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

(Online Appendix)

A Mixture Regressions: Additional Statistical Output

In this appendix, we provide additional graphical output of the mixture analysis of the technology-specific production functions.

Figure 5 and Figure 6 show the within-sector distribution of the WTFP and BTFP gaps, respectively. Recall that the WTFP gaps are obtained at the firm level as $WTFP_{\text{best5\%}} - WTFP_i$, where $WTFP_{\text{best5\%}}$ is the average $WTFP_i$ of the best 5% of firms in the WTFP distribution in a sector, while the BTFP gaps are obtained as $BTFP_i$ multiplied by minus one. The sectoral panels in both figures are censured on the right-hand side where convenient to ensure graphical clearness. For both the WTFP and the BTFP gaps, we observe substantial heterogeneity within and between sectors. For the BTFP gaps, in particular, sectors characterized by a relatively large group of firms using the locally optimal technology also show distributions with higher skewness and a thinner right-hand tail.

[insert Figure 5 about here]

[insert Figure 6 about here]

Figure 7 provides a sectoral example of the probabilistic clustering obtained by means of a mixture model estimation of the technology-specific production functions. For clarity, we choose the basic metals (BM) sector, where only two technological clusters emerge from the analysis, and plot the firm-level observations with a color scale reflecting the probability of belonging to cluster 1 (i.e., $Prob_1$). Given that only two clusters are obtained for this sector, the firm probability of belonging to cluster 2 can be obtained as $1 - Prob_1$. The figure shows that firms with a relatively high probability of belonging to cluster 1 are in fact clustered in a defined region of the distribution, which we interpret as the pattern of a technology-specific production function.

[insert Figure 7 about here]

Figure 8 plots the correlation between the benchmark and re-estimated BTFP and WTFP values discussed in Section 7. The benchmark values are those obtained by running the mixture model estimation of the technology-specific production functions on worldwide international data, while the re-estimated values are obtained on a restricted sample of data for six countries (Finland, Italy, Germany, France, the Netherlands, and Spain), as in Bos *et al.* (2010). Reduced cross-country coverage affects our technology clustering by reducing the number of technologies possibly identified (when run on the subsample, our mixture model can identify one or two clusters in most of the sectors, with only two sectors showing a larger number of clusters). Figure 8 shows that a positive correlation emerges between the benchmark and re-estimated BTFP and WTFP values, suggesting that the rank correlation between the BTFP and WTFP values obtained in the two cases is generally preserved. As expected, however, the measures obtained in the two estimation exercises do not precisely overlap. This confirms that only large data coverage allows our mixture model to identify all the technologies possibly available worldwide.

[insert Figure 8 about here]

B 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 the results with and without controlling for simultaneity.

As a first comparison, Figure 9 reports the production functions estimated by 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 weighted least squares, 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, namely, $\hat{\beta} = \sum_{m=1}^{M} \hat{\beta}_m \frac{\Theta_m}{\sum_{m=1}^{M} \Theta_m}$. The same reasoning applies to α.

[insert Figure 9 about here]

Consistently, Figure 9 shows that the dashed line lies essentially in between the technology-specific production functions. Columns (2) to (5) of Table 10 report the OLS-estimated coefficients.

[insert Table 10 about here]

As discussed in Section 3, among the issues highlighted by the literature on estimating production functions, recent works have focused on simultaneity bias. The source of simultaneity bias is the fact that information on actual productivity, although unknown to the econometrician, is known to the firm when it decides on the amount of inputs. This biases the production function parameters obtained through the least squares estimates because of the potential correlation between the regressors and error term.

A successful stratagem suggested by the literature for addressing this issue consists of recovering the a_i component from the traces it leaves in the observed behavior of the firm. Key studies examining this approach, which is commonly referred to as the proxy variable method, include the semi-parametric approach put forward by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg *et al.* (2006) as well as the GMM estimation adopted by Wooldridge (2009). The basic idea of this methodology consists of identifying a (proxy) variable that reacts to the changes in 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), who extend Olley and Pakes (1996), show that a firm's TFP is stochastically affected by its investment in knowledge (considered in terms of R&D).[13]

The implementation of such a 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 firms' TFP. Our model of technology adoption developed in Section 3 is meant to deal with these two sources of simultaneity separately, without the need to rely on a specific proxy variable.

Similarly to the semi-parametric strategy, our approach to simultaneity entails a two-step estimation. However, instead of trying to include the whole productivity term (as proxied by the inverted investment or intermediates demand function) in the production function, our strategy seeks to take its effect (on the capital and labor choice) into account by controlling for its covariance with labor and capital. We exploit the fact that the correlations between capital and technology as well as between either capital or labor and TFP flow into the residuals of the system of equations in Equation (11), consisting of the K policy function and static condition for L. Once estimated, these residuals allow us to control for simultaneity in the mixture analysis. As well as controlling for the simultaneity caused by idiosyncratic TFP, this strategy can control for any other factor affecting the input choice through the relationships in Equation (11). This aspect is particularly relevant in light of the results provided by Gandhi *et al.* (2018) on the identification problems characterizing the semi-parametric approach. Such problems stem from the circumstance that even when the invertibility conditions (for the proxy variable demand function) identified by the literature are satisfied, it is still possible to construct a continuum of observationally equivalent production functions that cannot be distinguished from the true production function in the data.[14] By not resorting to any proxy variable, our approach is in principle immune to this order of problems.

Second, our timing of input choice is strictly in line with Olley and Pakes (1996), with labor dealt with as a "perfectly variable" input decided at the time of production. While this is also true in Levinsohn and Petrin (2003), Ackerberg *et al.* (2015) highlight the collinearity problems associated with such decision timing and suggest a slightly different specification in which labor is a "less variable" input than intermediates chosen one "subperiod" before productivity is observed. This implies that differently from Olley and Pakes (1996) and Levinsohn and Petrin (2003), in which the labor and capital coefficients are identified in the first and second steps respectively, the first step is only used to net the output function of the idiosyncratic productivity (and in our case also technology) shock, with both the capital and the labor coefficients retrieved in the second stage.[15] Although we use the same timing of input choice as Olley and Pakes (1996) and Levinsohn and Petrin (2003), our approach is not subject to the Ackerberg *et al.* (2015) critique, as both coefficients are estimated in the second stage in our case.

To understand how the different estimation strategies are reflected in the firm TFP distribution, Figure 10 compares our WTFP with the OLS-estimated TFP and TFP estimated through the Olley and Pakes (1996) procedure (the coefficients are reported in the four last columns of Table 10), used as a benchmark estimation

[13] Firms' productivity is assumed to evolve according to a Markov process, which is "shifted" (either positively or negatively) by R&D expenditure. 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 us to estimate firms' TFP while controlling for simultaneity and the effect of innovation choices at the same time.

[14] The reason why is shown to be the assumption of flexible elasticity for the input used as a proxy.

[15] The most obvious hypothesis of the data-generating process for labor demand is for it to be a function of capital and productivity. Thus, labor demand is only a function of capital plus the variable chosen as the proxy (i.e., investment in Olley and Pakes (1996) and intermediates in Levinsohn and Petrin (2003)), showing that the labor coefficient cannot be identified in the first stage, as one cannot simultaneously estimate a fully non-parametric function of two variables along with a coefficient of a variable (labor) that is only a function of those same variables.

within the semi-parametric approach. The OLS approach tends to fatten the tails of the distribution, particularly by overstating the TFP of the most productive firms. Our methodology results in a distribution that lies in the middle of the OLS and Olley–Pakes ones because part of the correction imposed by the Olley–Pakes method is recognized to be related to firms' choice of technology rather than to TFP, and this is thus captured by our BTFP term.

[insert Figure 10 about here]

The OLS estimates in Figure 9 and Figure 10 include a correction for the simultaneity suggested by our model. To illustrate the effect of this correction, Table 10 reports the estimated coefficients and Figure 11 illustrates the distribution of the difference between the OLS estimates with and without the correction. This distribution looks reasonable and suggests the absence of specific patterns (e.g., a stronger effect on a more productive firm). Table 10 reports the estimated coefficients obtained without the correction.

[insert Figure 10 about here]

[insert Figure 11 about here]

C Relationship with the Misallocation Literature

A growing body of the literature studies how firm-level differences in TFP are reflected in aggregate productivity, including Alfaro *et al.* (2008), Banerjee and Duflo (2005), Bartelsman *et al.* (2013), Hsieh and Klenow (2009, 2010), Jones (2011), Restuccia and Rogerson (2008), and Olley and Pakes (1996). A key word in this stream of the literature is misallocation, namely lower aggregate TFP due to distortions in the allocation of inputs across units (Restuccia and Rogerson, 2013). The extent of misallocation is easily understood in terms of the deviation from the efficiency condition (i.e., in efficient markets, the MRP of an input equals its price) as well as, according to Hsieh and Klenow (2009, 2010), of the dispersion of revenue TFP.

Several authors have focused on the misallocation patterns in single countries: misallocation has increased in Spain (Garcia-Santana *et al.*, 2015; Gopinath *et al.*, 2015), Portugal (Dias *et al.*, 2016), and Italy (Calligaris *et al.*, 2018); remained constant in France (Bellone and Mallen-Pisano, 2013); and declined in Germany (Crespo and Segura-Cayuela, 2014) and Chile (Chen and Irarrazabal, 2014). The general conclusion reached by these studies is that the aggregate productivity losses associated with misallocation are substantial and that, as a consequence, eliminating or reducing the within-industry distortions is crucial to improve the performance of countries.

One may wonder how our approach with technological heterogeneity is reflected in the quantification of misallocation. As stated, technological heterogeneity is not a source but a manifestation of misallocation.

To understand why, it is useful to briefly resume the Hsieh and Klenow (2009) model. The rational for misallocation is that from standard profit maximization, firms choose the amount of capital K and labor L by equalizing the MRP of each input to its marginal cost. While this process equalizes the MRP of capital (MRPK) and MRP of labor (MRPL) across firms, when all firms face the same input cost, the presence of market distortions (e.g., access to credit) can drive wedges between MRPK and MRPL across firms. In this case, we say that capital and labor are "misallocated" across firms.

Let us start with a standard Cobb–Douglas technology with sector-specific production coefficients:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \tag{19}$$

and follow Hsieh and Klenow (2009) (hereafter HK) in denoting distortions that increase the marginal products of capital and labor by the same proportion as an output distortion (e.g., government restrictions on size, transportation costs, public output subsidies) by τ_{si}^{Y} and distortions that raise the marginal product of capital relative to labor (i.e., capital distortions) by τ_{si}^{K} (e.g., different access to credit). From the first-order condition of firm i, active in sector s, we find that

$$MRPK_{si} = P_{si} \frac{\partial \tilde{Y}_{si}}{\partial K_{si}} = \beta_s^K P_{si} \frac{Y_{si}}{K_{si}} = \tilde{W}^K \tag{20}$$

and

$$MRPL_{si} = P_{si} \frac{\partial \tilde{Y}_{si}}{\partial K_{si}} = (\beta_s^L) P_{si} \frac{Y_{si}}{L_{si}} = W^L, \tag{21}$$

where $\tilde{Y}_{si} = (1-\tau_{si}^Y)Y_{si}$ and $\tilde{W}^K = (1+\tau_{si}^K)W^K$, with W^K and W^L referring to the costs of capital and labor, respectively.

If $\tau_{si}^Y = \tau_{si}^K = 0 \ \forall i \in s$, firms face the same input cost, and the MRP of the two inputs is equalized across firms. In this case, capital and labor are perfectly (i.e., efficiently) allocated. When this happens, the within-sector distributions of MRPK and MRPL exhibit zero dispersion around the mean, as average MRPK in sector s (i.e., $\overline{MRPK}_s$) equals $MRPK_{si} \ \forall i \in s$ (and the same for MRPL). No misallocation emerges in this case.

The MRP equalization condition holds true independently of the way in which firms set P_{si} (i.e., independently of market structure), the only condition being the absence of distortions in the capital and labor markets.

Since the higher the dispersion, the more effective are the distortions, it would be relatively easy to investigate the presence, and magnitude, of resource misallocation by looking at the within-industry dispersion of MRPK and MRPL. However, if one is interested in the aggregate effects of the documented distortions, more structure is needed.

To this end, a useful strategy is suggested by HK, whose approach enables us to study the effect of misallocation on aggregate TFP. The intuition is simple and rests on the proportionality between firm TFP and the MRP of inputs.

Using (19), it is possible to write firm i's TFP as

$$TFP_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}. \tag{22}$$

As statistical information on the physical output Y_{si} or firm price P_{si} is hardly available (see Foster *et al.*, 2008), TFP is usually calculated on the basis of firms' revenues (TFPR hereafter). Using (19), this yields

$$TFPR_{si} = P_{si}A_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}. \tag{23}$$

While using $TFPR_{si}$ instead of TFP_{is} usually represents a shortcoming in the analysis, this is not the case in the HK framework. Under specific assumptions on market structure, $TFPR_{si}$ can be shown to be not influenced by other firm-specific factors than the distortions τ_{si}^Y and τ_{si}^K. In particular, if each sector s is monopolistically competitive, firms' set prices according to

$$P_{si} = (\frac{\sigma}{\sigma-1})\beta_s (W^K)^{\beta_s^K} (W^L)^{\beta_s^L} \frac{(1+\tau_{si}^K)^{\beta_s^K}}{(1-\tau_{si}^Y)} \frac{1}{A_{si}}, \tag{24}$$

where $\frac{\sigma}{\sigma-1}$ is the markup and $\beta_s = \beta_s^{K-\beta_s^K} (\beta_s^L)^{-\beta_s^L}$ is the bundle of parameters associated with the Cobb–Douglas production function (19). Apart from A_{si}, the only firm-specific terms in Equation (24) are the distortions. When substituted into Equation (23), the pricing rule in Equation (24) yields

$$TFPR_{si} = \frac{\sigma}{\sigma-1}\beta_s (W^K)^{\beta_s^K} (W^L)^{\beta_s^L} \frac{(1+\tau_{si}^K)^{\beta_s^K}}{(1-\tau_{si}^Y)}. \tag{25}$$

According to Equation (25), the cross-firm variability of $TFPR_{si}$ is not influenced by other firm-specific factors than τ_{si}^K and τ_{si}^Y (in fact, term A_{si} cancels out).[16]

As a result, *the extent of misallocation can be studied by looking at the dispersion of the* $TFPR_{si}$ *distribution* instead of considering the distributions of $MRPK_{si}$ and $MRPL_{si}$.

Our framework introduces an additional misallocation mechanism. Indeed, in the presence of frictions in the capital and/or labor market(s), firms can be unable to switch to superior technologies and thus retain misaligned MRPs. Hence, the presence of different technologies can be a possible consequence of the firm-level distortions preventing firms from being located on the technological frontier.

To gain an intuition of the relationship with the HK approach, consider the simplified version of our setting presented in Section 2 and imagine two firms identical in everything to firm i except for the technology they adopted, with one of them (say firm h) using the frontier technology H and the other (firm l) using the non-frontier

[16]Moreover, HK show that $TFPR_{si}$ is proportional to the geometric average of $MRPK_{si}$ and $MRPL_{si}$:

$$TFPR_{si} \propto (MRPK_{si})^{\beta_s^K} \propto (MRPL_{si})^{\beta_s^L} \propto \frac{(1+\tau_{si}^K)^{\beta_s^K}}{(1-\tau_{si}^Y)}. \tag{26}$$

technology l. Now (abstracting, for ease of comparison, from the fact that description in Section 2 is carried out in intensive form) focus on the efficiency condition of capital and imagine that

$$MRPK_{s,h} = \beta_H^K P_{si} \frac{Y_{si}}{K_{si}} = \tilde{W}^K > W^K \tag{27}$$

and

$$MRPK_{s,l} = \beta_L^K P_{si} \frac{Y_{si}}{K_{si}} = \tilde{W}^K < W^K. \tag{28}$$

While eliminating misallocation would require shifting capital from firm l to firm h, *allowing the former to switch to the superior technology would increase $MRPK_{s,l}$ but it would not solve the misallocation issue*, as the inefficiency condition would persist until the two firms are not allowed to employ a higher amount of capital. Thus, *eliminating technological heterogeneity by bringing all firms to the technology frontier would not eliminate misallocation.*

On the contrary, the HK strategy of measuring misallocation through the lens of TFPR dispersion is crucially affected. In fact, in terms of Equation (25), we would have

$$TFPR_{sh} = \frac{\sigma}{\sigma-1}\beta_h (W^K)^{\beta_s^K}(W^L)^{\beta_s^L}\frac{(1+\tau_{si}^K)^{\beta_s^K}}{(1-\tau_{si}^Y)} > \frac{\sigma}{\sigma-1}\beta_l (W^K)^{\beta_s^K}(W^L)^{\beta_s^L}\frac{(1+\tau_{si}^K)^{\beta_s^K}}{(1-\tau_{si}^Y)} = TFPR_{sl}. \tag{29}$$

With firm l switching to the superior technology, TFPR dispersion would drop to zero even if, as seen, misallocation is still present. Thus, taking the presence of multiple technologies into account in the HK framework entails that *TFPR dispersion is no longer a sufficient statistic for the dispersion of the MRP of factors and thus cannot be used to quantify the extent of misallocation.*[17] The reason why is that TFPR can also differ across firms due to technological differences as well as because of differences in the MRPs of inputs.

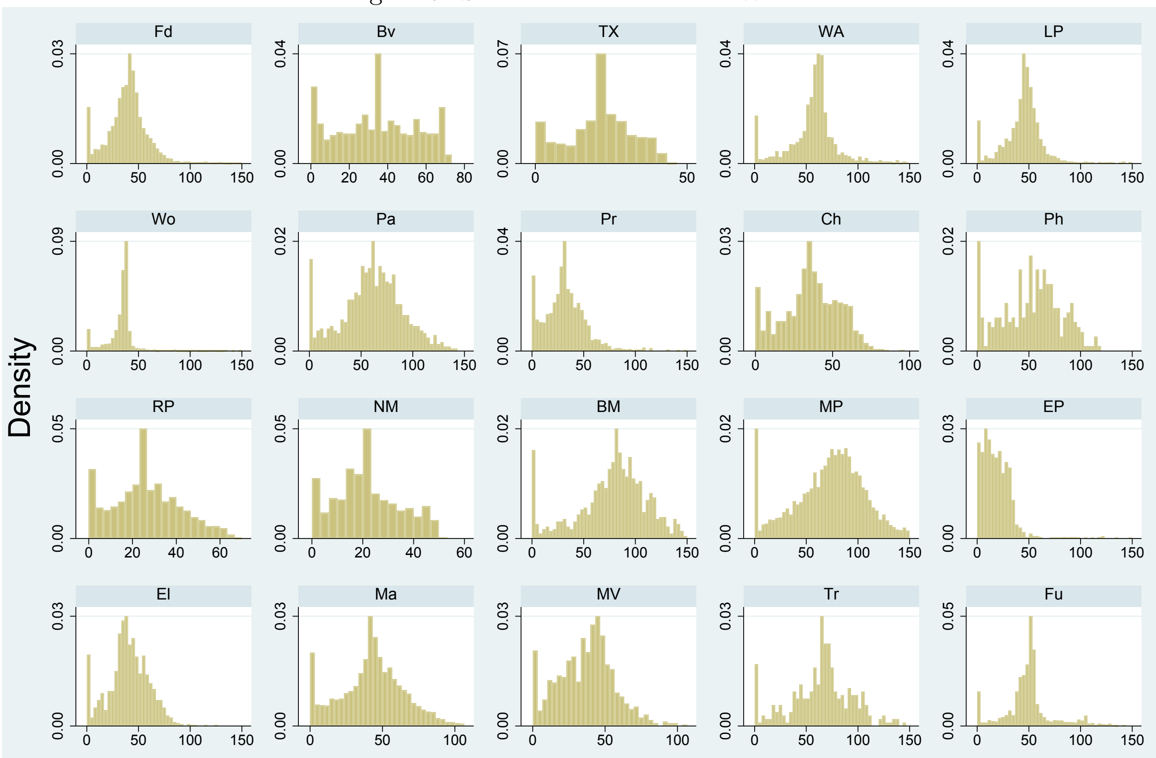
[17] The statistical counterpart of this argument may be drawn by Duclos *et al.* (2004). In a unimodal distribution, a reduced dispersion (a single squeeze) is indicative of less inequality, which, in the HK setting, would mean less misallocation. In a bimodal (or higher-order) distribution, reduced dispersions around the modes (a double squeeze) would imply less dispersion but more polarization, so only firms within a technological cluster would become more similar.

Table 10: Sectoral production functions estimated using different methodologies.

	OLS with correction				**OLS without correction**				**Olley–Pakes**			
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

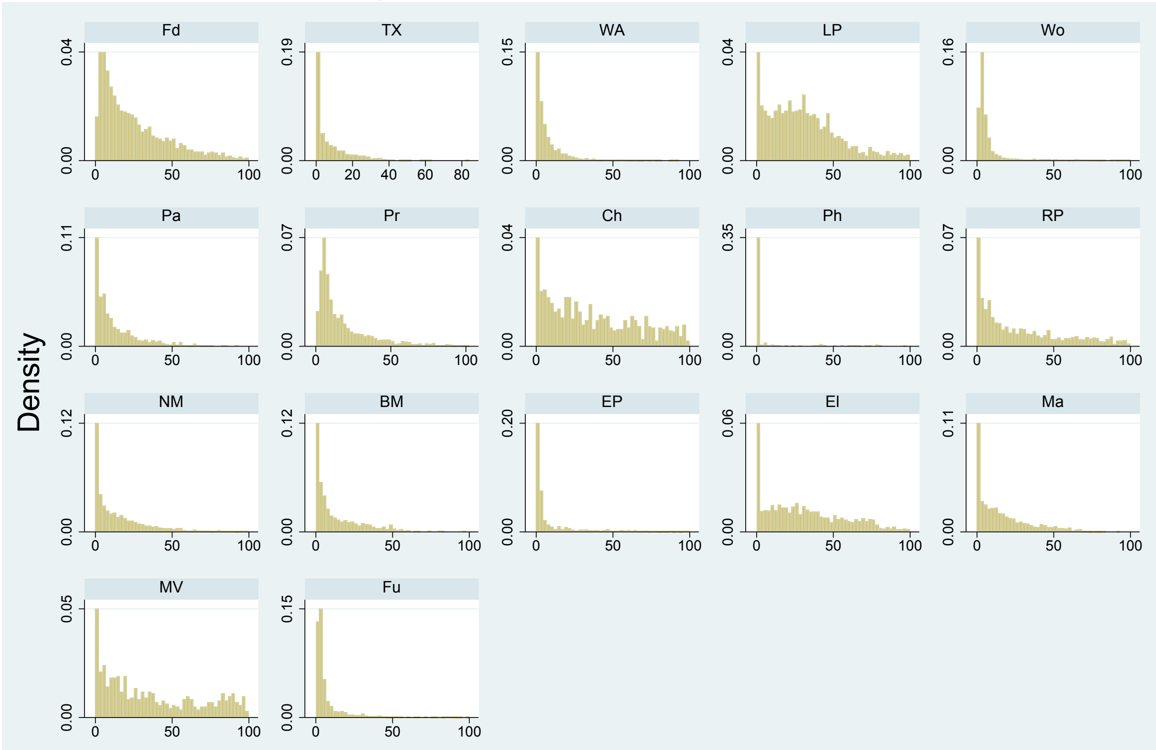
Legend. Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Apparel; LP: Leather and related products; Wo: Wood and products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and 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 5: Sectoral distribution of WTFP.



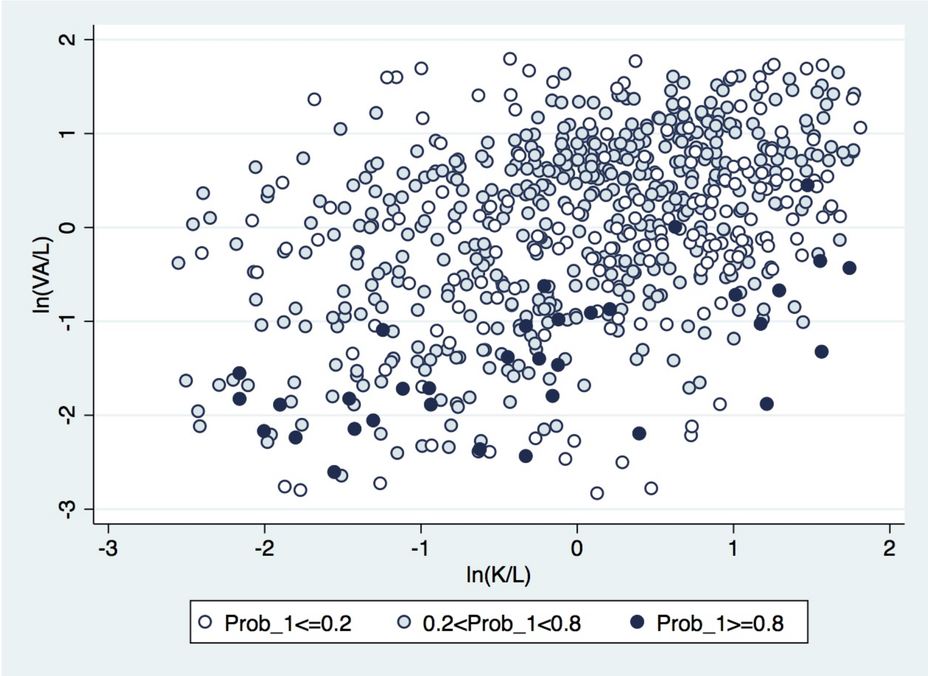
Legend. Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Apparel; LP: Leather and related products; Wo: Wood and products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and 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 BTFP.



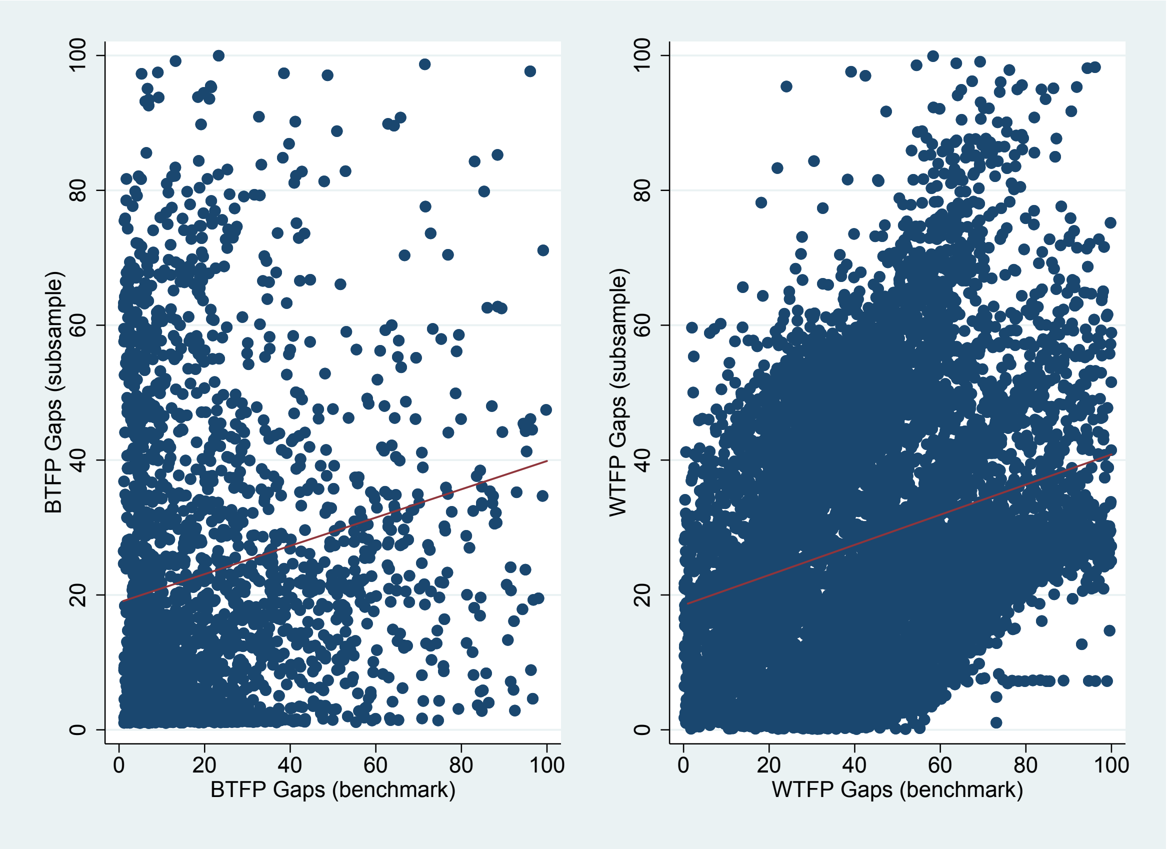
Legend. Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Apparel; LP: Leather and related products; Wo: Wood and products of wood and cork; Pa: Paper and paper products; Pr: Printing and reproduction of recorded media; PC: Coke and refined petroleum products; Ch: Chemicals and 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: Estimated probability of belonging to a given technology cluster: The basic metals (BM) sector.



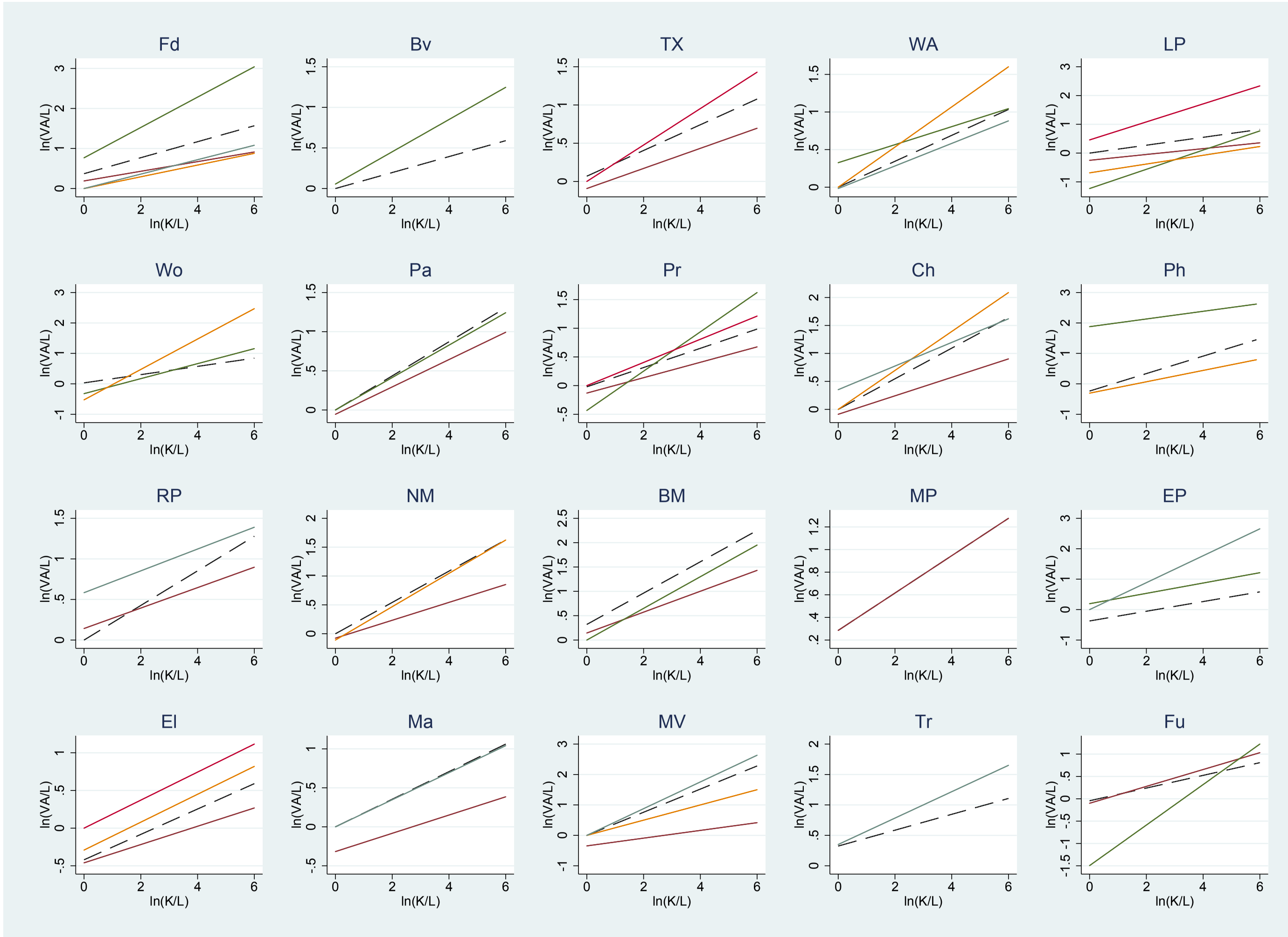
Note. Firm-level observations are plotted. Color scale reproduces the probability classes of belonging to technology cluster 1 (for BM, two clusters are obtained from the mixture analysis).

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.

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



Legend. Fd: Food products; Bv: Beverages; Tb: Tobacco products; TX: Textiles; WA: Apparel; LP: Leather and related products; Wo: Wood and 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

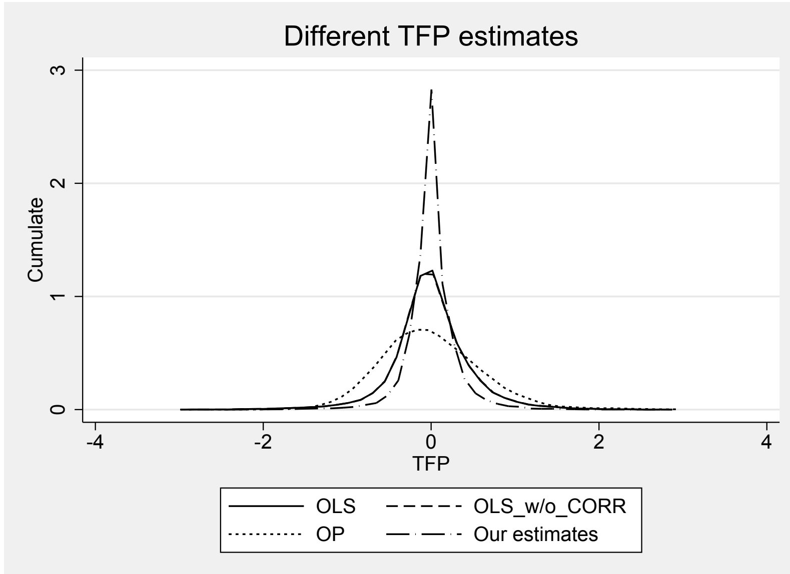


Figure 11: Difference between corrected and non-corrected OLS-estimated TFP