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The Determinants of TFP Growth in the Portuguese Manufacturing Sector

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Abstract

Given the linkage between Total Factor Productivity growth and economic growth, it becomes relevant to understand, at the firm level, which are the main determinants of such growth path. We use an extensive panel data covering Portuguese manufacturing firms, between 2010 and 2014, in order to assess which are the main determinants of the Total Factor Productivity. Through a second stage estimation we present a fixed-effects model that captures different dimensions of firm level characteristics that impact TFP growth, suggesting policy recommendations amid the model's results. Our results show that age and debt influence negatively TFP growth, whereas size, exports and training expenses prompt TFP growth.

JEL Classification: D22, D24

Keywords: Total Factor Productivity, Industry

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List of Abbreviations

FDI: Foreign Direct Investment

LP: Levinsohn and Petrin

OLS: Ordinary Least Squares

OP: Olley and Pakes

R&D: Research and Development

TFP: Total Factor Productivity

1. Introduction

“...Productivity isn’t everything, but in the long run it is almost everything”

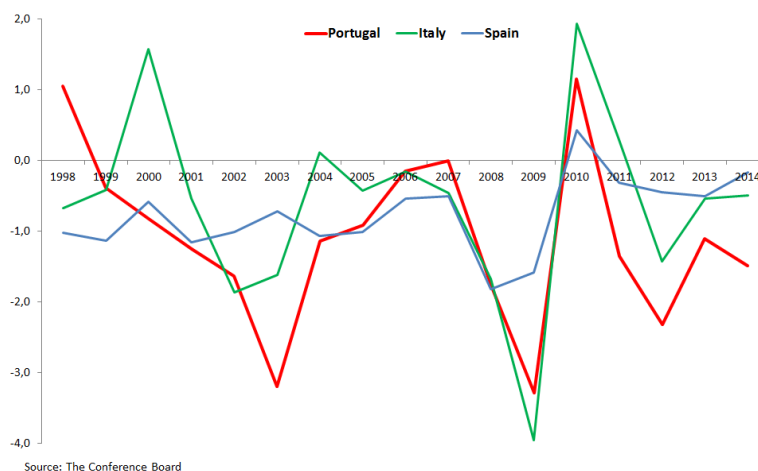
Krugman (1997)

The sole combination of inputs such as labour, capital and, at some extent, intermediate inputs does not entirely explain output creation. The remaining share of output variation which cannot be explained by such endowment of inputs is a measurement of technical efficiency and provides insights on aggregate economic growth. Assessing the determinants of Total Factor Productivity Growth at the firm-level aware policymakers to which extent they should enhance some policies in order to provide firms an economic and financial environment keen to prompt its performance and achieve higher levels of technological efficiency. In fact, a hand of authors state that a great part of growth in income per capital is explained by the residual of production and not by the accumulation of capital and labour¹.

The current global crisis has reinforced concerns on growth prospects, and firms provide an accurate insight not only on how the aggregate economy performs but also on how economic activity can be driven into a sustainable growth path. In general, productivity evolution is being decreasing since the beginning of the current century in the major developed countries, pointing to a linkage between weakness of competitiveness and slowdown of economic activity.

Chart 1 considers TFP Growth for some Southern European Countries according to data from The Conference Board (2015), the productivity of labour and capital together (measured by Total Factor Productivity - TFP), has consistently decreased (with the exception of a slight increase in 2010) since the late nineties.

Chart 1: TFP Growth - Southern Europe Countries



¹ Recall Abramovitz (1956) and (Solow 1957) for more on the subject.

What we propose to do in this paper is, through the study of a microdata database of Portuguese manufacturing companies (in panel, in the period 2010-2014), test the significance of the main determinants suggested by the literature such as innovation variables (namely training and fixed intangible assets), export activity, internal firm characteristics like age and dimension, and debt-to-equity as a proxy to firms financial health.

The paper is organized as following. Section 2 includes a brief literature review on the topic. Section 3 provides Data description and the methodology applied on cleaning the dataset according to the purpose of our research. Next, we explain the chosen method for TFP estimation and provide result comparisons amongst different estimating methods on Section 4. Section 5 approaches the methodological issues concerning second-stage estimations and includes our econometric framework on the robustness of the model. The estimated model and the interpretation of the results with linkage to others from the literature is compiled on Section 5. The paper is concluded with Section 6, on which we suggest policy recommendations according to the results from the estimated model.

2. Literature Review

The assessment of TFP Growth determinants at the firm-level is broadly approached in the literature, providing an extensive result comparison among different countries, sectors and specific industries. Moreover, it is more common to observe researches on specific topics of determinants instead of considering simultaneously different spectrums of determinants.

Innovation and technological progress is considered on the main enhancers of TFP Growth. Romer (1986,1990) endorses the endogenous knowledge creation as a factor for perpetual economic growth. One of the main challenge of measuring innovation and its effects on TFP Growth is to define accurate proxies for such purpose, namely Research and Development (R&D), patent data or Foreign Direct Investment (FDI). For instance, Castany *et. al* (2005) studied the impact of innovative activity and skilled labour usage on TFP Growth using information from *Encuesta sobre Estrategias Empresariales* on Spanish manufacturing firms. He finds that firm size restricts the effect of R&D and employees' qualification on productivity and that size affects indirectly TFP Growth. Other literature focuses on the notion of knowledge, as the impacts of factors such as Information and Communication Technologies, patents or scientific publications may be interpreted as a function of openness and institutions, and therefore has positive effects on TFP Growth (Chen and Dahlman (2004). Calligaris *et. al* (2016) find that innovation (measured by intangible assets such as R&D, branding, marketing) prompts productivity growth. In the same line, Crass and Peters (2014) used a panel data for German companies covering the period 2006-2010, investigates how intangible assets affect productivity at the firm level and find strong productivity-enhancing effects for R&D and Human Capital (proxied by training expenditure and share of high skilled labour). Innovation may also be linked with firm's age. Dabla-Norris *et. Al* (2010) show that older firms that hold the exporter status and engage on innovation activities present higher productivity levels.

Trade is also pointed as one of the main determinants of TFP Growth at the firm level. Bernard *et al.* (2003) shows that as there is a decrease in trade costs, then there will be a better reallocation of resources and, consequently, the most productive firms will be favoured. Trade

enhances firm-level productivity due to its externalities that may have different forms, such as learning-by-doing effects, import of more innovative products or better managerial practices. Learning-by-doing effects are important as firms may self-select themselves into foreign markets, leading to a higher level of TFP Growth for exporters compared to non-exporters (Arvas and Uyar, 2014). Ortega *et. al* (2013) studied the relationship between exports and productivity in Chilean firms via four main theories: Self-selection hypothesis (whereby high productivity generates exports), Learning-by-exporting hypothesis (whereby exports increase productivity), Exporting-by-innovating hypothesis (whereby R&D is a determinant of exports) and Innovating-by-exporting hypothesis (whereby exports promote innovative practices). They find that exports explain productivity rather than productivity influencing exports.

Financial constraints also hold an important role on economic growth, conditioning savings and investment decisions and, consequently, impact TFP Growth. The impact of such variable holds as perfect financial markets stimulate long-term investments on productivity-enhancing projects (Aghion *et. al*, 2007). At a certain level, investments in risky opportunities usually related to R&D investments may be constrained as firms must hold a solid financial performance in order for banks to lend the needed resources (Fazzari *et. al*, 1988). The European Commission (2014) reported that firms' TFP Growth is constrained by the availability of internal funds, and this holds especially for micro firms relatively, suggesting a linkage between productivity growth and internal financing.

Capital structure is also approached in the literature, as it is linked to bankruptcy risks and may constrain a firm on obtaining the needed funds to invest in productivity-enhancing activities. Jensen (1986) shows that higher levels of debt prompts managers' efforts on increasing the firm's performance in order to avoid bankruptcy. Productivity can be enhanced on a firm with high level of debt as workers may work harder on the shadow of bankruptcy possibilities (Nickel and Nicolitsas, 1999). Köke (2001) investigated the effect of financial pressure on productivity growth for Germany manufacturing firms and found that financial pressure has a positive impact on productivity growth, and that this effect is larger when the amount of bank debt is high.

Finally, on what concerns the role of wages on determining TFP Growth, Gehringer *et. al* (2013) which examines the development of total factor productivity (TFP) and the drivers of TFP for a panel of 17 EU countries in the period of 1995-2007, find that wages (unit wages, per worker) are the main driver of TFP. They interpret it assuming that more efficient workers are paid higher salaries and so industries employing workers with a higher labour productivity are also more productive (in terms of TFP).

3. Dataset

The firm-level panel dataset we use was constructed from *Informação Empresarial Simplificada* (IES) provided by Banco de Portugal, which consists on a broad collection of accounting and financial data apart from other descriptive data and firm-specific characteristics, such as district, size, number of workers and industry. We have performed a pre-check on the disposable firms, excluding all firms that have less than five workers (following Barbosa and Pinho, 2016). The

dataset only considers the period between 2010 and 2014, as the data for 2015 and the previous to 2010 is currently not available. The main disadvantage we point out to our time span is that it starts immediately after the beginning of the financial and economic crisis of 2008, and possibly the results from our model will be downward biased as it is a sensitive period characterized by bankruptcies, merges or even cession of operations, as a consequence from the economic activity slowdown. Nevertheless, we hope that this study may provide fruitful results that may be compared in the future with a dataset with a wider time span. Another limitation is that the database does not provide qualitative information on employees.

Apart from considering all firms with more than five workers (and in this way still considering the micro firms category with plants operating with five to ten workers) we pursued some specific data cleaning in order to exclude outliers and firms whose values for several variables were not correctly plotted.²

Table 1 disposes the number of firms in our dataset per year, as well as the number of companies that fulfill the Exporter Status criteria defined by the Bank of Portugal:

1. At least 50% of annual turnover is from exports of goods and services; or
2. At least 10% of annual turnover due to exports and its value overpasses 150.000€.

Table 1. Export dynamics for the 2010-2014 period

Year	Nr of firms	Nr of exporters	Export participation (%)
2010	20,423	4,251	21%
2011	19,647	4,548	23%
2012	18,455	4,738	26%
2013	17,415	4,682	27%
2014	16,610	4,413	27%

Source: Author's calculations with IES database.

The total number of firms (that sum up to 92,550 observations for all five years) has a decreasing path throughout the sample period, a trend that is not verified in what concerns the export firms. Although the number of exporters decreases in 2012-2014, its weight on total manufacturing firms increases between 2010 and 2014. (In Annex 1 one can observe the firm dynamics by industry considering CAE 2-digit used by the Instituto Nacional de Estatística and in Annex 2 we present our self-made aggregation of the CAE 2-digit nomenclature).

² We have dropped all firms with negative values for Gross Revenue, Utilities and Services, Total Number of Worked Hours and Fix Tangible Assets. For convenience, we have not considered firms with negative values for Total Assets, Total Liabilities, Number of Workers and Total Personnel Spending.

4. Total Factor Productivity

4.1. Estimating Total Factor Productivity

In order to calculate the total factor productivity (henceforth TFP) at the firm-level and, subsequently, for each of the considered years we have relied on the Levpet algorithm (henceforth LP) introduced by Levinsohn and Petrin (2003).

Box 1: Definition of Total Factor Productivity

TFP represents the part of the output which is not explained by the firm's choice on the amounts of inputs. Its measurement is related to the level of efficiency and intensity of the use of those inputs in the production process (Comin, 2006). On what concerns the TFP growth, is usually measured by the Solow residual. In this way, TFP growth is considered in the literature as being an important determinant of economic growth and it is intrinsically related with differences on per-capita income across countries (Solow, 1957). OECD considers Multi-Product Productivity (a concept similar to TFP) as the total contribution of input factors in output growth.

The production technology assumed by the referred authors is the Cobb-Douglas Production Function (1). The consideration of a Cobb-Douglas production function can be devoted to the seminal work of Solow (1957), whose work took into account the separation of growth in factors of production from the increase in efficiency of using these factors (Arvas and Uyar, 2014).

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m} \quad (1)$$

where Y_{it} represents the physical output of the firm i in the period t ; K_{it} , L_{it} , M_{it} represent respectively the inputs from capital, labor and intermediate input. A_{it} is the Hicksian neutral efficiency level output of the firm i in the period t . Table 2 presents the proxy variables and its descriptive statistics.

Table 2. Descriptive Statistics for the Main Variables in Production Function

Variables	Proxy	Mean	Standard Deviation	Min.	Max	Observations
Output (Y)	Gross Revenue	3867519	66700000	24.64	9630000000	92,550
Capital (K)	Fixed Tangible Assets	1171367	18000000	.01	2450000000	92,550
Labor (L)	Total Work Hours	53113.41	138667.1	2	6406960	92,542
Material (M)	External Services and Utilities	660280.7	5170006	17.33	497000000	92,550

Source: Author's calculations with IES database.

Given its irregular representation in order to be econometrically estimated, taking the logarithms from (1) derives a linear Cobb-Douglas production function, easily interpretable:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \varepsilon_{it} \quad (2)$$

with $\ln(A_{it}) = \beta_0 + \varepsilon_{it}$, where β_0 measures the mean efficiency level across firms and over time and ε_{it} the time and producer specific deviation from that mean, which can be further decomposed into an observable (or at least predictable) and unobservable component (van Beveren, 2007), resulting in the following equation:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + w_{it} + \eta_{it} \quad (3)$$

w_{it} represents the transmitted productivity component, whereas η_{it} denotes an error term uncorrelated with labor, capital and intermediate inputs (Petrin *et. al* ,2004) . The error term represents unexpected deviations from the mean due to measurement error, unexpected delays or other external circumstances (van Beveren, 2007) and further on impacts firm level decisions (Petrin *et. al*, 2004). The transmitted productivity component is related to the firm's decision problem, and thus intrinsically determined both firm selection and input demand decisions (Olley and Pakes, 1996).

In what concerns the transmitted productivity component w_t , the algorithm created by Levinsohn and Petrin (2003) assumes productivity as the a result of a first-order Markov process, holding $w_t = E[w_t|w_{t-1}] + \xi_t$. The authors also assume that the demand function for the intermediate input m_t is monotonically increasing in w_t , provided its dependence on the firm's state variables k_t and w_{it} , holding $m_t = m_t(k_t, w_t)$ and thus the inverted intermediate demand function $w_t = w_t(k_t, m_t)$.

Amid the two options of the LP command and data restrictions we have use gross revenue as our dependent variable in the production function instead of value-added. Firstly, production function estimation with value-added as it generally yields biased estimates of returns to scale in the presence of imperfect markets³. Secondly, gross revenue estimates allow for intermediate inputs and therefore they provide a more accurate perspective on the production process (Sichel, 2001).

Denoting y_t as the gross revenue in logarithms we estimated Equation (2)⁴. The estimated results from LP are analyzed further on.

4.2. Comparing different methods

Although the scope of our research does not rely on investigating the accuracy of different methodologies for the calculation of TFP, we have performed comparison calculations to ensure that the one from LP would better fit the purpose of our work.

We have calculated the production function under 3 parametric and semi-parametric approaches: Ordinary-Least-Squares (OLS), Least Square Dummy Variable with time fixed-effect (LSDV) and finally LP. We have not estimated TFP with Olley and Pakes (1996) estimator (henceforth OP) as we did not have available data on investment accurate enough in order to be considered a proxy for unobserved productivity. Given the lack of information

³ Basu and Fernald(1997) prove the biased returns to scale under value-added production functions and show that the omitted variable in the equation that creates that bias is zero only in the presence of perfect competition (price equals marginal costs) and elasticity between inputs and materials equal to zero. As we consider in our database imperfect competition markets, we relied instead on gross-output. Another branch of the literature studies the problems on value-added production functions, such as Sudit and Finger (1981), Oulton and O'Mahony (1994).

⁴ For such purpose we have used the *levpet* command – see Levinhson *et. al* (2003). We consider 50 bootstraps (number of iterations).

concerning investment from most firms, considering intermediate inputs (utilities and services) as proxy for unobservable productivity ensures a bigger dataset, as m_{it} is positive whenever the firm production is positive (Eberhardt and Helmers, 2010). Another advantage of LP over OP is that the latter requires additional depreciation costs over investment spending, as its “non-convexity” violates the monotonicity imposed in OP (Eberhardt and Helmers, 2010).

On what concerns the selection bias⁵ in our data set, we have decided to keep all disposable firms instead of creating a balanced panel. Regarding the limitations of the LP method, we cannot omit all firms that enter and exit during the considered sample, as it is possible with the OP algorithm since it includes an additional correction to account the probability of firm’s survival (Olley and Pakes, 1996). As this study focus on a very sensible period – right after the start of the 2008 economic and financial crisis - it would be risky to apply self-defined methods to decide which firms should be studied, as new firms that were founded between 2010-2014 were keen to be excluded – moreover, Olley and Pakes highlight the importance of not using artificially balanced panels. In line with Levinsohn and Petrin (2003) we do not focus also on selection issues as Olley and Pakes (1996) show little different on the TFP estimates between unbalanced and balanced panels. Simply using an unbalanced panel avoids the problem of selection bias (van Beveren, 2007). As a great branch of literature enhances the importance of the entry-exit patterns of firms during a certain period (such as Jovanovic,1982 or Hopenhayn,1992), it would be imprudent to reduce significantly the dataset. Nevertheless, the use of an unbalanced panel does not mean a full overpass of the bias problem if in fact the explicit exit decision is not taken into account, as exit firms have prior knowledge of their productivity level w_{it} before exiting markets (Ackelberg *et. al* , 2007). Moreover, Van Beveren (2010) states that omitting exiting firms in the dataset , even though they tend to be less productive, will induce lower elasticities on the balanced panel firms and higher estimated TFP values (on average).

Table 3 presents a brief summary of methodological issues concerning TFP estimation, as already stated:

Table 3: Summary of Methodological Issues on TFP estimation

Origin of the bias	Definition	Direction of the Bias	References
Selection Bias (endogeneity of attrition)	Causes correlation between ε_{it} and the observable inputs	Biased downward	Eberhardt and Helmers (2010) Beveren (2007) Olley and Pakes (1996) Wedervang (1965)
Simultaneity bias (endogeneity of inputs)	Correlation between ε_{it} and the observable inputs if firms’ prior beliefs on ε_{it} influence its choice of inputs	Biased upward and downward if: $\hat{\beta}_L > \beta_L$ or $\hat{\beta}_L < \beta_L$ Biased upward if: $\hat{\beta}_M > \beta_M$ Biased downward if: $\hat{\beta}_K > \beta_K$	Eberhardt and Helmers (2010) Beveren (2007) De Loecker (2007) Levinsohn & Melitz (2002)

Source: Retrieved from Sulimierska(2014). Does not include other methodological problems concerning input price bias and multiproduct firms (as stressed by Beveren 2007, De Loecker 2007). Major source is Eberhardt and Helmers (2010) and Beveren (2007). ε_{it} is the time and producer specific deviation from the mean of efficient production

⁵ The problem of selection bias was firstly approached by Wedervang (1965).

Several estimation techniques are suggested to solve problems of endogeneity and simultaneity provided from OLS estimations⁶, but as Basu *et. al* (2009) stresses no method can be considered better than another under all possible circumstances. As said before, we have also estimated our production function Least Square Dummy Variable (LSDV) estimation, including time-specific fixed-effects⁷. It assumes that the unobserved productivity w_{it} is time invariant and a plant specific attribute. Arnold (2005) presents some disadvantages from the usage of such method: firstly, the fixed-effect estimator uses only the across time variation (and thus the coefficients will be weakly identified) and secondly the reasonability of the fixed assumption on the plant attribute. Harris(2005) also considers that using LSDV may infer biased coefficients because of incidental parameters problem as the result from the correlation between fixed effects and the explanatory variables, as it also produces sensible and unbiased results (Van Beveren, 2007).

One great advantage of the LP algorithm is that addresses the problem of simultaneity and endogeneity. Marschak and Andrews (1994) approached the contemporaneous and serial correlation between input demands, and proved that OLS estimated production functions may give inconsistent estimates for input coefficients as it ignores the existent correlation between input demands and the productivity term. Estimating the production function with OLS requires that the inputs are exogenous, *i.e.*, determined independently from the firm's efficiency level (Van Beveren, 2007). The existence of simultaneity bias might induce different reactions on the inputs' coefficients, as the profit maximization problem "*implies that the realization of the error term of the production function is expected to influence the choice of factor inputs*" (Arnold, 2005). The degree of correlation between capital and labor inputs biases the capital coefficient (although it is not clear the direction of such bias), whereas the simultaneity bias causes an upward bias on the labor and materials coefficients (De Loecker, 1997). If such correlation exists, the capital coefficient will be biased downwards (Levinsohn and Petrin, 2003), assuming labor as the only variable factor and capital to be a quasi-fixed input (see Table 3 above for a related literature on the subject).

On Table 4 there are presented the estimated coefficients for capital, labor and material inputs for the three different methods OLS, FE and LP. We have a lower coefficient value to the intermediate goods in LP compared to OLS, in line with the results from Muendler (2004), and in both methods there is a significantly gap between the capital coefficient and the material coefficient. The results from Table 3 confirm the ones from Levinhson and Petrin (2003), as the coefficients of all the inputs are higher in OLS estimation when compared to the LP⁸.

⁶ Several alternative techniques are suggested in the literature. For instance, Harris (2005) indicates within-group fixed effects (WG) least squares models, 2SLS within group fixed effects, frontier models and GMM system model (Blundell and Bond, 1998). The semi-parametric alternative using Olley and Pakes (1996) routines is also broadly used, although we have not applied it as we relied on LP. The author also mentions the extensions from Akerberg *et. al* (2006).

⁷ Introduced by Mundlak(1961) and Hoch(1962). Pavcnik(2002) Levinsohn and Petrin (2003) use also LSDV estimator.

⁸ Following van Beveren (2010), we performed all regressions with STATA 14. OLS estimation was computed with command *reg*, FE estimation computed with *xtreg* and LP with *levpet* from Levinhson and Petrin (2003).

Table 4: Comparison among alternative production function estimates

Variables (Dependent Variable “Log of Gross Revenue”)	OLS	Fixed Effects	LP
Observations (2010-2014)	92,542	92,542	92,542
Total Number of Firms	25,324	25,324	25,324
Capital (K)	0.073 (0.0014)	0.042 (0.0029342)	0.05 (0.0588408)
Labor (L)	0.302 (0.0049)	0.19 (0.0109367)	0.257 (0.0062028)
Material (M)	0.658 (0.00294)	0.545 (0.0087708)	0.58 (0.2310618)
Sum of Elasticities	0.93	0.89	0.9

Source: Authors’ calculations with IES database. Robust Standard Errors in brackets (to control for heteroscedasticity and autocorrelation)

In line with the results from Muendler (2004), our estimated coefficients for the intermediate inputs share the same pattern across the three different estimations, as its value is always the higher and around the double of the elasticity from labor input (in the case of the FE, the coefficient for material input is more than the double of the labor input coefficient). Still in comparison with Muendler (2004), the intermediate inputs coefficient from LP estimation is lower than the one from OLS and FE. Following Van Beveren (2010), we confirm that as the fixed effects estimation allows for simultaneity and selection bias its coefficients for labor and material inputs will be lower than the ones from OLS. Still in line with the results from Van Beveren (2010), we do not have a higher coefficient for capital in LP compared to OLS, nor higher estimates for material and labor elasticities. Nevertheless, we confirm that all estimates for LP present higher values compared to the FE estimation. On what concerns the returns to scale, our three estimates present decreasing returns to scale. We present the same results as Levinsohn and Petrin (2003) on the sum of elasticities: OLS with the highest value, followed by LP and finally by FE.

5. Estimated Model

5.1. Second-Stage Regressions and its Methodological Issues

Amid the estimation of the TFP values in the first-stage, we proceed to assess which variables are significantly determinants of its growth.

Wang and Schmidt (2002) refer to the problems resulting from second-stage regressions as the omitted variable problem not resolved in the first stage may provide inefficient and downward-biased estimates in the second-stage regression (the model *per se*).

We pursued the same methodology as in Harris *et. al* (2005): firstly we estimated the production function, getting the elasticities for each different input and secondly, we considered the residuals from the estimated production function as being TFP⁹. If we consider the matrix X as

⁹ Crass and Peters (2014) also rely on a second-stage estimation, having calculated TFP with the LP algorithm as well. Gatti e Love (2006) is also a fair example of second-stage estimation.

being a vector for observed (proxy) variables for the determination of the TFP values, we hold the following equation:

$$\ln \widehat{TFP}_{it} = y_{it} - \hat{\alpha}_L l_{it} - \hat{\alpha}_M m_{it} - \hat{\alpha}_K k_{it} = \hat{\alpha}_i - \hat{\alpha}_X X_{it} + \hat{\alpha}_T t + \varepsilon_{it} \quad (5)$$

As Harris and Moffat (2011) remind, in the literature is quite common (and thus we chose such path of analysis) to estimate (5) without accounting for X and include it in ε_{it} . On the second-approach the determinants of TFP are regressed, enlarging the problem of omitted variables that will bias the estimates for the elasticities of output.

For instance, Harris and Li (2009) rely on a system-GMM approach that allows for fixed effects and endogenous inputs, amid several other options.

In fact, several authors confirm the econometric problematic from this issue, although Van Beveren (2010) showed that TFP estimated with different methods still present close results on the second-stage estimation, using the estimated TFP as dependent variable.

On Table 5 we present correlations between the estimated TFP values for each of the three chosen methods. We have found a higher correlation value between FE and OLS (0.84) compared to van Beveren, 2010 (that registered 0.6840). The correlation between FE and LP is also higher in our results (0.5602 compared to 0.3672) and we present a lower, but indeed high, level of correlation between LP and OLS (0.8498 compared to 0.9262).

Table 5: Correlation between different estimated TFP

	Fixed Effects	OLS	LP
Fixed Effects	1		
OLS	0.8498	1	
LP	0.5602	0.5472	1

Source: Author's calculations with IES database.

5.2. Robustness of the Model

Our estimated model for the TFP determinants consists on a fixed effects model, which allows for the inclusion of group-specific components that are correlated with other covariates in the form of “omitted variable”(Townsend *et. al*, 2013). The referred omitted variables, the so named “fixed effects” are in fact fixed or constant variables common to all sample firms in the dataset, invariant for all the time frame. The fixed effects estimation (or within estimators) do not intend to explain those inner-firm characteristic differences, nor are included in the model since “the demeaning process will cause their value to be zero for all time periods” (Wooldridge, 2002).

Following Hausman (1978) we have performed the Hausman test in order to justify the choice of fixed effects over random effects, rejecting the null hypothesis of consistency that the within estimator and that the individual and time-effects are not correlated with the explanatory variables (Baltagi, 2005), we found a correlation of -0.0040 between the fixed effects and the explanatory variables, showing a weak negative correlation.

While analyzing the robustness of our model we have not given strong emphasis on serial correlation of errors, following Wooldridge (2002) as the within estimators yield consistency with large datasets with a small number of periods. As suggested in Wooldridge (2002) and Bertrand *et. al* (2004) we have considered cluster-robust standard errors as the normal standard errors from the within estimator provide inconsistent values in the presence of serial correlation¹⁰. As autocorrelation and heteroscedasticity are corrected, we overpass the problem concerning biased statistical inference and we are able to pursuit the correct analysis of estimated coefficients (Hoechle, 2007).

5.3. Estimated Model and Results

In Table 6 we present our estimated fixed-effects model, with dependent variable as being the logarithm of TFP estimated with LP with a sort of statistically significant variables as determinants for TFP growth:

$$\ln TFP = \beta_0 + \beta_1 Size_{it} + \beta_2 Age_{it} + \beta_3 Wages_{it} + \beta_4 Training_{it} + \beta_5 ExporterStatus_{it} + \beta_6 Debt - to - Equity + \beta_7 Innovation_{it} + \varepsilon_{it}$$

Table 6: Estimated model for all firms and Big Firms

Variable	Estimated Coefficient (p-values) All Firms	Estimated Coefficient (p-values) Big Firms	Description
2 – Small Size Firm	0.0345 (0.000)*	-	Dummy Variable
3 – Medium Firm	0.1365 (0.000)*	-	Reference group is (1) Micro Firm
4 – Big Firm	0.298 (0.000)*	-	
Age	- 0.008 (0.000)*	-0.007 (0.845)	
Wages	0.2084 (0.000)*	0.0392 (0.570)	Logarithm of Average Annual Gross Wage per Worker
Training	0.3644 (0.005)*	0.0758 (0.598)	Share of Training Expenses on Personnel Global Costs
Exporter Status	0.059 (0.000)*	-0.0074 (0.827)	Dummy Variable 1 – Firm has Exporter Status 0 – Firm has not Exporter Status
Debt-to-Equity	- 0.0244 (0.000)*	-0.0189 (0.128)	Logarithm of the Ratio Total Liabilities by Equity
Innovation	0.014 (0.001)*	-0.0413 (0.123)	Dummy Variable 1 – Firm has the ratio Fix Intangible Assets/Total Assets different from 0 0 – has the ratio Fix Intangible Assets/Total Assets equal to zero
Number of Observations (Number of Firms)	78,879 [±] (12,082)	1,369 [±] (353)	-
corr(u _i , X _b)	-0.0040	0.1680	Correlation between Fixed Effects and Explanatory Variables
R ²	88% ^{±±}	-	-

Source: Author's calculations with IES database.

¹⁰ We rejected the Null Hypothesis of no serial autocorrelation of errors on our model.

*Significant at 5% | Controlled for heteroscedasticity and serial autocorrelation with cluster-robust standard errors

± Although the total number of firms in the dataset is 92,550, only 78,879 had available information on Fix Intangible Assets, reducing the final cleaned dataset to the latter number of observations.

±± R² was calculated with the STATA command *areg*, followed with *absorb* of the variable representing the firm's anonymous identity number.

On what concerns the explanatory variables, we divide its analysis according to four different categories of determinants of TFP growth (descriptive statistics from the variables can be accessed on Annex 2):

1. **Internal Firm Characteristics:** Dimension and Age;
2. **Trade:** Export Status;
3. **Financial Constraints:** Debt-to-Equity;
4. **Research & Development, Innovation and Human Capital:** Training Expenses, Innovation and Wages.

5.3.1. On Firms Internal Characteristics

On what concerns the effects of firm's age on TFP growth, we have found the existence of a negative effect, indicating that as a firm gets older than less productive it will be (at least a decrease of 0.8% per added year). As stressed in Harris and Moffat (2011), this might be due to the case of not accounting properly for capital obsolescence, leading to an advantage for younger firms to adopt more properly new technologies as older ones face sunk costs¹¹. These results are in line with the ones from Hill and Kalirajan (1993) but diverge from Biggs *et. al* (1996). Fernandes (2008) suggest the existence of a robust inverse-U shaped relationship between firm age and TFP on which she states that the most productive firms are the ones between 10-20 years old. Van Biesenbroeck (2005a) finds that TFP is higher in younger firms with a dataset of African countries and Jensen *et.al* (2001) finds the same results for a panel of US firms – recall Chart 6, where it is shown that younger firms have higher levels for TFP when compared to older firms. Our results contradict the “learning-by-doing” effects referred in Jovanovic and Nyarko (1996), on which they state that older firms achieve higher levels of productivity. Gatti e Love (2006), contrarily to previous results, also measure the effects of age on TFP growth with a second-stage estimation and found that it is negative.

Considering the effects of firm level dimension, our results contrast the ones from Fernandes (2008) on which she states that Bangladeshi small firms are more productive than bigger firms (although we are aware of the social, economic and cultural differences between Portugal and Bangladesh that may infer different results). Jovanovic (1982) states that bigger firms are more productive, which is line with our results. For instance Biesebroeck (2005a) finds that TFP increases monotonically with size for firms in nine African countries although not indicating on how much large firms were indeed more productive. Although considering a different sizing scale, Lee and Tang (2001) using firm-level data from Canada find that firms with more than 500 employees register more 17% of TFP compared to firms with less than 100 employees. In the same line, our results point to a difference of 30% between big and micro firms and 18.5% between medium and micro firms, suggesting that as size increases the higher is the different in

¹¹ According to Lambson (1991) the sunk cost effect may be more visible on industries were entry firms have to choose between older and newer technologies simultaneously.

TFP growth considering micro firms as the reference group. This might be due to the usage of more advanced technologies as suggested by Baldwin and Diverty (1995).

5.3.2. On Trade

For the purpose of measuring the marginal impacts of exporting, we have relied on a dummy variable concerning the fulfillment of the Bank of Portugal export status criteria. In this respect, we have found that the exporter status impacts, *ceteris paribus*, the growth rate of TFP 5.9% on average. The dimension of such impact may be due to several reasons, namely the import of technology or attraction of Foreign Direct Investment that offers firm's more innovative production methods (Mayer, 2001). Other reason may be due to the fact that exporters tend to have a higher endowment of capital, which makes them more innovative when compared to other firms that are more orientated to domestic markets (Baldwin and Hanel, 2000). For instance, we might relate the export status with the higher level of efficiency from the exporters firms, as stressed by UNIDO (2007). In the same line, Arvas and Uyar (2014) state that firms may self-select themselves in exporting to foreign markets as they achieve higher levels of efficiency. Greenaway and Kneller (2007) confirm that exporting activities will provide productivity gains only prior, with the so called "learning-by-exporting" effects post-entry.

5.3.3. On R&D, Innovation and Human Capital

Innovation and Research&Development (henceforth R&D) are commonly pointed out in the literature as enhancers of TFP Growth. Endogenous growth theory, explored by Romer (1990) or Grossman and Helpman (1991) among others, enhances the positive linkage between innovation spending and increases in production, prompting a rise in total factor productivity. Unfortunately we could not get any information concerning investments on R&D and therefore we have look into alternative ways of measuring the impacts of this category on TFP growth.

We proxy Research & Development and Innovation with the variables *Innovation* (which is a dummy variable that assumes the value 1 if the company has positive Fix Intangible Assets by Total Assets Ratio), *training* (which measures the ratio training expenses by total personnel costs) and average annual gross wages (which appears in logarithm in the final model). Unfortunately we could not have access to any data concerning the education from workers, therefore only having human capital variables in the presence of the training ratio.

On what concerns the *Training* variable, we follow the work of Crass and Peters (2014) that consider training expenses as part of Human Capital. Their second-stage estimation using TFP calculated with LP yields a positive coefficient for training expenses in line with our results, as we show that a unit increase on the ratio leads to a TFP growth of around 36%. Dearden *et. al* (2006) also prove that training expenses have a positive impact on productivity, considering a panel of British manufacturing firms. In another perspective, Konings and Vanormelingen (2009) found that the productivity premium of a trained worker is around 23% while analyzing firm-level from Belgian firms.

Next we consider a ratio of Fix Intangible Assets by Total Assets, assessing its effects on TFP growth through a dummy variable on which 1 represents a positive ratio value and 0 for a 0

value¹². Our results show that a firm with a positive ratio, *ceteris paribus*, sees its TFP grow by more 1.4% than a firm that does not account for Fix Intangible Assets. As differently from several studies from the literature, we do not include Fix Intangible Assets on the production function as part of the capital variable in order to account for its effects on TFP growth. In this way, we avoid endogeneity and bias on the results and enrich the model with a variable broadly used in the literature. In line with our results, Greenhalgh and Longland (2005) used patents and trademark registrations (a component of Fix Intangible Assets) and find positive effects on productivity. On a different perspective, Marrocu *et.al* (2012) show that considering intangible capital assets measured on current expenses has less impact on TFP growth when compared with capitalized intangible capital – a difference that we cannot overcome due to our database.

Finally in this category, we conclude that average annual gross wages growth has a positive impact on TFP growth. We use this variable as a proxy for different schooling levels as we do not have access to more precise data on that. Gehringer *et. al* (2013) show on their model that unit wages are the major driver of TFP growth with a 0.19% growth on TFP as a result of 1% growth on unit wages (we achieve a result of 0.2% growth per 1% growth on average annual growth wages, a quite similar result). The same authors suggest that this variable can be in fact interpreted in two ways: firstly, more efficient employees get higher salaries, which will mean that they achieve higher levels of labor productivity and therefore they are more productive; secondly, the authors consider that industries that pay higher wages will achieve higher levels of TFP.

5.3.4. On Financial Constraints

In line with a great branch of the literature we considered a financial variable, keen to represent the firm's financial health on the model. We have relied for such purpose on debt-to-equity, although we describe firm-level heterogeneity concerning the variable leverage before on this paper, but did not include it to avoid endogeneity (both ratios include the variable Total Liabilities).

Our results show that an increase in 1% on the debt-to-equity ratio decreases TFP growth on 0.02%. The literature states that in general debt accumulation is a “cumulative result of hierarchical financing decisions overtime” (Shyam-Sunder and Myers,1999), and as a result firms not aim to a target debt ratio while respecting an optimal capital structure (Coricelli *et. al*, 2012). These authors show that debt may have positive impacts on TFP growth under a threshold effect, on which after a certain level of debt reached the firm would see its TFP growth decrease. For instance, Gatti & Love (2008) prove that access to credit prompts TFP growth using a panel with Bulgarian firms, contrarily to Nucci *et. al* (2005) that found a negative impact of debt ratio on productivity while analyzing Italian firms¹³. The authors consider also that firms with higher levels of TFP are likely to generate higher levels of profit (and cash flows) and therefore rely less on debt to finance its activity.

5.3.4. Comparing the all firm's sample with the big firm's sample

¹² Fixe Intangible Assets are considered in several works in the literature (Griliches, 1979; Griliches, Hall and Pakes, 1991; Geroski, Van Reenen and Walters, 2002; Bosworth and Rogers, 2001) among others. Kleinknecht (1996) and Hinloopen (2003) consider also innovative non intellectual property fixed intangible assets as proxy for innovation.

¹³ The work of Nucci *et. al* (2005) refers also that is important to overpass the endogeneity problem arising from the bond between debt and intangible assets, whose problem we avoid has we do not include intangible assets in the capital structure of the production function and thus is not part of the TFP estimates directly.

We estimated the model for a sample only with manufacturing big firms, having estimated firstly the TFP values with LP as well. On Table 6 it is possible to observe that none of the variables from our model are significant in the big firm's sample, showing that considering such sample individually may need a different effort on assessing the determinants of TFP growth. Going forward, it would be interesting to assess other set of determinants specific for this firm size group.

6. Concluding remarks

On the light of our model's results, we propose some intuitive and practical measures keen to be applied by policymakers in order to prompt TFP growth, considering the manufacturing sector. We divide our suggestions in key thematic relating such possible reforms and consider its effects on the variables that are included in our final equation.

This analysis has identified several determinants that have an impact on or are associated with TFP growth. Of these, dimension, age, being an exporter, training, leverage, appropriate internal financing and wages seem to directly affect TFP growth of Portuguese companies in the industry sector. Therefore, according to our results, public incentives to promote Portuguese firms productivity should be targeted at:

Creation of new firms - Younger firms are more dynamic and have a higher probability of engaging in export and innovative activities. To stimulate the creation of new firms policies such as the reduction of entry barriers or the improvement of the access to finance of start-ups should be pursued. Also, bankruptcy legislation and judicial efficiency can encourage experimentation with innovation and new technologies: bankruptcy should not be penalised too severely;

Promotion of exports – Policies that increase the ability of domestic firms to overcome the export-entry barriers should be pursued; Lower bilateral trade costs and lifting barriers to competition in goods markets;

Dimension - Since productivity increases with size, policies that stimulate mergers and acquisitions and the expansion of the activity of companies should be pursued ;

Leverage – Given that productivity decreases with the debt-to-equity ratio policies that support the development of complementary sources of debt, such as venture capital markets, should be pursued; also reduce the corporate debt overhang to facilitate resource allocation, policies that encourage equity over debt such as the removal of tax incentives that favour debt over equity and the simplification of equity rules which increase costs of private equity;

Training and Innovation - Policies that develop absorptive capacity are key to ensuring productivity spillovers. Building absorptive capacity includes developing local innovation and enhancing human capital; incentives to collaborate between firms and universities, R&D fiscal incentives and state funding of basic research; Encouraging investment in R&D and human

capital; Policies that encourage stronger links between firms and research, educational and training institutions can facilitate knowledge transfer;

Skilled Labour - Facing higher wages as a proxy for higher qualifications (rewarded with higher salaries), policy measures should give incentives to invest in skills, encourage the use of more skilled labour, specialized and efficient work and make a greater use of training.

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Annex 1

Number of Firms per Industry in the 2010-2014 period

CAE 2-digit Code	Sector	2010	2011	2012	2013	2014	Total Variation
10	Food	3,149	3,072	2,983	2,815	2,645	-16%
11	Beverages	327	328	338	332	329	+ 0.6%
12	Tobacco	3	3	4	3	3	=
13	Textiles	1,113	1,066	991	957	944	-18%
14	Wearing apparel	2,726	2,597	2,429	2,349	2,336	-17%
15	Leather and leather products	1,235	1,248	1,251	1,284	1,257	+1,8
16	Wood and wood products	1,221	1,178	1,084	959	902	-35%
17	Pulp, paper and paper products	254	248	234	225	210	-21%
18	Publishing and printing	794	734	665	612	559	-42%
19	Refined petroleum products	1	4	3	2	4	+75%
20	Chemicals and chemical products	331	327	305	277	276	-20%
21	Pharmaceutical products	69	71	64	54	46	-33%
22	Rubber and plastic products	570	567	576	540	518	-10%
23	Other non-metallic mineral products	1,466	1,349	1,216	1,097	989	-48%
24	Basic metals and fabricated metal products	152	152	142	130	121	-27%
25	Fabricated metal products, except machinery and equipment	3,244	3,124	2,894	2,719	2,586	-25%
26	Electronic and optical equipment	88	90	89	81	73	-21%
27	Electric equipment	275	254	243	236	224	-23%
28	Machinery and equipment	668	612	575	563	523	-28%
29	Transport equipment	293	268	246	231	215	-36%
30	Other transport equipment	90	84	89	77	77	-17%
31	Furniture and Mattresses	1,310	1,250	1,087	973	913	-43%
32	Other industries	477	451	410	389	372	-28%
33	Maintenance and repair of equipment	567	570	539	510	488	-16%
Totals		20,423	19,647	18,455	17,415	16,610	-23%

Source: Authors' calculations with IES database.

Annex 2

Descriptive Statistics of the variables for the 2010-2014 period (Mean and Standard Deviations)

Variable	All firms (92,550 observations)	Exporters (22,632 observations)	Non-Exporters (69,918 observations)
Real Gross Output	3867519 (66700000)	1.16000000 (1340000000)	1379613 (8020118)
Real Intermediate Outputs	660280.7 (5170006)	1920519 (9930981)	252349.9 (1666571)
Fix Tangible Assets	1171367 (18000000)	3260006 (35700000)	495287.6 (3989831)
Total Worked Hours	53113.41 (138667.1)	120924.1 (247226.7)	31162.3 (60809.25)
Wages	9092.883 (5602.439)	11407.54 (5683.22)	8343.601 (5366.272)
Training	.0007234 (.0098501)	.0009907 (.0105815)	.0006367 (.0095996)
Debt-to-Equity	.7150533 (707.2224)	5.567647 (179.1517)	-.8555832 (807.2518)
Age	19.79696 (14.6649)	23.24056 (15.81478)	18.68083 (14.09303)
Fix Intangible Assets	59768.39 (2430596)	166394.9 (4401660)	25254.1 (1242587)
Total Assets	3966042 (54600000)	11300000 (105000000)	1603238 (18900000)
Total Liabilities	2450666 (37500000)	6892940 (73500000)	1012731 (10200000)

Source: Authors' calculations with IES database. Standard Deviation in brackets.