and Jaumandreu, 2012), productivity estimation at the firm level involves simultaneity issues. Our multiple technology framework amplifies this order of problems, which make the OLS estimation output distorted.

A first source of simultaneity stems from the fact that the term a_i, m is to some extent known to the firm when it makes input levels decisions. This is usually expressed saying that $Cov(K_{i,t}, A_{i,t}) \neq 0$ and/or $Cov(L_{i,t}, A_{i,t}) \neq 0$, with index t used to denote time. Additionally, in our multiple technology case ($M > 1$), it can be the case that $Cov(K_{i,t}, m_{i,t}) \neq 0$ and/or $Cov(L_{i,t}, m_{i,t}) \neq 0$. This introduces an additional potential source of simultaneity, associated with the technological choice.

Since we want to avoid any type of ex-ante assumption on the degree of technological sharing across firms, and leave the number of available technologies unconstrained, we have to address both issues. To this aim, we present an "empirical model" of technology adoption and develop an estimation strategy, consistent with the model assumptions, that allows us to estimate the production function controlling for both sources of simultaneity.

First of all, we introduce the quite standard (see e.g. Olley and Pakes, 1996) "one period time-to-build" hypothesis, according to which the new technology is productive one period after its acquisition. Second, we assume that idiosyncratic productivity follows the first order Markov process $a_{i,t} = E[a_{i,t} \mid a_{i,t-1}] + \xi_{m,i,t}$, where $\xi_{m,i,t}$ denotes innovation in either the adopted technology (in which case we have that $m_{i,t} \neq m_{i,t-1}$) or the ability to exploit it (in which case, $m_{i,t} = m_{i,t-1}$).

Adopting the terminology $X[t]$ to remember that variable X is chosen at time $[t]$, we assume the following decision timing. At the end of period $[t]$, firm chooses $(K_{i,t+1}[t], m_{t+1}[t])$. At the beginning of period $[t+1]$, $a_{i,t+1}$ and Z_{t+1} (i.e. a vector of exogenous market-level state variables) are observed, so that the firm freely chooses the amount of labour (i.e. $L_{i,t}[t]$). Finally, firm chooses $K_{i,t+2}[t+1]$ and $m_{t+2}[t+1]$, at the end of period $[t+1]$, on the basis of $a_{i,t+1}$ and Z_{t+1}.

In period t, firm i maximizes the present value of its future profits conditional to the information set Ω:

$$\max_{(K_{i,t+1}, m_{i,j+1})} E_t\left[\sum_{j=t}^{\infty} \delta^{j-t} P_{i,j} \mid \Omega_{i,j}\right], \tag{2}$$

with net profit

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

and

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

δ is the discount rate and firm's investment $I_{i,j} = K_{i,j+1} - K_{i,j} + D_{i,j}$ encompasses disinvestment costs $D_{i,j} = \varepsilon_{i,j} K_{i,j}$ (with $0 \le \varepsilon_{i,j} \le 1$). While disinvestment costs are borne independently of changing technology or not, the technology adjustment cost in the third term on the LHS includes the costs associated to switching to a different technology in period [j+1].

Capital accumulates according to

$$K_{i,j+1} = K_{i,j} - \delta K_{i,j} + I_{i,j} - D_{i,j} \tag{3}$$

and the Bellman equation can be written as

$$V_{i,t}(\Omega_{i,t}) = \max_{(K_{i,t+1}, m_{i,t+1})} \left(P_{i,t} + \delta E_t\left[V_{i,t+1} \mid \Omega_{i,t}\right]\right) \tag{4}$$

The solution of (4) consists of the values of $(K_{i,t+1})$ and $(m_{i,t+1})$ that satisfy the policy function for K:

$$K_{i,t+1}(m_{i,t+1}, K_{i,t}, a_{i,t}, Z_{i,t}) \tag{5}$$

with the firm choosing, at time [t], the technology $m_{i,t+1}$ that maximizes

$$\left[\delta E_t\left(V_{i,t+1} \mid \Omega_{i,t}\right) - C(K_{i,t+1}, K_{i,t}, m_{i,t+1})\right] \mid m = m_{i,t+1}$$

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

This framework provides with the chance to take the simultaneity associated to both the choice of inputs and the choice of technology into account while estimating the production function.

Operationally, this boils down to preliminary estimating the system of equations consisting of the K policy function in (5) and the static condition for L

$$\begin{cases} \ln K_{i,t}[t-1] = \rho_0 + \rho_1 \ln K_{i,t-1}[t-2] + Z_{c,t} + e_{i,t}^K + u_{i,t}^K \\ \\ \ln L_{i,t}[t] = \rho_0 + \rho_1 \ln K_{i,t}[t-1] + Z_{c,t} + + e_{i,t}^L + u_{i,t}^L \end{cases} \tag{6}$$

where $Z_{c,t}$ captures country-year effects.

Under the assumption that $u_{i,t}^K$ and $u_{i,t}^L$ are iid error terms, $e_{i,t}^K$ embodies the covariance terms $Cov(K_{i,t}[t-1], m_{i,t}[t-1])$ and $Cov(K_{i,t}[t-1], a_{i,t-1})$, while $e_{i,t}^L$ embodies $Cov(L_{i,t}[t], a_{i,t})$. In other words, as far as $Z_{c,t}$ effectively absorbs all the country-level heterogeneity in the data, the regression residuals of the two equations in (6) can be thought of to embody the firm-level variability in input choices correlated to both the idiosyncratic productivity shock and the technological choice.

Thus, the estimated residuals $\hat{\Phi}_i = e_{i,t}^K + u_{i,t}^K$ and $\hat{\Psi}_i = e_{i,t}^L + u_{i,t}^L$ can be seen as correction factors to be included as additional regressors in a second step of regressions in order to obtain simultaneity-free production function parameters.

3 Production Function(s) Estimation

Differently from the standard approach to firm-level TFP estimation (see the surveys by Del Gatto *et al.*, 2011 and Van Beveren, 2012), our framework requires estimating as many sets of production function coefficients as the number of available technologies in each sector. However, we want to avoid any type of ex-ante assumption on the degree of technological sharing across firms, countries, or regions. In other words, we do not want to cluster the firms ex-ante. To this purpose, we rely on *mixture models* (Mc Lachlan and Peel, 2000). In this way, since the number of available technologies is endogenously determined by the mixture estimation algorithm, the distribution of technologies is indeed observed ex-post.

To allow our algorithm to potentially capture all possible technologies available worldwide, it is important to use internationally comparable data with the largest possible coverage. To this aim, we take advantage of information provided from the Orbis database (Bureau van Dijk, 2015), on a large sample of around 73.000 worldwide distributed firms, over the 2013-2014 period and across 22 2-digit sectors.[5]

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[5] Arguably, a larger country coverage comes with a lower representativeness in terms of the cross-country distribution of firms (as known, the national standards of balance sheet disclosure vary across countries). However, this issue is not crucial in our empirical strategy. More important is the chance to identify as many technologies as possible, by observing as many worldwide distributed (and potentially

In particular, in the production function estimation, we use information on value added (VA), capital inputs (K , i.e. tangible assets, including buildings, machinery and all other tangible assets) and labour inputs L . Value added and capital are deflated using the OECD-STAN sector-country specific deflators. Descriptive statistics are presented in Table 1, while a detailed variables description is provided in the Appendix 7.

We follow the approach described in Section 2 to estimate our technology specific production functions controlling for the simultaneity associated to the choice of inputs and the choice of technology.

We first use three-stage least squares to estimate the system of equations in (6), then use the estimated regression residuals of the two equations as additional regressors in a second step of regressions based on mixture models, in order to obtain simultaneity-free production function parameters.

In this second step of regressions, we want to estimate the technology specific α_m and β_m for each technology m avoiding any ex-ante assumption on the degree of technological sharing across firms. To this aim, we adopt a mixture approach. The idea is that the probability distribution of y_i can be seen as a weighted average of the M unknown segment (i.e., technology) distributions, each with proper mean (μ_m) and variance (σ_m^2): $f(Y_i \mid \mu, \sigma^2) = \sum_{m=1}^{M} \omega_m f_m(Y_i \mid \mu_m, \sigma_m^2)$. The weights ω_m are given by the ex-ante probability of belonging to group m .

The fact that these probabilities are unknown generates a problem of missing data that is solved by applying the EM (expectation-maximization) algorithm of Dempster *et al.* (1977) to the estimation of the following production function through weighted least squares (WLS), as suggested by De Sarbo and Cron (1988):

$$y_i = \alpha_m + \beta_m k_i^{\delta_{i,m}} + \varphi \hat{\Phi}_i^{\delta_{i,m}} + \psi \hat{\Psi}_i^{\delta_{i,m}} + FE_s + \varepsilon_i \tag{7}$$

where FE_s are 4-digits industry fixed effects.

The estimation is carried out sector-by-sector (at the 2-digit level) for the year 2014[6] and starts with random values of ω_m (see below) to compute the posterior probability $p_{i,m}$ that firm i belongs to group m , and thus the observation weights in (7) as:

technologically different) firms as possible in each sector.

[6] The estimation in (6) requires a minimum of two years, the reference year [t] and the previous year [t-1], for the lagged term $\ln K_{i,t-1}[t-2]$. Here, the time index is dropped since the estimation is based on cross-section regressions for year [t].

$$\delta_{i,m} = \sqrt{p_{i,m}} \qquad \text{with} \quad p_{i,m} \equiv pr(i \in m) = \frac{\omega_m f_m\{y_i \mid \mu_m; \sigma_m^2\}}{\sum_{m=1}^{M} \omega_m f_m\{y_i \mid \mu_m; \sigma_m^2\}} \tag{8}$$

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

$$\omega_m = \frac{\sum_i p_{i,m}}{\sum_m \sum_i p_{i,m}} \tag{9}$$

with the following constraints:

$$\omega_m \geq 0 \qquad \forall m = 1, \dots M \qquad \text{and} \qquad \sum_{m=1}^{M} \omega_m = 1. \tag{10}$$

The algorithm iteratively alternates the WLS production function estimation and the computation of probabilities until a log-likelihood convergence criterion is satisfied (Grun and Leisch, 2013).[7]

To leave the routine free to set the number of available technologies M, we try different numbers of clusters and pick the optimal choice following a Bayesian Info Criterion based on the following log-likelihood function:

$$M = argmax\left\{ -2 \cdot \log[\sum_i \omega_m f_m(y_i \mid \mu_m, \sigma_m^2)] - \zeta(m) \right\} \mid m = 1, \dots, M \tag{11}$$

Here $\zeta(m_s)$ is a penalty function that implements the trade-off between a higher number of clusters and more parameters to be estimated.[8] Figure 1 shows the results of the Bayesian Info Criterion for the 19 sectors. In all sectors except one (i.e., "Computer, electronic and optical products"), results always point towards the presence of more than one technology. Then, in order to avoid unuseful duplications we collapse together sectors for what the capital returns technology coefficients are close and the number of observations is very small.[9]

Estimation results are displayed in Table 2, reporting the estimated α and β for each technology group and for each sector. The estimated production functions are visualized in Figure 2. It is noteworthy how the standard hypothesis of a single technology is a restrictive assumption

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[7] We use Flexmix R package (Grun and Leisch, 2008) with 50 random starting points.

[8] In the case of the Bayesian Info Criterion, this is equal to the natural log of the number of observations (i.e., firms) multiplied by the number of parameters. The latter grows with the number of segments: regressions' coefficients, variances and weights for each segment, minus one because the weights sum up to one (one of them is a linear combination of the others).

[9] The results under the alternative scenario are unchanged and available under request.

never supported by data. The magnitude of the α and the β coefficients is even substantial within many industries. This entails that the usually estimated sectoral parameters hide substantial heterogeneity, as Appendix 8 discusses more in details.

In Table 3 we report the total probability of each technology group. This is computed as $prob_m = \sum_i p_{i,m}$ and collapses to the number of firms in the sector when summed up across all technology groups in the sector (i.e., $\sum_m \sum_i p_{i,m}$). As the Table reveals, none of the groups presents a negligible probability. This is due to the fact that, on average, the firm-level probability is distributed across the technology groups with a certain degree of variability.[10]

4 Between-technology TFP and Within-technology TFP

The technology adopted by the firm, that is the technology that solves the problem in (4), may or may not coincide with the technology that would provide the maximum productivity level associated with the given level of k_i – i.e., frontier technology.

To formalize this, let us refer to the frontier technology as the technology m^H that maximizes labour productivity at the capital-labour ratio actually chosen by the firm: $y_{i,m^H} \mid k = k_i > y_{i,m} \mid k = k_i \quad \forall m \neq m^H$.

Since our estimated production function parameters are technology specific, and since we do know how many technologies are available in each sector, we are able to identify, for each firm, the predicted labour productivity associated to each technology (at the actual level of k). In particular, we are able to identify the predicted labour productivity associated with the actual technology ($\hat{y}_{i,m}$) and the frontier technology ($\hat{y}_{i,m^H}$) as, respectively:

$$\hat{y}_{i,m} = \hat{\alpha}_m + \hat{\beta}_m k_i \qquad and \qquad \hat{y}_{i,m^H} = \alpha_{m^H} + \hat{\beta}_{m^H} k_i \tag{12}$$

These two values can be used to compute the Solow residual, in the two cases, as difference between the observed and the predicted productivity:

$$\hat{a}_{i,m} = y_i - \hat{y}_{i,m} \qquad and \qquad \hat{a}_{i,m^H} = y_i - \hat{y}_{i,m^H} \tag{13}$$

The difference between the two terms in (12) and in (13) provides us with a measure of how distant the predicted labour productivity of a firm (under the actual technology) is from the

[10] We show an example of our firm clustering at a sectoral level with Figure 3, on chemicals and food products. To plot the clustering, we assigned each firm to the technology cluster it belongs to with the relatively higher (estimated) probability, i.e. "hard assignment". Each number in the Figure, thus, shows the position and the "hard assigned" cluster (the clusters are numbered from 1 to 4) of each firm, in the y_i - k_i space.

frontier labour productivity. This provides us with a quantification of the labour productivity gap with respect to the productivity that the firm could have reached, with the given k, had it chosen technology m^H. The weighted average of this term, across all the technologies available in the sector, is our measure of *Between-technology Total Factor Productivity* (BTFP):

$$\text{BTFP} = \sum_{m=1}^{m^H} pr_{i,m} \cdot (\hat{y}_{i,m} - \hat{y}_{i,m^H}) = \sum_{m=1}^{m^H} pr_{i,m} \cdot (\hat{a}_{i,m^H} - \hat{a}_{i,m}) \tag{14}$$

where the weights $pr_{i,m}$ correspond to the estimated probability of firm i belonging to the technology group m defined in Equation (8).

Similarly, we can define the firm's *Within-technology Total Factor Productivity* (WTFP) as

$$\text{WTFP} = \sum_{m=1}^{m^H} pr_{i,m} \cdot \hat{a}_{i,m}. \tag{15}$$

This term is the empirical analogous of the idiosyncratic productivity term $a_{i,m}$ in Equation (1) and can be thought of as the firm's ability to exploit the given technology, compared to the other firms using the same technology.

The BTFP component is zero for firm i if the firm uses m^H with probability one (i.e., $pr_{i,m^H} = 1$) or when one single technology is available (i.e., $m = 1 = m^H$). In contrast, when a number $M > 1$ of technologies is available, the firm may or may not adopt the frontier technology. Figure 4 helps the intuition. Consider, for example (panel b), that firm i adopts technology $m2$ with probability one. On the one hand, we can see that this technology is sub-optimal in correspondence of k_i, as the predicted productivity associated to technology $m1$ is higher. This productivity gap can be completely attributed to the technological choice and is captured by our measure of BTFP. On the other hand, the distance between the actual and the predicted output under technology $m2$ (WTFP) provides us with a measure of the firm's ability to exploit the technology in use, expressed in relative terms with respect to the other firms in the same technology group.

Note how the above TFP measures can be seen as the static counterpart of the technical change components in a setting à la Kumar and Russell (2002) (see also Los and Timmer, 2005), the difference being the focus on distance from the local technological frontier, rather than on technological change. A related experiment is the one reported by Bos *et al.* (2010), based on a pooled sample of firms, in which technical change and efficiency are expressed in terms of shift in a time trend and output per worker relative to the maximum level of output per worker, respectively. Compared to this approach, a feature of our analysis is the possibility to carry out counterfactual exercises in terms of the gains/losses associated to changing the adopted technology, as well as to improving the ability to exploit it (i.e. efficiency). In this, our approach resembles the notion of "localized technological progress" (Atkinson and Stiglitz, 1969).

To gain the intuition on the relationship between our approach and conventional TFP estimation carried out without allowing for technological heterogeneity, compare the term $\hat{a}_i = y_i - \hat{y}_i$ in panel a of Figure 4 with the WTFP and BTFP measures reported in panel b. While $\hat{a}_i$ would coincide with our WTFP measure in the case of one single technology available in the sector, conventional estimates conflates our within and between productivity measures in the general case of $M > 1$.

To see this formally, consider the estimated version of (1) under $M = 1$ and $M \neq 1$, to obtain the following decomposition of the standard TFP:

$$\left.\begin{array}{l} y_i = \hat{a}_i + \hat{\alpha} + \hat{\beta} k_i \\ \\ y_i = \hat{a}_{i,m} + \hat{\alpha}_m + \hat{\beta}_m k_i \end{array}\right\} \hat{a}_i = \hat{a}_{i,m} + (\hat{\alpha}_m - \hat{\alpha}) + (\hat{\beta}_m - \hat{\beta}) k_i \qquad (16)$$

This decomposition highlights that the standard estimated TFP (i.e., $\hat{a}_i$) is a composition of three terms: $\hat{a}_{i,m}$, that is our WTFP measure; $\hat{\alpha}_m - \hat{\alpha}$, which can be seen as a bias in the Hicks-netural component of technology; and $\beta_m - \hat{\beta}$, which can be seen as a bias in the slope of the production function.

Overall, 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/or overestimation of the intercept - i.e. $\alpha_m > \alpha$). The coefficients estimated on the whole sector, that is without clustering ($M = 1$), can be seen as a weighted (across technology clusters) average of the mixture regressions. These aspects are discussed in Appendix 8.

Finally, two considerations are in order. First, being our production functions estimated without controlling for workers' skills, one may wonder to what extent our estimated BTFP term effectively captures productivity effects associated to technology, intended in a strict sense (i.e. effects that are distinct from human capital). Although our methodology would allow us to control for human capital, our data do not contain information in that sense. Thus, throughout the paper we widely attribute BTFP difference across firms to differences in technology in a strict sense (e.g. different machineries, softwares etc.), as well as to the differences in human capital attached to adopting a given technology. This notwithstanding, to roughly control for the role played by human capital differences, we constructed a country-sector human capital endowment variable by interacting the Cohen and Soto (2007) measure of education of each country in 1970 and 2005 with the industry schooling intensity of the US in 1980, drawn from IPUMS (in 2015). The regressions of our WTFP and BTFP terms on this country-sector specific human capital variable (plus country and sector controls) yields (results available upon request) an insignificant effect on the latter and a negative and significative effect on the former. Under the assumption that sectoral schooling intensity is the same in all countries, and keeping in mind the limits involved in such a measure of human capital, this might suggest that the largest part of the technological differences across firms detected in the analysis does not stem from the omission of human capital.

Second, as difference between predicted values, the BTFP term should not be affected by firms' markups. Eventually, only (average) systematic differences across prices applied by the firms in different technology clusters (i.e. using different technologies) flow into the BTFP. Conversely, cross-firm differences in markups entirely reflect onto WTFP differences, together with differences in management practices.

5 Productivity gaps

5.1 Quantification of WTFP and BTFP gaps

We now focus on the labour productivity gaps associated with either being relatively less productive within a given technology group (that is, displaying a relatively low ability in exploiting the given technology, as measured by the idiosyncratic component $a_{i,m}$) or not choosing the frontier technology. This is equivalent to quantifying 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.

To quantify the former, we measure the difference between a firm's observed WTFP and that of the best performing firms in the group (identified as the average WTFP of the best 5% of the WTFP distribution).[11] Formally, we consider $\text{WTFPgap}_i = \text{WTFP}_{\text{best5\%}} - \text{WTFP}_i$. This represents a firm-level measure of the expected productivity gain which would be obtained by eliminating the WTFP dispersion within a technology cluster.

To quantify the BTFP gaps, we can simply consider $\text{BTFPgap}_i = -\text{BTFP}_i$. This gap is a measure of the productivity gain that would be obtained by eliminating the technology dispersion within each sector and having all firms at the local frontier technology.[12]

The sectoral distribution of the estimated BTFP and WTFP gaps is reported in Figures 5 and 6, respectively. The two figures highlight that neither dimensions are correlated with the within-sector number of technologies suggested by the analysis (see Table 2 and Figure 2). In Figure 7, we look at the firm-level distribution of the relative weight of WTFP and BTFP gaps by plotting the firm-level ratio BTFP/WTFP, which, again, does not seem to be correlated with the suggested number of within-sector technologies. Figure 7, in particular, unveils that, while BTFP gaps are generally higher than WTFP gaps, the distribution shows the presence of substantial

[11] Notice that the estimated WTFP tends to zero when averaged at the sectoral level.

[12] This makes sense as far as we are willing to accept that a firm, switched from a given technology m to m^H, is able to use m^H with the same ability it uses the actual technology m.

heterogeneity, with the exception of the wood products industry, where the within-sector BTFP/WTFP profile of firms is rather homogeneous.

We can then obtain aggregate figures of the gaps by averaging WTFPgap_i and BTFPgap_i by sector. These are reported in Table 4 and visualized in Figure 8, where the WTFP gaps are plotted against the BTFP gaps. The average gaps in Table 4 range from less than 40% for electronic products to around 140% for beverages. The overall contribution of the WTFP is much smaller. In fact, when aggregated at the sectoral level, the WTFP of the top 5% firms (in terms of WTFP) is on average 90% higher than the other firms, while having all firms at the technological frontier (i.e. eliminating the BTFP dispersion) would increase the aggregate labour productivity of firms by 5.3 times roughly, with smaller potential gains in the electronic products and pharmaceuticals, where only one significant technology emerges from our mixture analysis, and larger potential gains in the non-metallic products, basic metals and chemicals.

5.2 Markers of WTFP and BTFP gaps and relationship with international exchanges of technology

To help with the interpretation of the documented WTFP and BTFP gaps, we consider their relationship with the country-sector international flows of knowledge and technology in a very simple cross-sectional regression analysis. Whilst not establishing causality, a statistically significant correlation between these two dimensions might support our emphasis on the opportunity to isolate the technological component of the labour productivity differentials by adopting an international perspective allowing to potentially observe all the available technologies in a given industry.

In particular, we study how our firm-level measures of the productivity loss associated with WTFP and BTFP correlate with country-sector patterns in the global markets of knowledge and technology, and how such patterns are associated with the dispersion of the labour productivity (as reflected in the WTFP and BTFP gaps).

We use 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.[13]

[13] Technology receipts depend on firms' R&D effort and correspond to foreign sales of the marketable results of that effort. Technology payments correspond to the acquisitions technology inputs that are immediately useable by the firms. Thus, technology receipts and payments may reflect different dimensions, including the ability of firms in a country-sector to sell their disembodied technology abroad and the extent to which they make use of foreign technologies, the degree of technological autonomy (i.e. the ability to assimilate foreign technologies) and, more in general, the choice between domestic production of technology or foreign absorption, which is a crucial dimension of globalization and growth (Perla *et al.*, 2015).

In this exercise, as baseline controls, we also consider a vector of firm-level characteristics (intangible assets intensity, firm age, liquidity, and whether the firm is listed in a stock market and is part of a multinational group; provided by Bureau van Dijk, 2015).[14]

Results are collected in Table 5.

We find that both WTFP and BTFP gaps, on average, tend to be negatively correlated with technology receipts. That is, country-sectors with relatively higher outcoming flows of technology are characterized by higher rates of firms better positioned in the WTFP distribution and using the relatively more productive technologies. BTFP gaps are also higher for firms in country-sector environments with higher technology payments, that is higher incoming technology flows.

These correlations are likely to be associated with different dispersion patterns. The most intuitive way to investigate this aspect would be that to study the correlations in terms of the first and the second moment at a country-sector level. However, this would be highly problematic given the country bias in the Orbis database. We thus follow an alternative strategy. We sub-sample our firms according to having WTFP and BTFP gaps above or below the median value in the WTFP gap and BTFP gap distributions and perform separate regressions on the two sub-samples (see columns 2-3 and 5-6 in Table 5). Under this approach, a significative relationship with dispersion emerges if the estimated coefficients in two sub-samples are opposite in sign and significative: a positive (negative) coefficient in the above (below) the median regression is revealing of a positive (negative) correlation with the WTFP and BTFP gap dispersion.

Indeed, this is what we find for the BTFP gap dispersion, which is higher in country-sectors with a higher degree of technology inflows and lower in country-sectors with a higher degree of technology outflows. Mindful that the BTFP gaps are not relative to a country benchmark but the identified frontier technology is the same for all the sample firms in the same sector, and assuming that firms tend to trade relatively better technologies, this might suggest that international exchanges of technology favour the technologically advanced firms in the importing country-sectors but not in the exporting country-sectors, where firms tend to be concentrated around the median. This can somehow reflect a "competition effect" of globalization, in the form highlighted by, e.g., Baldwin and Robert-Nicoud (2008).

Moreover, only firms with above-median WTFP gaps are negatively correlated with aggregate technology receipts, while firms with below-median WTFP gaps are positively correlated with aggregate technology payments. Again, this can be interpreted in terms of dispersion: country-sectors with high volumes of both technology outflows and inflows are associated with lower dispersion.

[14] Details on all the variables' construction are provided in Appendix 7.

6 Conclusions

A long standing literature tends to attribute large differences in output per worker among firms to differences in total factor productivity, i.e. the firm's ability to exploit production inputs. At a country level, it is shown that the contribution of TFP to explain differences in total output per worker is around 50% or even more (see Kumar and Russell, 2002; Caselli, 2005; Hsieh and Klenow, 209,2010; Battisti *et al.*, 2017). In this literature, a firm's difference in output per worker with respect to its counterparts in a sector is given by an idiosyncratic factor, likely attributable to managerial ability, that remains unexplained after estimating a sector-specific production function through which the available technology is framed. This approach, extensively used to measure both firm-level and aggregate productivity differences, with notable influences on policy studies and growth dynamics modeling, neglects a real-world source of heterogeneity: the presence of multiple technologies, possibly chosen by different groups of firms in a same sector.

Only few empirical studies have directed their attention towards how to take into account the technological dimension in firm-level production function estimation.

In this paper, we tackled this issue stressing the importance of using internationally comparable data in order to potentially capture all possible technologies available worldwide. We have relaxed the standard, often implicit, assumption of all firms sharing the same technology and proposed a novel approach based on mixture regression, which allows to unbundle the technology and the TFP component of a firm's productivity. In particular, we have estimated technology-specific production functions and decomposed the generic notion of TFP into a technology-specific component and a firm-specific term.

Our approach also allows to identify the most productive technologies in each sector and to quantify the productivity gaps associated with either not choosing the frontier technology or being relatively less productive within a given technology group.

From our empirical exercise, it emerges that the technology component (BTFP) of the firm-level productivity gaps within sectors is significantly larger than the "pure" TFP component (WTFP). Specifically, we found that the WTFP of the top 5% firms is on average 90% higher than the other firms in the same technology group, while having all firms at the technological frontier would increase the aggregate productivity of firms by 5.3 times roughly. Moreover, the dispersion of the productivity gaps associated with both components is shown to correlate with the international patterns of knowledge and technology trade, consistently with a dynamics of technology exchanges favouring the technologically advanced firms in the importing country-sectors relative to their exporting counterparts.

In light of these results, our analysis suggests giving more emphasis to the technological component of TFP in defining firm-strategies and public policies aimed at reducing the labour productivity gaps across firms and countries.

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Appendix

A Appendix: Variables description

Added Value. Log of added value. Added value is defined as profit for period + depreciation + taxation + interests paid + cost of employees. Firm-level variable, 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. Firm-level variable, deflated using the OECD-Stan sector-country specific deflators (source: Orbis (2015)).

Capital Input. Log of tangible assets. Tangible assets include buildings, machinery and all other tangible assets. Firm-level variable, deflated using the OECD-Stan sector-country specific deflators (source: Orbis (2015)).

Firm Intangibles. Log of intangible to tangible assets ratio. Intangible assets include formation expenses, research expenses, goodwill, development expenses. Tangible assets include buildings, machinery and all tangible assets. Firm-level variable (source: Orbis (2015)).

Firm Age. Age of the firm (years). Firm-level variable (source: Orbis (2015)).

New Entrant. Dummy variable (1 = firm age is below or equal to five years, 0 = otherwise). Firm-level variable (source: Orbis (2015)).

Listed Firm. Dummy variable (1 = the firm is listed in the stock market, 0 = otherwise). Firm-level variable (source: Orbis (2015)).

Multinational. Dummy variable (1 = the firm is part (as a controller or controlled enterprise) of multinational group. Firm-level variable (source: Orbis (2015)).

Liquidity Ratio. Cash and cash equivalents as a percentage of total asset. Firm-level variable (source: Orbis (2015)).

Tech Payments. International technology payments for licence fees, patents, purchases and royalties paid, know-how, research and technical assistance, weighted by sectoral value added, drawn from the WDI database. Country-sector-level variable (source: OECD Stat, Technology Balance of Payments (TBP) Database).

Tech Receipts. International technology receipts for licence fees, patents, purchases and royalties paid, know-how, research and technical assistance, weighted by sectoral value added, drawn from the WDI database. Country-sector-level variable (source: OECD Stat, Technology Balance of Payments (TBP) Database).

B Appendix: comparison with conventional TFP estimates.

In this Section we re-estimate the production functions at the sectoral level without taking the presence of different technologies into account. We present results with and without controlling for simultaneity.

As a first comparison, we report in Figure 9 the production functions estimated through simple OLS (dashed line), together with our technology-specific production functions. Essentially, the former can be seen as one-technology mixture regression ($M = 1$). More precisely, being the mixture regression carried out through WLS, we might see the OLS-estimated coefficients as a weighted average of the M technology-specific coefficients, with weights (i.e. Θ_m) given by the ratio of the number of firms in the m-technology group to the total number of firms in the sector - i.e., $\hat{\beta} = \sum_{m=1}^{M} \hat{\beta}_m \frac{\Theta_m}{\sum_{m=1}^{M} \Theta_m}$. The same reasoning applies to α.

Consistently, we see in Figure 9 that the dashed line lies essentially in between, respect to the technology-specific production functions. The OLS-estimated coefficients are reported in columns 2 to 5 of Table 6.

As highlighted in Section 2, among the issues highlighted by the literature on production function estimation, recent works have focused on the "simultaneity bias". The source of the simultaneity bias is the fact that information on actual productivity, although unknown to the econometrician, is known to the firm when the decision concerning the amount of inputs is made. This makes the production function parameters obtained through least squares estimates biased by the potential correlation between the regressors and the error term.

A successful stratagem suggested by the literature, in order to cope with this issue, consists of recovering the a_i component by the traces it leaves in the observed behaviour of the firm. Key studies examining this approach, which is commonly referred to as "semi-parametric", include Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg *et al.* (2006), and Wooldridge (2009). The basic idea of this methodology consists of identifying a (proxy) variable that reacts to the changes in the TFP observed by a firm and is thus a function of these changes. Insofar as this function is invertible, its inverse may be calculated and plugged into the production function estimating equation. Olley and Pakes (1996) suggest resorting to investment as a proxy, whereas Levinsohn and Petrin (2003) use intermediates. Doraszelski and Jaumandreu (2012) develop an extension of Olley and Pakes (1996) in which a firm's TFP is stochastically affected by its investment in knowledge (considered in terms of R&D)[15]

[15] Firms' productivity is assumed to evolve according to a Markov process, which is "shifted" (either positively or negatively) by R&D expenditures. The R&D choice gives rise to an additional policy function (besides the policy function for investment in physical capital) that, under the crucial assumption that the error in t is uncorrelated with the innovation choice in $t-1$, may be exploited in the production function estimation to purge the estimates from the part of the error correlated with the input choice. Loosely speaking, this approach allows for the estimation of firms' TFP while controlling for simultaneity and the

The implementation of a such semi-parametric approach within our mixture model framework raises identification problems. In particular, the way in which the proxy variable (either investment or materials) reacts to changes in technology and TFP should be specified separately because firms' input choices may be differently correlated with the technology parameters and the firms' TFP. Our model of technology adoption developed in Section 2 is meant to deal with these two sources of simultaneity separately, without the need to rely on a specific proxy variable. In our setting, the correlation between capital and technology, as well as between either capital or labour and TFP flows into the residuals of the system of equations in (6), consisting of the K policy function and the static condition for L. Once estimated, these residuals give us the chance to control for simultaneity in the mixture analysis.

To get a sense of how the different estimation strategies reflect on the firm TFP distribution, we compare in Figure 10 our WTFP with the OLS-estimated TFP and the TFP estimated through the Olley and Pakes (1996) procedure (the coefficients are reported in the four last columns of Table 6), used as a benchmark estimation within the semi-parametric approach. As known, the OLS approach tends to fatten the tails of the distribution, in particular by overstating the TFP of the most productive firms. Our methodology results in a distribution that lies in the middle between the OLS and the OP ones. This is because part of the correction imposed by the OP method is recognized to be related to firms' technological choices, rather than to TFP, and thus captured by our BTFP term.

The OLS estimates reported in Figures Figure 9 and 10 includes the correction for simultaneity suggested by our model. To illustrate the the effect of this correction, we reporte the estimated coefficients in Table 6 and, in Figure 11, the distribution of the difference between the OLS estimates with and without the correction. The distribution looks quite reasonable and suggests the absence of specific patterns, for example a stronger effect on more productive firm. The estimated coefficients obtained without correction are reported in table 6.

effect of innovation choices at the same time.

Tables and Figures

Table 1: Descriptive statistics

SECTOR	CODE	VA (% of all sectors)	K (% of all sectors)	# firms	VA/L (avg)	K/L (avg)
Food products	Fd	6.7%	7.6%	7601	25.15	37.29
Beverages	Bv	2.7%	5.1%	1053	45.08	122.99
Tobacco products	Tb	1.7%	1.7%	32	67.02	102.66
Textiles	TX	1.1%	1.3%	2253	26.73	30.04
Wearing apparel	WA	1.0%	0.6%	3438	16.02	10.39
Leather and related products	LP	0.8%	0.4%	1802	21.93	13.06
Wood and of products of wood and cork	Wo	0.5%	0.3%	3435	23.79	26.74
Paper and paper products	Pa	2.7%	3.0%	1237	39.95	61.85
Printing and reproduction of recorded media	Pr	1.2%	1.4%	2643	30.96	27.95
Coke and refined petroleum products	PC	1.7%	2.7%	168	83.95	222.14
Chemicals and chemical products	Ch	6.6%	8.0%	2082	54.38	87.46
Basic pharmaceutical products and pharmaceutical preparations	Ph	13.5%	15.8%	504	59.90	94.14
Rubber and plastic products	RP	4.0%	2.8%	3308	36.47	41.98
Other non-metallic mineral products	NM	5.9%	8.9%	3702	31.13	55.49
Basic metals	BM	6.4%	7.8%	1355	46.94	75.12
Fabricated metal products, except machinery and equipment	MP	4.7%	2.6%	11732	34.75	30.04
Computer, electronic and optical products	EP	11.2%	8.9%	2372	43.00	38.57
Electrical equipment	El	4.6%	4.0%	2318	38.85	32.56
Machinery and equipment nec	Ma	12.8%	8.0%	5601	47.04	37.05
Motor vehicles, trailers and semi-trailers	MV	7.4%	7.1%	1463	35.40	46.24
Other transport equipment	Tr	2.3%	1.7%	619	37.42	47.50
Furniture	Fu	0.5%	0.3%	2673	20.60	20.75
TOTAL		-	-	61391	-	-

Table 2: Mixture regressions: estimated production function parameters

SECTOR	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4	α_5	β_5
Fd	-1.925*** (0.002)	0.275*** (0.000)	-0.774* (0.054)	0.719 (n.a.)	-0.853 (0.258)	0.677*** (0.000)	0.131 (0.528)	0.127 (n.a.)		
Bv	-0.001 (0.981)	0.765*** (0.000)	-0.711*** (0.000)	0.582*** (0.000)						
TX	1.715*** (0.005)	0.139*** (0.000)	1.329* (0.093)	0.465*** (0.000)	1.725 (0.418)	0.113 (0.174)				
WA	-0.075 (0.672)	-0.004 (0.609)	-0.217 (0.847)	0.210*** (0.000)	-0.817*** (0.000)	0.242*** (0.000)	-0.491 (0.518)	0.545*** (0.000)	-0.039 (0.962)	0.237*** (0.000)
LP	0.866 (0.074)	-0.254 (0.304)	-0.507*** (0.000)	0.722*** (0.000)	1.139*** (0.000)	0.251*** (0.000)				
Wo	-0.374 (0.628)	0.431*** (0.000)	-0.485 (0.838)	0.506*** (0.000)	0.068 (0.866)	0.095 (n.a.)				
Pa	-0.473 (0.611)	0.617*** (0.000)	-0.505 (0.136)	0.178*** (0.000)						
Pr	0.935*** (0.000)	0.072*** (0.000)	-0.538*** (0.000)	0.418*** (0.000)						
Ch	0.997*** (0.000)	0.217*** (0.000)	0.238 (0.469)	0.710*** (0.000)						
Ph	1.529** (0.043)	0.158 (0.211)	0.324 (0.789)	0.736*** (0.000)						
RP	-0.614 (0.233)	0.581*** (0.000)	-0.133 (0.583)	0.106*** (0.000)						
NM	-0.180 (0.450)	0.282*** (0.000)	-0.705*** (0.000)	0.739*** (0.000)	-1.020*** (0.000)	0.687*** (0.000)	0.918*** (0.000)	0.146*** (0.000)		
BM	1.034*** (0.000)	0.141*** (0.000)	0.879* (0.078)	0.552*** (0.000)						
MP	-1.459** (0.012)	0.273*** (0.000)	0.625 (0.225)	0.526*** (0.000)	0.556* (0.100)	0.112*** (0.000)	0.591 (0.147)	0.309*** (0.000)		
EP	-1.732*** (0.000)	0.012 (0.579)	1.024 (0.127)	0.155*** (0.000)						
El	-0.413 (0.758)	0.338*** (0.000)	-0.337 (0.530)	0.105*** (0.000)						
Ma	0.323 (0.176)	0.328*** (0.000)	0.639*** (0.000)	0.115*** (0.000)						
MV	-0.059 (0.626)	0.327*** (0.000)	1.013*** (0.000)	0.107*** (0.000)						
Tr	0.737 (0.605)	0.543*** (0.000)	0.933 (0.116)	0.152*** (0.006)						

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parenthesis.

Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Wearing apparel; LP: Leather and related products; Wo: Wood and of products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and chemical products; Ph: Basic pharmaceutical products and pharmaceutical preparations; RP: Rubber and plastic products; NM: Other non-metallic mineral products; BA: Basic metals; MP: Fabricated metal products, except machinery and equipment; EP: Computer, electronic and optical products; El: Electrical equipment; Ma: Machinery and equipment nec; MV: Motor vehicles, trailers and semi-trailers; Tr: Other transport equipment; Fu: Furniture.

Table 3: Mixture regressions: total probability by technology group

SECTOR	$prob_1$	$prob_2$	$prob_3$	$prob_4$	$prob_5$	# firms
Fd	916	1813	2829	2043	0	7601
Bv	648	405	0	0	0	1053
TX	526	1214	514	0	0	2253
WA	702	487	566	1346	336	3438
LP	117	1091	594	0	0	1802
Wo	2031	778	626	0	0	3435
Pa	770	467	0	0	0	1237
Pr	696	1947	0	0	0	2643
Ch	990	1092	0	0	0	2082
Ph	241	263	0	0	0	504
RP	2029	1279	0	0	0	3308
NM	838	1100	934	830	0	3702
BM	625	730	0	0	0	1355
MP	1261	4438	3403	2631	0	11732
EP	1144	1228	0	0	0	2372
El	1232	1086	0	0	0	2318
Ma	2543	3058	0	0	0	5601
MV	1008	455	0	0	0	1463
Tr	352	267	0	0	0	619
Total	18668	23199	9466	6850	336	58518

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

Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Wearing apparel; LP: Leather and related products; Wo: Wood and of products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and chemical products; Ph: Basic pharmaceutical products and pharmaceutical preparations; RP: Rubber and plastic products; NM: Other non-metallic mineral products; BA: Basic metals; MP: Fabricated metal products, except machinery and equipment; EP: Computer, electronic and optical products; El: Electrical equipment; Ma: Machinery and equipment nec; MV: Motor vehicles, trailers and semi-trailers; Tr: Other transport equipment; Fu: Furniture.

Table 4: Aggregate gaps (sectoral averages)

SECTOR	WTFP gap	BTFP gap
Fd	70.6	517.4
Bv	139.0	1154.3
TX	89.8	396.4
WA	118.4	159.5
LP	108.0	251.2
Wo	80.2	37.6
Pa	85.7	1286.8
Pr	66.0	0.0
Ch	103.0	1391.9
Ph	67.5	0.0
RP	91.0	988.3
NM	113.4	1496.7
BM	91.3	1346.0
MP	90.4	543.8
EP	43.3	0.0
El	97.2	284.4
Ma	85.3	242.7
MV	93.9	500.3
Tr	110.6	698.2
Total	89.0	544.4

Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Wearing apparel; LP: Leather and related products; Wo: Wood and of products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and chemical products; Ph: Basic pharmaceutical products and pharmaceutical preparations; RP: Rubber and plastic products; NM: Other non-metallic mineral products; BA: Basic metals; MP: Fabricated metal products, except machinery and equipment; EP: Computer, electronic and optical products; El: Electrical equipment; Ma: Machinery and equipment nec; MV: Motor vehicles, trailers and semi-trailers; Tr: Other transport equipment; Fu: Furniture.

Table 5: Markers of WTFP and BTFP

	WTFP gap$_i$ (all firms)	WTFP gap$_i$ (> median)	WTFP gap$_i$ (< median)	BTFP gap$_i$ (all firms)	BTFP gap$_i$ (> median)	BTFP gap$_i$ (< median)
Tech Payments ^{cs}	32.582	31.480	25.858*	710.963**	1803.711***	-119.367**
	(20.074)	(22.403)	(13.793)	(326.796)	(426.759)	(58.826)
Tech Receipts ^{cs}	-54.449***	-108.717***	-10.855	-567.197*	-1764.148***	148.297**
	(18.120)	(35.637)	(11.972)	(312.453)	(502.529)	(60.014)
Firm Age ^{f}	1.093***	-0.138	0.779***	100.117***	51.610***	7.387***
	(0.380)	(0.554)	(0.255)	(7.745)	(11.058)	(1.430)
Listed ^{f}	9.738**	6.588	3.994	-130.738	-321.041**	-14.090
	(4.169)	(7.200)	(2.861)	(91.866)	(144.158)	(56.233)
Firm Intangibles ^{f}	-1.117***	0.130	-0.587***	8.242***	7.739*	0.213
	(0.148)	(0.220)	(0.095)	(3.170)	(4.363)	(0.520)
Liquidity Ratio ^{f}	-14.159***	-8.054***	-5.210***	-171.957***	-154.938***	-9.076***
	(0.461)	(0.614)	(0.291)	(9.727)	(13.581)	(1.543)
Multinational ^{f}	-3.051***	-3.857***	0.328	96.911***	31.274	21.369***
	(0.820)	(1.188)	(0.559)	(19.580)	(24.406)	(4.062)
Constant	19.447***	77.146***	35.924***	144.516***	646.709***	76.390***
	(2.403)	(6.205)	(1.609)	(49.322)	(68.108)	(10.149)
# obs.	21455	8896	12559	21455	13084	8371
Country FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes	yes	yes
R^2	0.406	0.422	0.245	0.267	0.439	0.442

^{f} firm-level; ^{cs} country-sector-level.
Median of the WTFP and BTFP distribution referred to in columns 2-3 and 5-6, respectively.
Robust standard errors are in parenthesis. All variables are in logs.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Sectoral production functions estimated through different methodologies

	OLS with correction				**OLS without correction**				**Olley-Pakes (OP)**			
SECTOR	α	Std.Err.	β	Std.Err.	α	Std.Err.	β	Std.Err.	α	Std.Err.	β	Std.Err.
Fd	-0.031	0.304	0.429	0.012	1.532	0.331	0.309	0.009	-0.198	0.019	0.370	0.106
Bv	0.145	0.069	0.525	0.029	1.734	0.137	0.461	0.026	-0.046	0.066	0.337	0.291
TX	1.420	0.005	0.314	0.020	3.896	0.029	0.179	0.011	-0.102	0.030	0.562	0.252
WA	-0.015	0.209	0.329	0.014	2.131	0.196	0.182	0.008	-0.100	0.019	0.285	0.224
LP	0.257	0.058	0.448	0.020	2.771	0.055	0.253	0.011	-0.104	0.026	0.492	0.138
Wo	-0.272	0.021	0.375	0.015	1.932	0.045	0.270	0.011	-0.134	0.026	0.575	0.153
Pa	-0.387	0.127	0.451	0.029	2.202	0.118	0.279	0.018	-0.072	0.054	0.290	0.146
Pr	-0.026	0.189	0.253	0.019	2.958	0.159	0.148	0.011	-0.175	0.028	0.312	0.139
Ch	0.512	0.169	0.414	0.023	3.227	0.175	0.284	0.016	0.049	0.043	0.330	0.096
Ph	0.994	0.420	0.312	0.051	4.096	0.457	0.238	0.039	0.052	0.191	-0.092	0.522
RP	0.002	0.246	0.326	0.018	2.425	0.227	0.221	0.012	0.011	0.033	0.378	0.147
NM	-0.006	0.355	0.428	0.016	2.230	0.362	0.284	0.011	-0.038	0.025	0.673	0.196
BM	0.820	0.127	0.384	0.029	3.456	0.126	0.255	0.019	0.082	0.076	0.191	0.179
MP	-0.022	0.302	0.307	0.009	3.126	0.253	0.168	0.005	-0.114	0.013	0.283	0.128
EP	-0.895	0.308	0.098	0.021	2.468	0.297	0.063	0.013	0.057	0.039	-0.063	0.164
El	-0.310	0.011	0.217	0.020	2.820	0.034	0.130	0.012	-0.094	0.031	0.075	0.077
Ma	0.411	0.081	0.178	0.014	3.760	0.065	0.093	0.007	-0.049	0.020	0.110	0.080
MV	0.310	0.079	0.221	0.028	3.211	0.080	0.128	0.016	0.063	0.059	0.152	0.151
Tr	0.714	0.027	0.284	0.041	3.661	0.075	0.161	0.023	-0.023	0.065	-0.047	0.177

Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Wearing apparel; LP: Leather and related products; Wo: Wood and of products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and chemical products; Ph: Basic pharmaceutical products and pharmaceutical preparations; RP: Rubber and plastic products; NM: Other non-metallic mineral products; BA: Basic metals; MP: Fabricated metal products, except machinery and equipment; EP: Computer, electronic and optical products; El: Electrical equipment; Ma: Machinery and equipment nec; MV: Motor vehicles, trailers and semi-trailers; Tr: Other transport equipment; Fu: Furniture.

Figure 1: Selection criteria results for the sectoral number of clusters

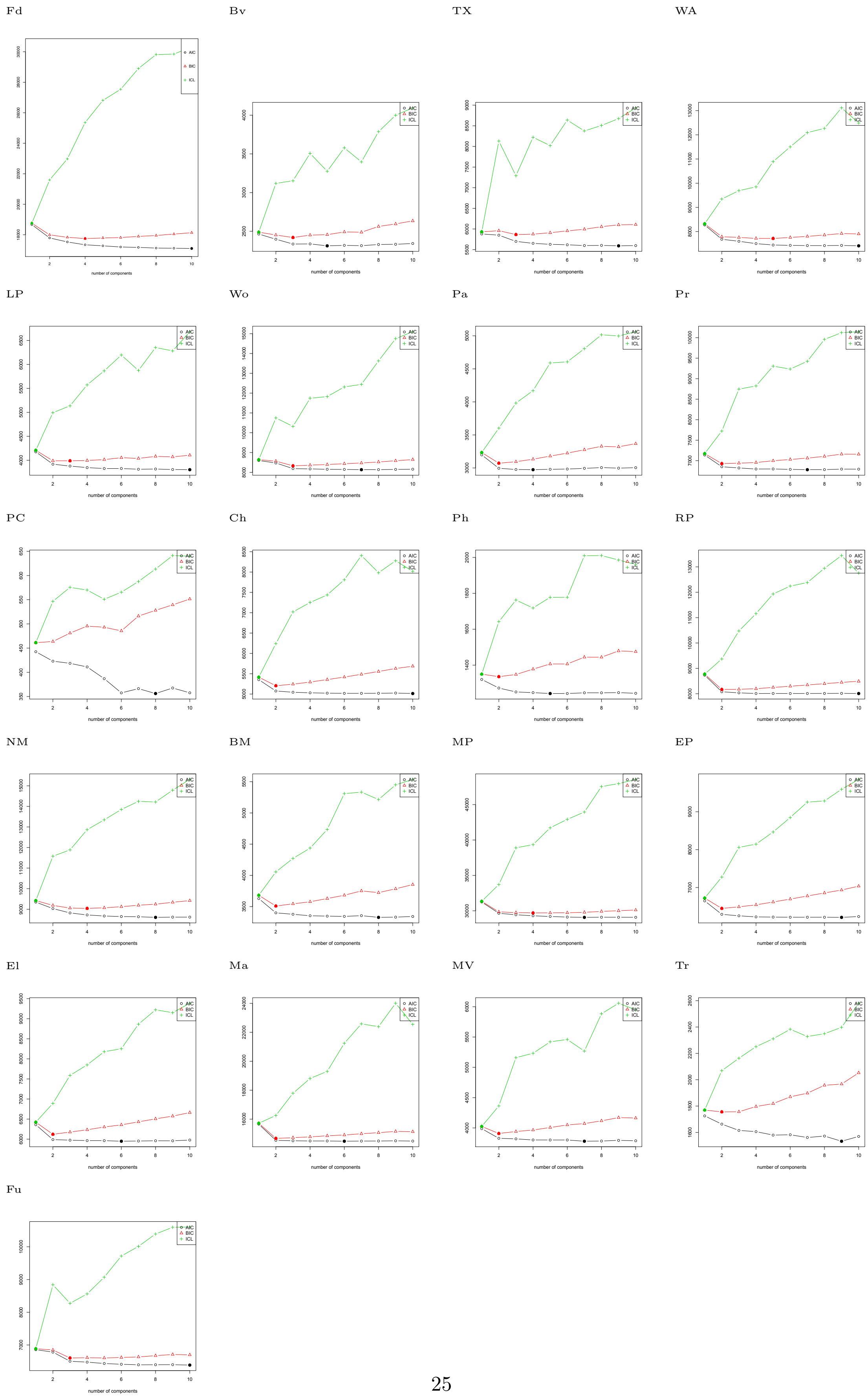
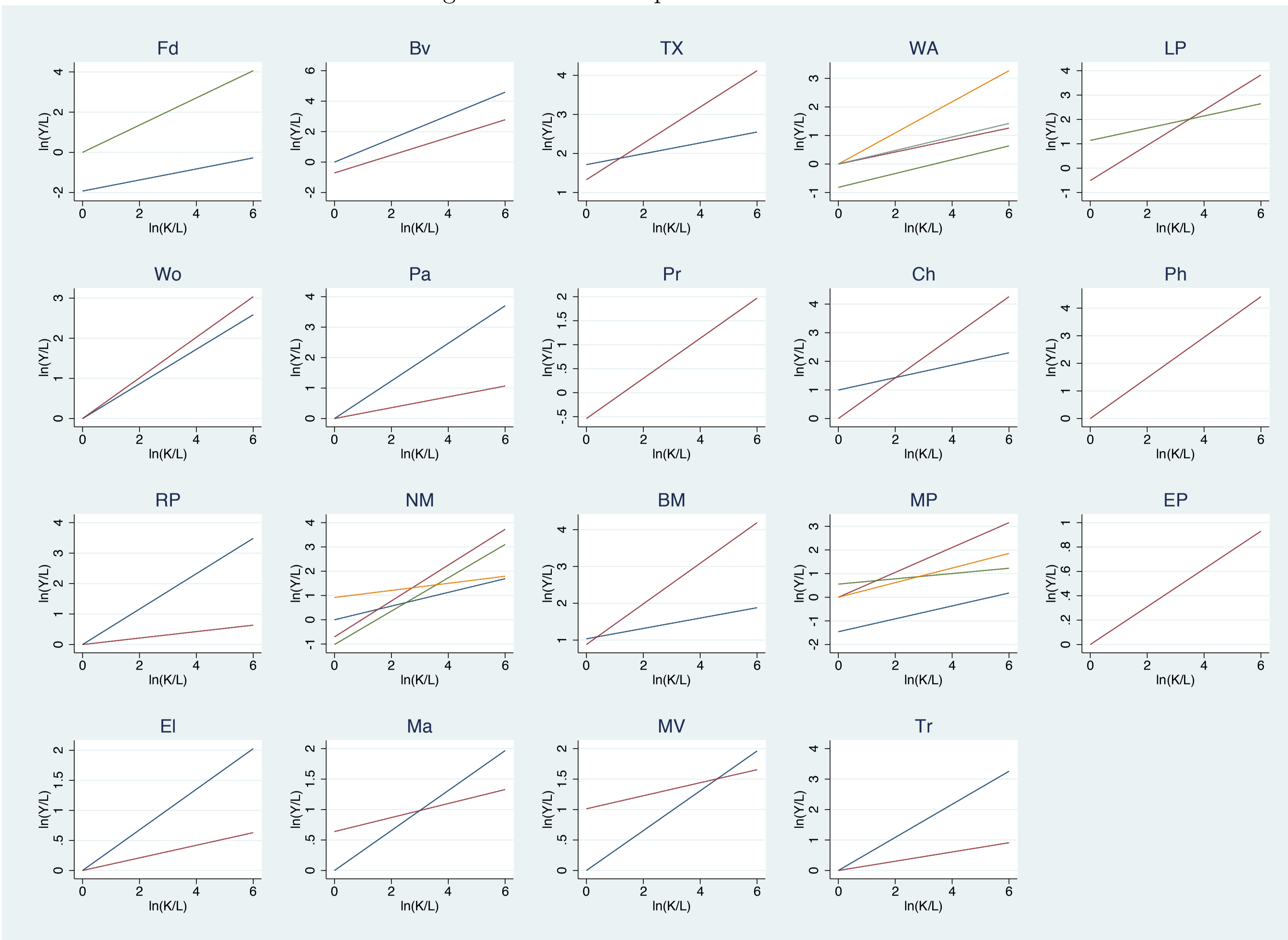


Figure 2: Estimated production functions



Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Wearing apparel; LP: Leather and related products; Wo: Wood and of products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and chemical products; Ph: Basic pharmaceutical products and pharmaceutical preparations; RP: Rubber and plastic products; NM: Other non-metallic mineral products; BA: Basic metals; MP: Fabricated metal products, except machinery and equipment; EP: Computer, electronic and optical products; El: Electrical equipment; Ma: Machinery and equipment nec; MV: Motor vehicles, trailers and semi-trailers; Tr: Other transport equipment; Fu: Furniture.

Figure 3: Estimated technology clusters: Chemicals (Ch) and Food (Fd) sectors

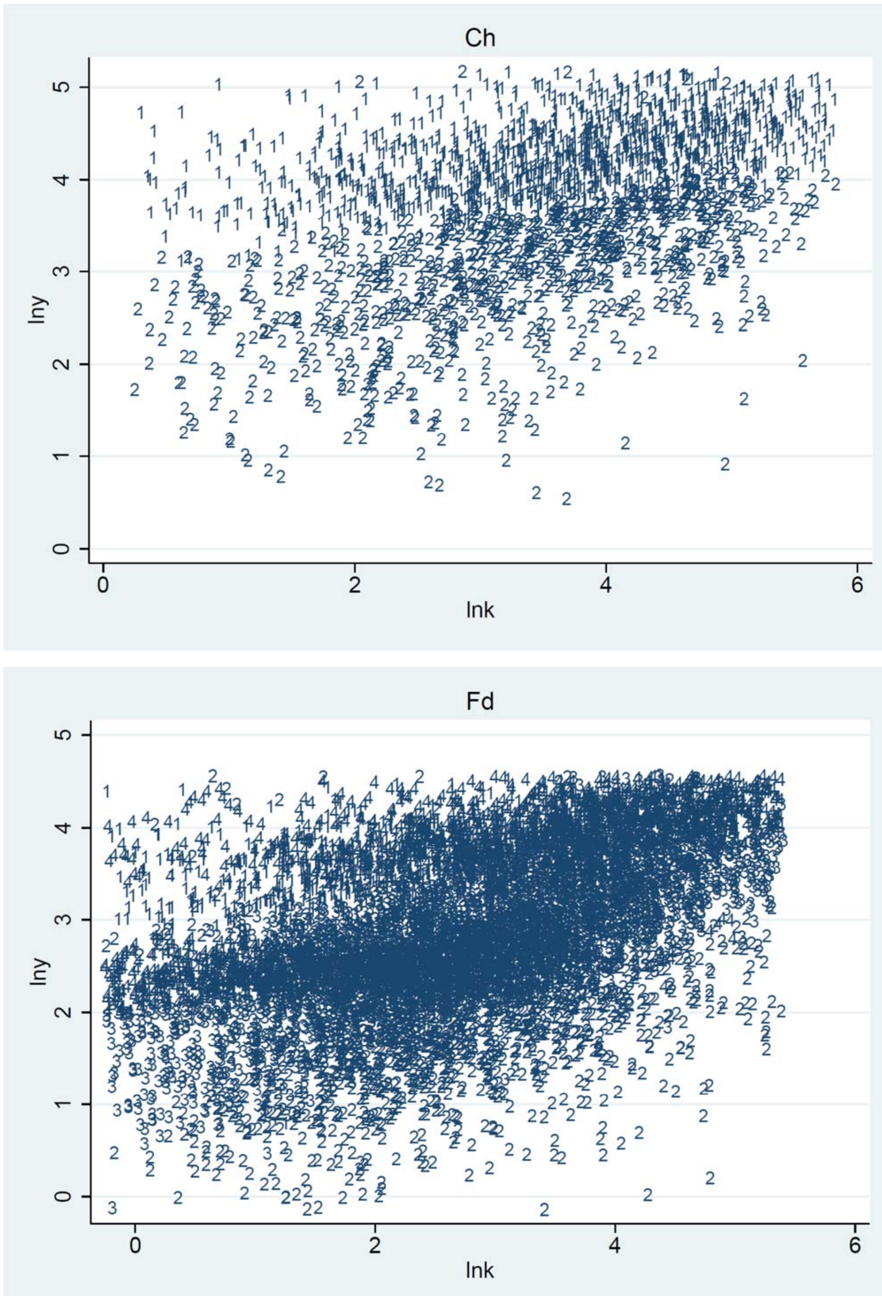


Figure 4: Definition of TFP with one technology (panel a) and two technologies (panel b).

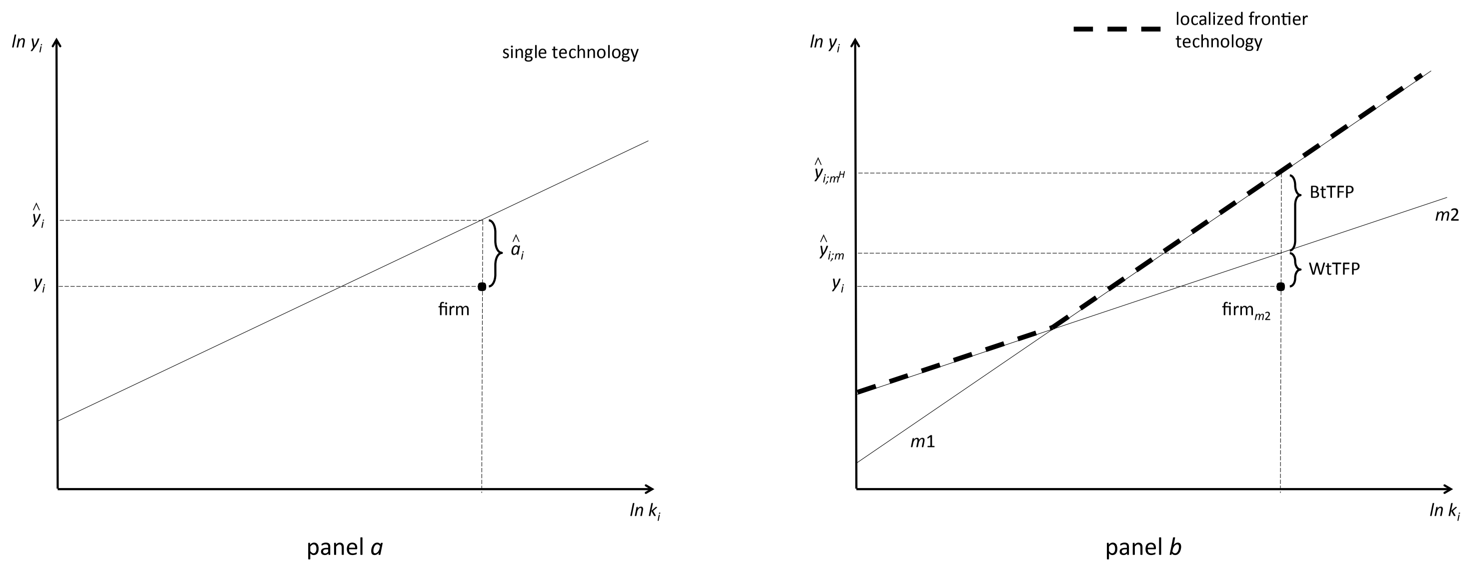
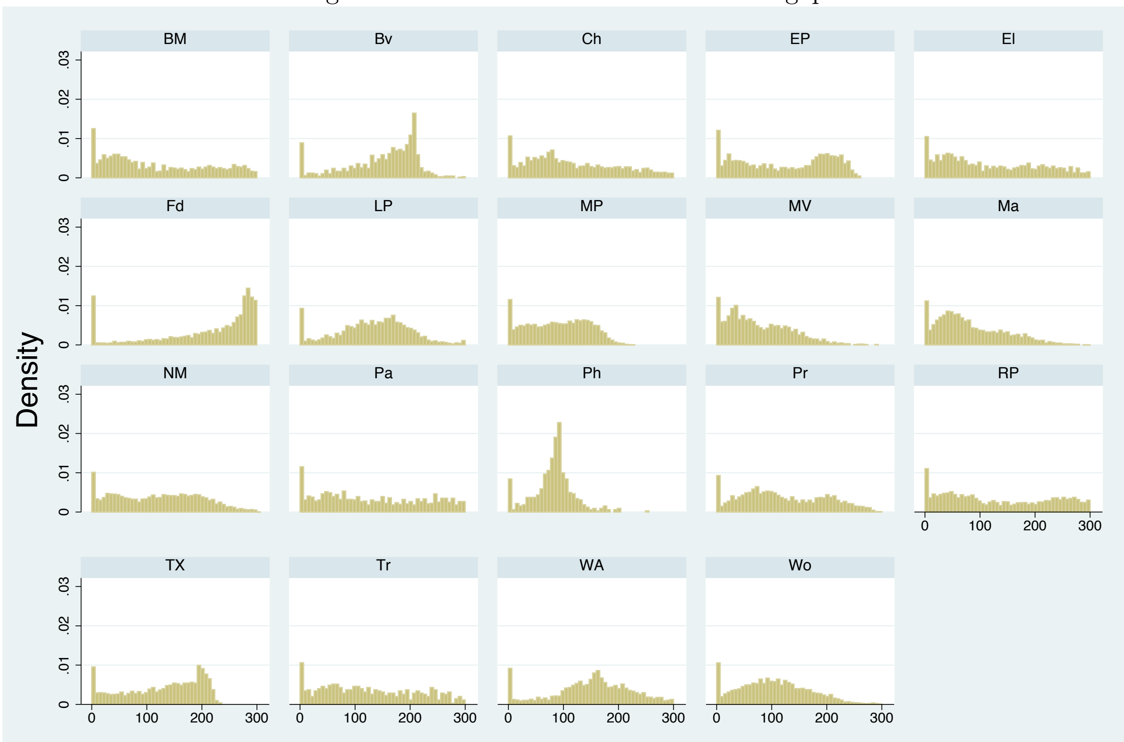


Figure 5: Sectoral distribution of BTFP gaps

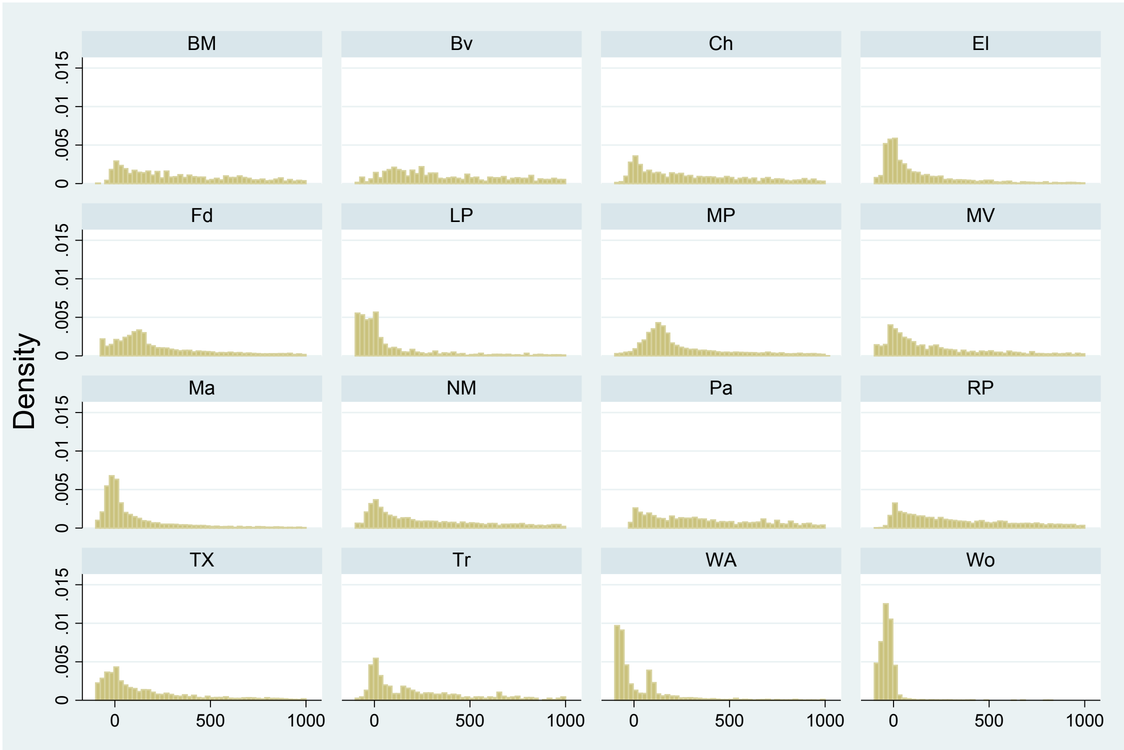
Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Wearing apparel; LP: Leather and related products; Wo: Wood and of products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and chemical products; Ph: Basic pharmaceutical products and pharmaceutical preparations; RP: Rubber and plastic products; NM: Other non-metallic mineral products; BA: Basic metals; MP: Fabricated metal products, except machinery and equipment; EP: Computer, electronic and optical products; El: Electrical equipment; Ma: Machinery and equipment nec; MV: Motor vehicles, trailers and semi-trailers; Tr: Other transport equipment; Fu: Furniture.

Figure 6: Sectoral distribution of WTFP gaps



Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Wearing apparel; LP: Leather and related products; Wo: Wood and of products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and chemical products; Ph: Basic pharmaceutical products and pharmaceutical preparations; RP: Rubber and plastic products; NM: Other non-metallic mineral products; BA: Basic metals; MP: Fabricated metal products, except machinery and equipment; EP: Computer, electronic and optical products; El: Electrical equipment; Ma: Machinery and equipment nec; MV: Motor vehicles, trailers and semi-trailers; Tr: Other transport equipment; Fu: Furniture.

Figure 7: Sectoral distribution of the BTFP/WTFP ratio

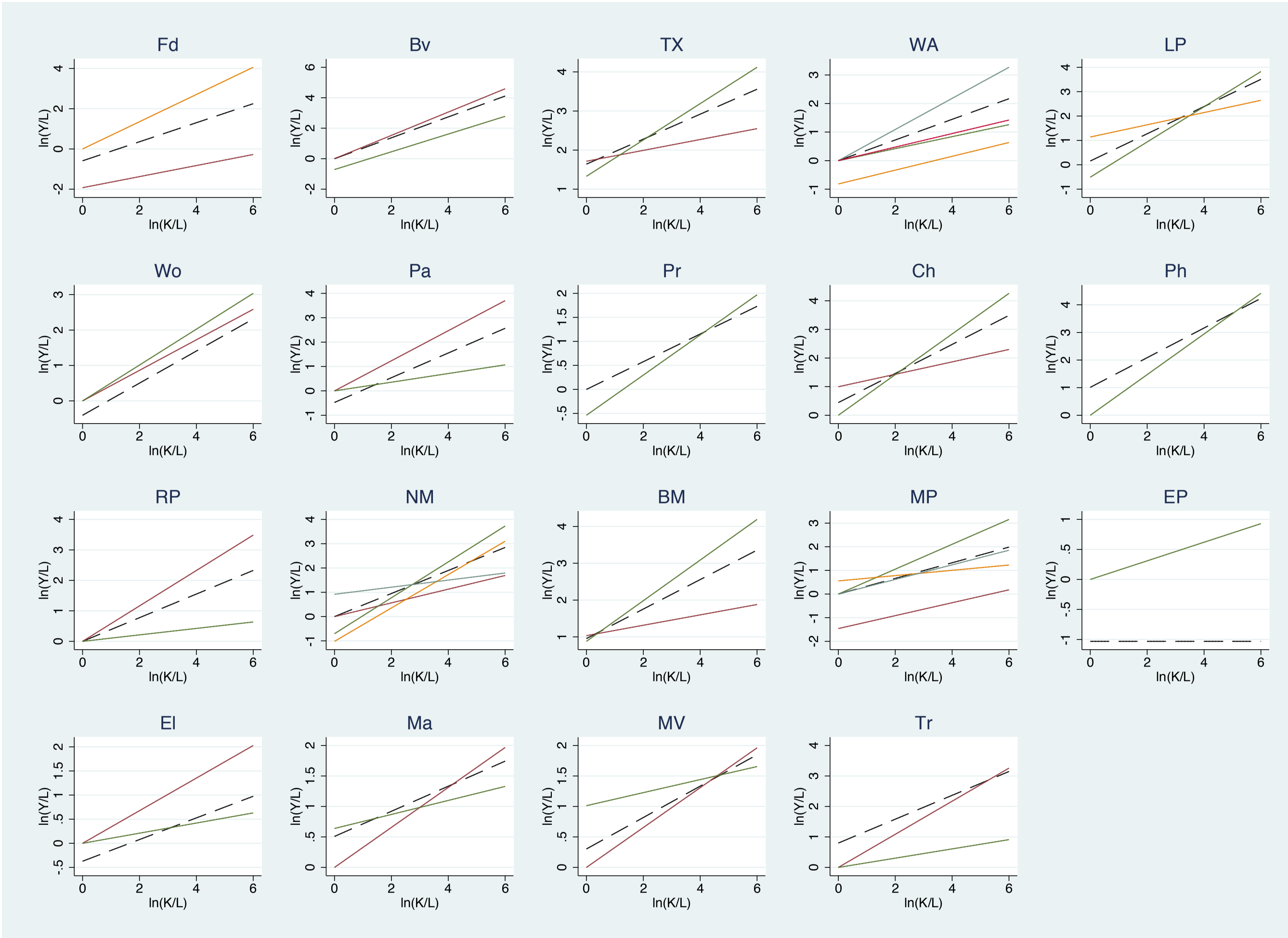


Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Wearing apparel; LP: Leather and related products; Wo: Wood and of products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and chemical products; Ph: Basic pharmaceutical products and pharmaceutical preparations; RP: Rubber and plastic products; NM: Other non-metallic mineral products; BA: Basic metals; MP: Fabricated metal products, except machinery and equipment; EP: Computer, electronic and optical products; El: Electrical equipment; Ma: Machinery and equipment nec; MV: Motor vehicles, trailers and semi-trailers; Tr: Other transport equipment; Fu: Furniture.

Figure 8: Scatterplot of the WTFP and BTFP gaps (sectoral averages)

Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Wearing apparel; LP: Leather and related products; Wo: Wood and of products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and chemical products; Ph: Basic pharmaceutical products and pharmaceutical preparations; RP: Rubber and plastic products; NM: Other non-metallic mineral products; BA: Basic metals; MP: Fabricated metal products, except machinery and equipment; EP: Computer, electronic and optical products; El: Electrical equipment; Ma: Machinery and equipment nec; MV: Motor vehicles, trailers and semi-trailers; Tr: Other transport equipment; Fu: Furniture.

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



Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Wearing apparel; LP: Leather and related products; Wo: Wood and of products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and chemical products; Ph: Basic pharmaceutical products and pharmaceutical preparations; RP: Rubber and plastic products; NM: Other non-metallic mineral products; BA: Basic metals; MP: Fabricated metal products, except machinery and equipment; EP: Computer, electronic and optical products; El: Electrical equipment; Ma: Machinery and equipment nec; MV: Motor vehicles, trailers and semi-trailers; Tr: Other transport equipment; Fu: Furniture.

Figure 10: Comparison across TFP densities estimated with different methods

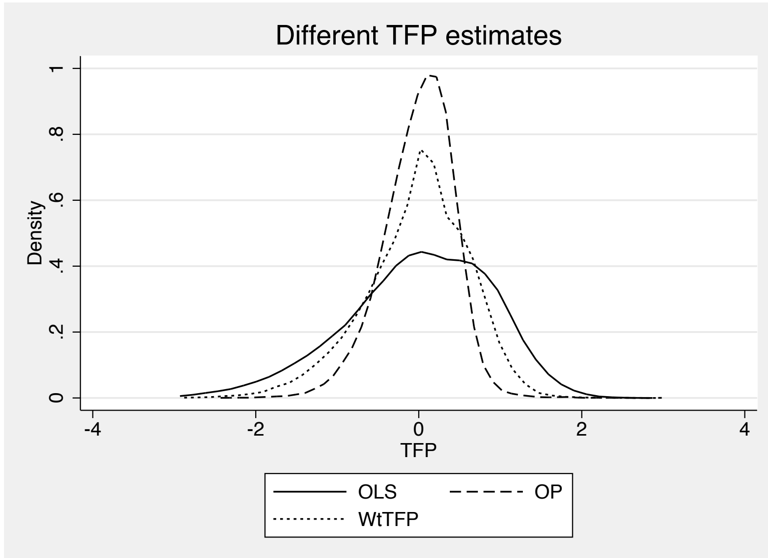
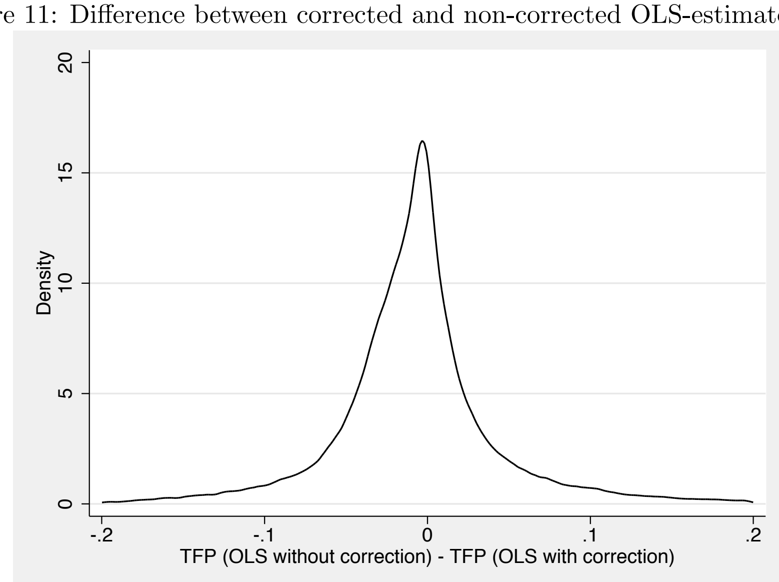


Figure 11: Difference between corrected and non-corrected OLS-estimated TFP



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