The determinants of TFP growth in the Portuguese manufacturing sector

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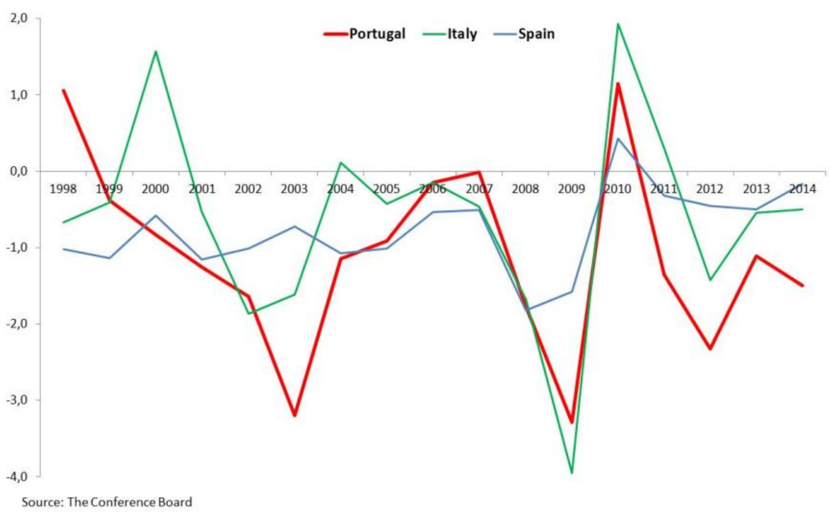
Introduction

The current global crisis has reinforced concerns about growth prospects. The evolution of productivity has been one of the issues of major concern especially since the beginning of the 2000s, when the productivity growth has slowed down in many advanced economies. This concern is due to the effects of productivity on economic growth and wages and on the competitiveness of economies because of its impacts on cost per unit of output.

According to the most recent data form the Conference Board, the total factor productivity (TFP) of the Southern European countries has consistently decreased (with the exception of a slight increase in 2010) since the late nineties.

Chart 1: TFP Growth - Southern European Countries



Given the low performance, and if TFP drives growth (as demonstrated in the literature), it is important to explore what determinants should policy focus on to enhance TFP growth and, thereby, future growth prospects. The linkage between Total Factor Productivity growth and economic growth turns relevant the understanding, at the firm level, of 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 further on policy recommendations amid the model's results. Our results show that age and debt influence negatively TFP growth, whereas dimension, exports and training expenses prompt TFP growth.

1 - 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

[1] GEE – Gabinete de Estratégia e Estudos. The views are those of the authors and do not necessarily coincide with those of the institution.

industry. We have performed a pre-check on the disposable firms, excluding all firms that have less than five workers. The dataset only considers the period between 2010 and 2014, as the data for 2015 is currently not available. We also pursuit 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:

I) At least 50% of annual turnover is from exports of goods and services; or

II) At least 10% of annual turnover due to exports and its value overpasses 150.000€.

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.

Table 1 – Firm 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.

2. Total Factor Productivity

2.1- 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).

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.

$$\boldsymbol{Y_{it} = A_{it} K_{it}^{\beta k} L_{it}^{\beta l} M_{it}^{\beta m}} \qquad \textbf{(1)}$$

where $\mathrm{Y_{it}}$ 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} denotes the Hicksian neutral efficiency level output of the firm i in the period t. Table 2 presents the proxy variables and its descriptive statistics.

[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.

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	0.01	2450000000	92,550
Labor (L)	Total Worked Hours	53113.41	138667.1	2	6406960	92,542
Material (M)	External Services and Utilities	660280.7	5170006	17.33	497000000	92,550

Source**:** Authors calculations with IES database.

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

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

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, resulting in the following equation:

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

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.

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

Amid the two options on the LP command, added to data restrictions we have relied on -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 markets[3].

Denoting $\boldsymbol{y_t}$ as the gross revenue in logarithms we estimated Equation (2)[4]. The estimated results from LP are analyzed further on.

2.2- Comparing different methods of estimation

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. On what concerns the selection bias in our data set, we have decided to keep all disposable firms instead of creating a balanced panel.

[3] Basu and Fernald (1997) prove that 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.

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

On Table 3 we present 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 depicted bellow confirm the ones from Levinhson and Petrin (2003), as the coefficients of all the inputs are higher in OLS estimation when compared to the LP[5].

Table 3 - Comparison among alternative production function estimates

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: Author's 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 allways 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 biggest value, followed by LP and finally by FE.

3 – Estimated Model

3.1. Robustness of the Model

Our estimated model for the TFP determinants, depicted on Table 5, 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*". 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). In addition, we found a correlation of -0.0040 between the fixed effects and the explanatory variables, showing a week 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) we have considered cluster-robust standard errors as the normal standard errors from the within estimator provide inconsistent values in the presence of serial correlation. As autocorrelation and heteroscedasticity are corrected, we overpass the problem

5 Following van Beveren (2010), we perfomed 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).

concerning biased statistical inference and we are able to pursuit the correct analysis of estimated coefficients.

Table 5: Estimated Model Coefficients

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

Dependent Variable: Logarithm of TFP		Estimated Coefficient (p-values)	Description
Size	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)**	-
Wages		**0.2084** *(0.000)**	Logarithm of Average Annual Gross Wage per Worker
Training		**0.3644** *(0.005)**	Share of Training Expenses on Personnel Global Costs
Exporter Status		**0.059** *(0.000)**	Dummy Variable: 1 – Firm has Exporter Status; 0 – Firm has not Exporter Status
Debt-to-Equity		**-0.0244** *(0.000)**	Logarithm of Ratio Total Liabilities by Equity
Innovation		**0.014** *(0.001)**	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)**	-
corr(u_i, Xb)		**-0.0040**	Correlation between Fixed Effects and Explanatory Variables
R^2		***88%*** [++]	-

Source: Author's calculations with IES database.

*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.

3.2. Estimated Model and Results

As referred previously, we have built a fixed effects model with dependent variable being the logarithm of TFP (estimated with LP) with a sort of explanatory variables supported by the literature that can be divided into different categories. On what concerns the explanatory variables, we divide its analysis according to four different categories of determinants of TFP growth:

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

<u>On Internal Firm Characteristics</u>

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 costs[6]. 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.

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 one should note the cultural, social and economic different while doing such comparisons). 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 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).

<u>On Trade</u>

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). 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.

<u>On Research & Development, Innovation and Human Capital</u>

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) 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

6 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.

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%.

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 value[7]. 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.

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.

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.

4. 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 themes 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.

7 Fixe Intangible Assets are considered in several works in the literature (for instance Griliches, 1979 and Bosworth and Rogers, 2001) among others.

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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