GEE

GEE Papers

Number 114

November 2018

The Determinants of TFP Growth in the Portuguese Service Sector

Catarina Branco, Tiago Domingues, Ana Martins

The Determinants of TFP Growth in the Portuguese Service Sector

Catarina Branco[1], Tiago Domingues[2], and Ana Martins[3]

Abstract:

As services today are of great complexity and usually a bundle of different individual inputs, it is sometimes hard to identify characteristics for the overall service sector. As such, empirical research on productivity is less common in this sector. Given the connection between Total Factor Productivity (TFP) and economic growth, and the importance of services for overall economic activity, it is crucial to study, at the firm level, which factors may drive TFP growth in this particular sector. Our empirical assessment is based on a firm-level panel dataset covering Portuguese service firms, between 2010 and 2016. We first estimate TFP through the Levinsohn-Petrin (LP) algorithm and compare results amongst different traditional estimating methods. Secondly, we conclude our econometric framework with a fixed-effects estimation, hence, trying to shed further light on the determinants of TFP growth in the Portuguese service sector. We found evidence for a positive correlation between financial health, innovation, wage premium, and TFP growth, whereas capital intensity, training, and age show a non-linear relationship with TFP growth.

JEL Classification Codes: C33; D22; D24; O47
Keywords: Total Factor Productivity; LEVPET; Fixed effects; Service Sector

Note: This article is sole responsibility of the authors and do not necessarily reflect the positions of GEE or the Portuguese Ministry of Economy.

[1]Nova School of Business and Economics (23779@novasbe.pt)
[2]Strategy and Research Office - Ministry of Economy (tiago.domingues@gee.min-economia.pt)
[3]Strategy and Research Office - Ministry of Economy (ana.martins@gee.min-economia.pt).

Contents

List of Figures

Acknowledgements:

The authors would like to thank Rita Bessone Bastos (Vice-Director of GEE), Ana Gouveia (Bank of Portugal), Vanda Dores and Guida Nogueira (GEE) and Daniel Gonçalves for the support and advice.

We also place on record our sense of gratitude to one and all who, directly or indirectly, have contributed to the realization of this study.

1. Introduction

"You can see the computer age everywhere but in the productivity statistics."
Solow (1987)

Productivity is slowing down in all advanced economies since the 1990s, a decline that accelerated after the financial crisis. At that time, sectors reacted to weak demand and uncertainty by holding back investment. After the crisis the recovery has been slow with households and corporations (who were highly indebted) deleveraging and banks becoming less willing to lend. Other factors holding back companies from investing were lack of managerial or technical capability to execute investment, and insufficient internal funds. So, the impact of weak demand and feeble investment have been some of the main drivers of productivity slowdown. A combination of other factors, such as excess capacity and economic, political, and regulatory uncertainty, created a dynamic of declining productivity growth (Remes et al., 2018).

Focusing on service sector, digital services may amplify this phenomenon creating other barriers to productivity growth, such as winner-take-most effects on industry structure. Technological diffusion takes time and comes with barriers to adoption. Real productivity gains required significant changes in business process, as well as managerial and technical innovation. With digitization, the transition to online services requires new supply-chain structures to deliver goods. Digital also requires investment and new skills in data analysis. Fear of technological obsolescence as well as gaps in technical and organizational capabilities represent considerable barriers. The current wave of digitization also requires customers the ability to use different payment methods in order to absorb new digital services such as e-banking and e-commerce.

Another explanation, according to Remes et al. (2018), to the observed productivity slowdown is mismeasurement of productivity. The measurement of productivity raises many difficult challenges, which are broadened in the service sector. Output is hard to measure in services. Quality improvements in many areas, especially tech and software, are hard to capture. Also, as we get wealthier, measured productivity may slow, and measuring GDP per capita may tell us little about human welfare. Information technology may improve human welfare in ways not captured in measured output. Indeed, measured GDP and gains in human welfare eventually may become entirely disconnected. One explanation for the productivity slowdown is based on the statistics we use to measure it failing to fully capture recent gains, especially those from higher-quality Information and Communication Technology (ICT). Moreover, standard measures of productivity are based on GDP, which, by definition, includes only output produced. In contrast, consumer surplus, which is growing fast in most cases at a market price of close to zero, is ignored.

Slowdown is also due to the increased weight of services in the economy and the fact that services have lower average productivity than manufacturing. This is due the fact that: 1) services are more prone to information asymmetries between supplier and consumer than goods as their quality can be more difficult to assess before purchase due to their less standardized nature, 2) certain services can involve spatial transaction costs because they have to be delivered in person (so firms cannot fully reap the potential benefits from economies of scale nor specialization of employees), 3) these characteristics of services also reduce their tradability within countries and across borders (Sorbe et al., 2018).

In order to better understand the productivity of the Portuguese economy, our goal is to assess the determinants of productivity growth at the firm-level for the Portuguese economy, providing useful information for the 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.

Total Factor Productivity (TFP) is often considered the primary contributor to GDP growth rate. While the combination of labour inputs, human capital and intermediate inputs does not entirely explain output creation, TFP measures residual growth in total output of a firm that cannot be explained by the accumulation of traditional inputs such as labour and capital. 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 economic growth and real business cycles. TFP can, thus, be taken as a measure of an economy's long-term technological change and accounts for part of the differences in cross-firm and cross-country income. This will be the productivity measure that will be used in this analysis.

As the study of the evolution of productivity measured by TFP consists on analyzing the evolution of a residual, sectoral analyzes are the best approach. Bearing in mind the sectoral approach to productivity focused on Manufacturing (see (Gonçalves et al., 2016)), the focus of this work will now be the service sector in order to complement the approach on productivity behavior of the Portuguese economy. Service sector input elements such as materials, machines and energy are not as important as in manufacturing industries since service sector output usually increases by the attempt to provide higher quality services to customers, seeking for better customer satisfaction, which is somehow unobservable and therefore even more difficult to consider in standard statistics. Therefore, concerns regarding productivity measurement are amplified by the generalized tendency for tertiarization of modern economies.

Through the study of a micro-database of Portuguese service sector companies during the period 2010-2016, we test the significance and magnitude of the main determinants of TFP growth suggested by the literature such as Internal Firms Characteristics (age and size); R&D, Innovation and Human Capital (training, fixed intangible assets, wage premium and staff assigned to R&D activities); Trade (exporter status); and Financial Health (equity ratio and capital per worker).

The remainder of the paper is organized as follows. Section 2 provides an overview of the main literature aimed at assessing the main determinants of TFP growth at a firm-level. Section 3 provides Data description and data cleaning techniques used according to the scope of our research. In Section 4 we present our TFP estimation through the Levinsohn and Petrin (LP) algorithm and provide result comparisons amongst different traditional estimating methods. The second-stage estimation with a fixed-effects model and its methodological issues concerning our econometric framework on the robustness of the model is present in Section 5, alongside with the final estimated model and interpretation of the results, according to our previous literature review. Finally, Section 6 concludes by presenting the policy implications and shed further light to future research.

2. Literature review

Literature on productivity is vast. However, it was not until the end of the twentieth century that productivity in the service sector started being analyzed. As a result, empirical research on productivity is less common in this sector. In contrast, studies on productivity in the manufacturing sector are much more predominant. As Rutkauskas and Paulavičienė (2005) argues, service sector input elements such as materials, machines and energy are not as important as in manufacturing. Accordingly, labour is the main element in the service sector because this sector is more labour-intensive comparing to manufacturing. Service sector output usually increases by the attempt to provide higher quality services to the customer, seeking for better customer satisfaction (Rutkauskas and Paulavičienė, 2005). As services today are of great complexity and usually a bundle of different individual parts, it is sometimes hard to identify characteristics for the overall service encounter (Becker et al., 2011). Many automation technologies are being enhanced with the use of data and machine learning to further raise efficiency and therefore, enhancing value-added content through digital is becoming a more important way to lift the “numerator” component of productivity Remes et al. (2018).

Based on an extensive literature review, we’ve identified several determinants that are broadly considered as relevant in explaining TFP growth, such as: Human capital, Training, Innovation, ICT investment, Financial Health and Market Efficiency, Management Quality, Ownership, Trade and Firms’ Internal Characteristics.

Human capital is considered to be one of the main determinants of TFP growth. Having skilled human capital is essential for the adoption and dissemination of new technologies and production processes (Kim and Loayza, 2017). More precisely, skilled human capital possesses necessary abilities, not only to become familiar with and efficiently use existing innovations, but also to contribute to the generation of brand-new innovative outcome (Gehringer et al., 2013).

Training costs are recognized by Crass and Peters (2014) as part of Human capital. Konings and Vanormelingen (2015) used a firm-level dataset for Belgium and considered the number of employees that received some kind of formal training as well as the training costs and the hours spent on training for the period. They conclude that training increases marginal productivity of an employee more than it increases its wage. Additionally, they found a slightly higher impact of training in non-manufacturing compared to manufacturing sectors. In the same line, using a firm-level dataset for Ireland, Barrett and O'Connell (2001) found that general training has a statistically positive effect on productivity growth. For the US economy, Cardarelli and Lusinyan (2015) confirm the previous findings that investment in human capital and R&D innovation are important factors associated with TFP growth.

It is widely known that one of the main factors contributing to multi-factor productivity comes from ***Innovation*** activities such as research and development (R&D), technological progress and investment in ICT. However, given the diversity measurement of innovation, one of the main issues of quantifying such activities is to find reasonable proxies according to available data. Mohnen and Hall (2013) measured innovation by its inputs (efforts made by firms to come up with new products, new ways to produce their output) and outputs (new products or processes successfully introduced). On the input side, innovation is measured R&D performance, acquisition of machinery, equipment and software to produce new products or processes, the purchase or licensing of patents, training related to the introduction of new products or processes, market research, etc. On the output side, Mortensen et al. (2005) distinguishes four types of innovation: product, process, organizational and marketing innovation. Calligaris et al. (2016) found evidence for a positive relationship between intangible assets (a proxy for innovation activities) and productivity. Mohnen and Hall (2013) conclude that both technological and non-technological innovations contribute to TFP growth. Goedhuys (2007) finds both R&D and product innovation as significant contributors to productivity growth. According to Pianta and Vaona (2007) and Crespi and Zuniga (2012), productivity is encouraged by product and process innovation, both in Europe and Latin America countries. However, according to Griffith et al. (2006), the relationship between different types of innovation and productivity across European countries are not uniform. Botrić et al. (2017) consider firms that, during the last three years, have developed new or significant improved products, production processes, organizational practices, marketing methods, business products and/or have invested in (intermural or extramural) R&D and employees training.

Other literature focusses on ***ICT investment*** as an important driver of productivity growth. ICT has made smaller contributions to labour productivity growth in the EU-15 than in the US, while TFP growth sharply declined in Europe and has remained relatively slow since the mid-1990s (Strauss and Samkharadze, 2011). Brynjolfsson and Hitt (2000) found that computer capital and information systems labour increase output significantly under a variety of formulations. Matteucci et al. (2005) considered the impact of ICT on productivity in European countries using both industry and firm-level data, concluding there is a productivity impact from investment in ICT activities. However, there is little evidence suggesting these impacts are as yet close to those found for the US. Additionally, they found little evidence of a significant impact from ICT on service sectors in the Continental European countries. Zwick (2003) studied the impact of ICT investments on TFP growth for Germany, using firm-level information from the Institute for Employment Research (IAB). He found that investments in ICT substantially increase the average productivity of German establishments and at least does not decrease during the three or four years after the investment.

Financial Health and ***Market efficiency*** can also be included as main determinants of TFP growth at the firm level, influencing firm's ability to produce innovation based practices and investments. In that sense, both external and internal factors can influence TFP at firm level. On the internal side, Fazzari et al. (1987) conclude that investment may depend on financial factors, such as the availability of internal finance, access to new debt or equity finance, or the functioning of particular credit market. Koke (2001) studied the relationship between financial pressure and TFP growth for Germany manufacturing firms and conclude that financial pressure has a positive effect on TFP growth. Commission et al. (2014) suggests a relationship between productivity growth and the availability of internal founds.

Management Quality also plays an important role on TFP Growth. Management is responsible for making key decisions on technology, inputs and production (Bartelsman and Doms, 2000). Caliendo et al. (2017) concludes that changing the number of management layers is important for firms to realize large productivity gains when they grow. Bloom et al. (2014) identified four main reasons for the existence of heterogeneity in management practices across firms: Perception (CEO does not know the firm is being poorly managed); Inspiration (CEO does not know how to change the firm's management for the better); Motivation (CEO has no incentives to change the firm's management); Persuasion (CEO may change the management practices for the worse). The scarcity of data on management quality constitutes a severe limitation to studies in this field as management quality cannot be directly measured. In some studies, authors are able to collect data on management quality through surveys (see Bloom et al. (2012) and Bloom et al. (2014)) where management practices are evaluated in accordance to three key areas: monitoring (how well firms are monitored by management), targets (whether target are well established), incentives (whether employees are being rewarded based on performance). Some authors focus on studying the impact of Ownership on management quality. Cucculelli et al. (2014) conclude that Italian family-run firms are less productive than firms run by outside managers. Bloom et al. (2012) found that United States has higher average management scores when compared to European countries mostly because U.S. firms appear to be rewarded more quickly with greater market share and the worse managed are forced to exit the market. They conclude that taxes and other distortive policies that favor family-run firms appear to hinder better management, while general education and multinational presence seem valuable in improving management practices. Government and founder-owned firms are usually poorly managed and multinationals achieve higher management scores than domestic firms (Bloom et al., 2014).

Trade is another key factor of TFP growth. According to Isaksson (2007), trade is often seen in the literature as a carrier of knowledge and foreign technology. He also highlights the importance of human capital, which is deemed as being an essential piece without which recipient countries are not able to adopt foreign technology. A possible theoretical explanation for the positive link between productivity and exporting is that high-performing firms self-select into the international market (Self-selection hypothesis), where competition is fiercer and sunk costs are too high for under-performers. Alternatively, the positive link between these two variables may also be a result from the learning effects of exporting i.e. learning-by-exporting (Arvas and Uyar, 2014). That is, firms that participate in international commerce are exposed to an international environment where knowledge is being exchanged between international buyers and competitors. Bravo-Ortega et al. (2014) identify four main channels that connect exports to productivity and innovation: (i) Self-selection hypothesis; (ii)

Learning by exporting; (iii) Exporting by Innovating (R&D is a determinant of exports); (iv) Innovating by Exporting (exporting stimulates innovation).

Firms' ***Size*** is also an important determinant of TFP growth. Brouwer et al. (2005) show that the relation between productivity and the size of firms is not linear. If a smaller firm increases in size, it will initially experience a positive effect in its productivity, due to economies of scale. However, after growing beyond a certain threshold, diseconomies of scale may have a dominating effect, resulting in a negative impact from the firm size on productivity. Measuring the size of a firm can be done in several different ways, depending on the criteria chosen. Some authors choose total assets (Dhawan, 2001) to measure the size of a firm. Others pick sales per employee (Leung et al., 2008) or number of employees (Acs et al., 1999).

Finally, ***Age*** also has an important role in TFP Growth. There are two different streams of research, each suggesting different theories on how age and productivity relate Majumdar (1997). On the one hand, one stream argues that older firms are also more experienced. Therefore they benefit from having more knowledge and are less exposed to newness. On the other hand, another stream of research, views older firms as being less flexible to adjust when necessary and more prone to inertia. Brouwer et al. (2005) state that younger firms tend to enter with fairly low productivity levels. However, in an attempt to survive, they're forced to catch up to existing firms, which results in considerably high productivity growth rates for the surviving young firms (through learning and selection effects). These productivity growth rates then start declining with age until they converge to the incumbent firms' average rate. In a study comprising 63 countries with low, middle and high income, Dabla-Norris et al. (2012) find a significant relationship between age and productivity i.e. older firms are more productive.

3. Data Description

Our empirical analysis is based on Informação Empresarial Simplificada (IES), a firm-level dataset provided by Banco de Portugal, which consists on accounting, financial and descriptive information on Portuguese companies (such as ordinary financial balance sheet indicators, number of workers employed, location, size, among others) and covers the period 2010-2016 which is a very interesting timespan.

We have pursuit a set of specific data cleaning techniques in order to exclude outliers and firms whose values for several variables were misreported. First, we exclude all firms that have less than three workers in order to eliminate possible bias in our sample (see for example Correia and Gouveia (2016)). Since our study is focused on the service sector, according to INE classifications, we exclude all firms from the manufacturing sector as well as primary sector firms. We considered the universe of the non-financial corporations whose principal activity is the production of non-financial services[4]. We also dropped all companies whose district was not specified as well as companies based in the free zone of Madeira. In order to compute the Levinsohn-Petrin (LP) algorithm, we only considered firms that reported positive values for the following variables: Turnover, Fixed Tangible Assets, Personal Expenses and External Services and Utilities.

Regarding Firm's size, we considered the Eurostat classification: Micro enterprises (less than 10 workers), Small enterprises (10-49 workers), Medium enterprises (50-249 workers) and Large enterprises (250 or more workers). In order to classify firm's according their exporter status, we considered the Exporter Status criteria defined by the Bank of Portugal that is, a firm is considered to be an exporter if at least 50% of its annual turnover is from exports of goods and services or at least 10% of its annual turnover due to exports and its value overpasses 150 000€.

One limitation of our dataset is that it does not provide qualitative information on employees, such as education, experience and skills. In most cases, studies that incorporate information relative to workers are based on surveys associated with the characteristics and different dimensions of human capital. Our dataset does not incorporate information regarding workers characteristics, skills, education and experience. In this sense, we chose to find alternative proxies in order to capture, to a certain extent, the impacts of Human Capital on TFP growth.

[4]Excluding Financial and Insurance activities, Public Sector, Education, Health and Social Care, Entertainment-related activities, Other Services, Activities for Final Consumption, International Organizations and other Institutions, and all the non-specified cases.

Figure 1 shows the universe of economic activities considered in the scope of the services sector, according to the information provided by Instituto Nacional de Estatística (INE)[5]. Information on the classifications of the economic activities considered is, from now on, present in two aggregations: CAE 2-digit and CAE-L. Based on CAE – REV 3[6] , we have considered the aggregation of CAE 2-digit from divisions 45 to 95 in these 8 new aggregations (CAE-L), built on our own criteria, to study industry effects on our model. Although the different aggregation methods (CAE 2-digit and CAE-L) would not affect the results, we continued to consider the new aggregation for analysis purposes.

CAE-L	Description	*CAE 2-digit*
G	Wholesale and retail trade, repair of motor vehicles and motorcycles	45+46+47
H	Transportation and storage	49+50+51+52+53
I	Accommodation and food service activities	55+56
J	IT and other information services	58+59+60+61+62+63
L	Real estate activities	68
M	Consulting, scientific, technical and similar activities	69+70+71+72+73+74+75
N	Administrative and support service activities	77+78+79+80+81+82
S	Other services	95

Figure 1: **Firms aggregation by *CAE-L* and *CAE 2-digit***

After a brief description of the dataset and specific data cleaning strategies applied, we are now able to visualize our data in a more clean and illustrative way, due to simple descriptive statistics. ***Figure 10*** on the Appendix shows the firm dynamics by CAE 2-digit. During the period 2010-2016 there was an increase in the total number of firms operating in the Portuguese service sector (from 40.797 in 2010 to 46.221 in 2016), despite the reduction in 2012, 2013 and 2014. In 2016, the highest number of firms was recorded in "Food and beverage service activities" (10.386 firms) and "Retail trade, except of motor vehicles and motorcycles" (10.020 firms), while the lowest values were recorded in "Water transport" (26 firms) and "Scientific research and development" (43 firms). Equivalently, ***Figure 11*** on the Appendix shows the distribution of the Portuguese service sector firms according to CAE-L sector aggregation. Most of service sector firms are from aggregations G "Wholesale and retail trade, repair of motor

[5]Statistics Portugal

[6]Portuguese classification of economic activities, Revision 3

vehicles and motorcycles" (41.60%), I "Accommodation, catering and similar" (25.26%) and M "Consulting, scientific, technical and similar activities" (14.84%). ***Figure 12*** on the Appendix displays the Portuguese service sector firms by its dimension, according to Eurostat classification. From our dataset, 92.97% of the Portuguese firms are considered as Micro firms (ie, employ less than 10 workers). Only 6.95% are Small, 0.08% are Median and 0.001% are Large firms.

Figure 2 illustrates the number of Portuguese service sector firms by dimension and sector aggregation (CAE-L). The figure confirms the previous conclusions that most of the Portuguese companies are classified as Micro firms. Additionally, one can conclude that most of the Portuguese service sector companies belong to aggregations G, I and M.

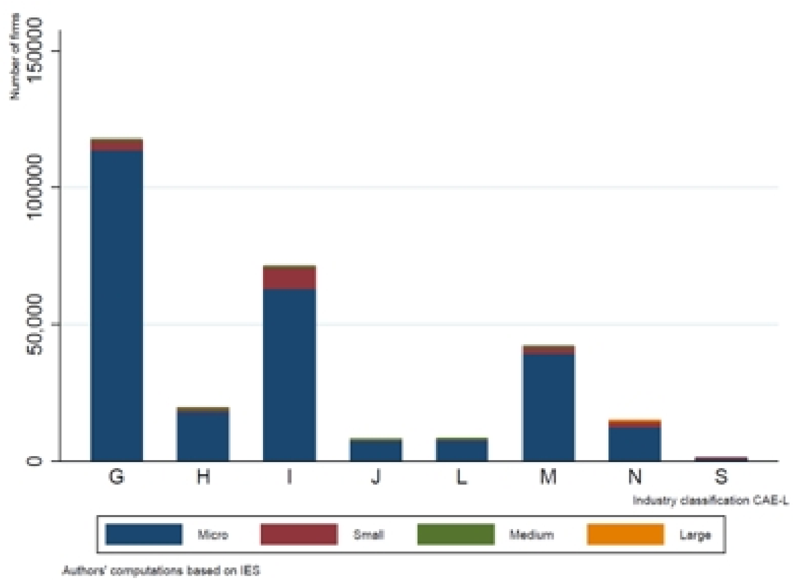

Figure 2: **Number of firms by dimension and *CAE-L***

Figure 3 presents the age distribution of the Portuguese service sector firms. As we can see, the age distribution is concentrated around 12 years old (median), while the average age of the Portuguese service sector firms is 15.49 years.

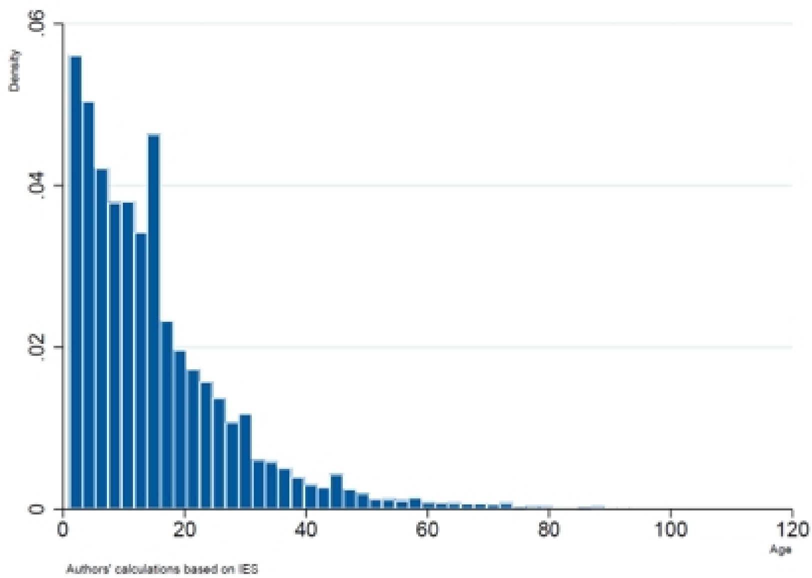

Figure 3: **Age distribution**

Figure 13 on the Appendix displays the number of Exporters in the service sector per district. Given the Banco of Portugal exporter criteria, total number of exporters increased during the period 2010-2016, from 1.094 firms in 2010 to 1.767 in 2016. The higher number of exporting firms was registered in Lisbon (24.0%), Porto (23.4%), Braga (10.5%) and Leiria (7.0%).

4. Total Factor Productivity (TFP) Estimation

4.1. Methodological Issues

When estimating total factor productivity at the firm-level, several methodological problems may arise. According to Van Beveren (2012), the main issues faced by researchers are (see ***Figure 4***): Selection bias; Simultaneity bias; Omitted output price bias; Omitted input price bias; and Endogeneity of the product mix.

Origin	Definition	Direction	References
Selection Bias	Endogeneity of attrition: Correlation between ε_{it} and K_{it}, conditional on being in the data set.	Downward bias in β_k	(Capet, 1967) (Olley & Pakes, 1992) (Ackerberg, 2007)
Simultaneity Bias	Endogeneity of inputs: Correlation between ε_{it} and inputs x_{it} if firms' prior beliefs about ε_{it} influence its choice of inputs.	Upward bias in β_l Upward bias in β_m Downward bias in β_k	(Marschak & Andrews, 1944) (Olley & Pakes, 1992) (Levinsohn & Petrin, 2003) (Ackerberg, 2007)
Omitted Output Price Bias	Imperfect Competition in output markets: Correlation between firm-level deviation of output price deflator (p_{it} - p_{it}) and inputs x_{it}.	Downward bias in β_l Downward bias in β_m Upward bias in β_k	(Klette & Griliches, 1996) (Levinsohn & Melitz, 2002) (De Loecker, 2007)
Omitted Input Price Bias	Imperfect competition in input markets: Correlation between firm-level deviation of input price deflators (p_{it} - p_{it}) and inputs x_{it}.	Downward bias in β_l Downward bias in β_m Upward bias in β_k	(Levinsohn & Melitz, 2002) (Katayama, Lu, & Tybout, 2009) (De Loecker, 2007)
Multi-product Firms Bias	Endogenous product choice: Differences in production technologies across products produced by single firm.	Undetermined	(Bernard, Redding, & Schott, Products and productivity, 2009) (De Loecker, 2007)

Source: (Van Beveren, 2012)

Figure 4: **Summary of methodological bias on TFP estimation**

Selection bias arises from omitting the firms that enter or exit over the sample period (Olley and Pakes, 1992). The probability of a firm exiting is a function of unobserved productivity and observed capital stock, which means that firms with lower level of capital stock and lower productivity are less likely to survive (Eberhardt et al., 2010). If firms have knowledge on their productivity level prior to exiting, this will result in a correlation between the error term and the capital stock (Ackerberg et al., 2007). This correlation originates from the fact that firms with higher levels of capital stock are able to withstand lower productivity levels without exiting (Van Beveren, 2012). Thus, the selection bias will result in a negative correlation between the error term and the capital stock (Ackerberg et al., 2007). As such, the capital coefficient will be downward biased (Sulimierska et al., 2014).

Simultaneity bias is a consequence of input decisions being determined by firms' beliefs about their productivity levels (Olley and Pakes, 1992). Therefore, if productivity is serially correlated, a positive productivity shock will translate into an increase in input levels (Van Beveren, 2012). This will result in upward biased input coefficients of materials and labour (De Loecker, 2007). ***Omitted output price bias*** originates from using industry wide prices instead of unobservable firm-level prices to deflate firm-level sales (De Loecker, 2007). If input decisions and firm-level price variation are correlated, this will lead to biased input coefficients (Van Beveren, 2012). In the context of imperfect competition in input markets, ***omitted input price bias*** is a consequence of deflating the values of inputs for materials and capital. Consequently, this will give rise to biased coefficients for capital and material inputs. Finally, ***endogeneity of the product mix*** may be a problem in the presence of firms that produce multiple products. If these products are part of the same industry but need different production technology or face different demands, estimates of total factor productivity will be biased because the production function assumes identical demand and production techniques (Van Beveren, 2012).

4.2. Traditional Methods

Typically, the traditional solutions for endogeneity problems are fixed effects and instrumental variables (Ackerberg et al., 2007). However, these traditional methods have turned out to be unsatisfactory for the case of production functions (Van Beveren, 2012).

In order to use instrumental variables (IV), a suitable instrument has to be found i.e. a variable that is correlated with the endogenous explanatory variable but not correlated with the error term. An IV can lessen the measurement error, which is usually more prominent in capital (Levinsohn and Petrin, 2003). Some examples of potential instrumentals are input prices (Eberhardt et al., 2010) or, in general, variables that shift demand for output or the supply of inputs(Van Beveren, 2012). However, according to Ackerberg et al. (2007), although using input prices as an IV may seem theoretically suitable, in practice, this approach has not been always successful. They identify four reasons for this phenomenon: (i) input prices are not always reported by firms and if they are, labour cost are usually reposted in a way that makes it hard to use it; (ii) there needs to be a significant variation in input prices across firms; (iii) with IV approach, we assume that productivity evolves exogenously over time (firms' input choices do not affect the evolution of productivity); (iv) the IV method tackles the problem of endogeneity of input choices but not the endogenous exit.

Another method is the fixed effect estimation which relies on the assumption that unobserved productivity does not vary over time (Van Beveren, 2012). Within estimation uses the variation within-firms which safeguards against possible correlation between unobserved firm-specific fixed effects and input choices (Levinsohn and Petrin, 2003). If this assumption is verified, this approach solves both the selection bias and the simultaneity problem (see (Van Beveren, 2012) and Ackerberg et al. (2007)). However, the fixed effects estimator does not fare well in practice for the following reasons identified by Ackerberg et al. (2007). First, the assumption that productivity is constant over time is very strong. Additionally, there might be measurement error in inputs which translates into higher biases in fixed effects estimators than in OLS.

4.3. Semiparametic Estimation : Olley-Pakes vs Levinsohn-Petrin

As Bernard et al. (2005) refer, firms' product choices are likely to be related to their productivity. In response to these methodological issues, several (parametric and semi-parametric) estimators have been proposed in the literature. Different traditional methods such as fixed effects, instrumental variables and GMM have not proved satisfactory for the case of production functions, mostly because of their underlying assumptions. As a result, different semi-parametric estimators have been proposed, namely Olley-Pakes (OP) and Levinsohn-Petrin (LP), addressing different methodological issues.

The main difference between OP and LP relies on the proxy chosen for unobserved productivity, being that the first uses investment and the latter uses intermediate inputs. In the first case, the endogeneity problem is incorporated into the production function equation through an investment function (Sulimierska et al., 2014). The monotonicity condition of OP requires that investment is strictly increasing in productivity. Therefore, depending on the available dataset, this can result in a significant loss in efficiency, since only firms with positive investment can be used in the estimation.

In contrast, LP suggest there are substantial adjustment costs from investment decisions, which may make the response of investment proxy to productivity shocks less smooth, thereby violating the consistency condition. Levinsohn and Petrin (2003) use intermediate inputs instead of investment as a proxy for unobserved productivity. Since firms typically report positive use of materials and energy in each year, it is possible to retain most observations (Van Beveren, 2012). Most firm-level datasets include data on the usage of intermediate inputs such as energy and materials, so Levinsohn and Petrin's estimator does not suffer from the truncation bias induced by Olley and Pakes' estimator, which requires firms to have non-zero levels of investment (Petrin et al., 2004). Another difference between the two estimators is that while OP allow for both an unbalanced panel as well as the incorporation of the survival probability in the second stage of the estimation algorithm, LP do not incorporate the survival probability in the second stage. However the efficiency gains associated with it in the empirical results presented by OP were very small.

We have calculated the production function under 3 different parametric and semi-parametric methods: ordinary least squares (OLS), least square dummy variable (LSDV) and LP. We decided to estimate TFP with LP instead of OP, given the fact that our dataset (IES) does not have significant information available on investment in order for it to be considered a proxy for unobserved productivity, and therefore we considered intermediate inputs as our proxy. This ensures a bigger dataset, since are positive positive for every level of production. As mentioned, another advantage of LP over OP relies on the fact that OP requires additional depreciation costs over investment expenditures, as it violates the monotonicity imposed in OP (Eberhardt et al., 2010).

4.4. The Levinsohn-Petrin Algorithm

An alternative to the traditional methods mentioned above is to employ structural estimators used by Olley and Pakes (1992), Levinsohn and Petrin (2003) and Ackerberg et al. (2007). For the purpose of this study, the Levinsohn-Petrin algorithm has been deemed as the most appropriate to calculate the total factor productivity at the firm-level. Following Levinsohn and Petrin (2003) the production technology is assumed to be a Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{B_k} L_{it}^{B_l} M_{it}^{B_m} \tag{1}$$

Where Y_{it} is physical output of firm i in period t; A_{it} represents the Hick-neutral efficiency level of firm i in period t; K_{it}, L_{it} and M_{it} are respectively the capital, labour and intermediate inputs. The proxy variables are summed up in ***Figure 5*** alongside their descriptive statistics.

Variable	Proxy	Mean	Stand. Dev.	Min	Max	Observations
Output (Y)	Turnover	246 135	362 355	7.50	77 600 000	282 516
Capital (K)	Fixed Tangible Assets	59 497	176 147	0.01	23 800 000	282 516
Labor (L)	Personnel Expenses	59 123	54 665	4.47	5 805 241	282 516
Intermediate Input (M)	External Services and Utilities	56 917	104 941	20.00	13 400 000	282 516

Source: Authors' computations based on IES database

Figure 5: **Descriptive statistics for the main variables in TFP estimation**

By transforming equation 1 into logarithm form, the following linear production function can be obtained:

$$Y_{it} = B_0 + B_k k_{it} + B_l l_{it} + B_m m_{it} + \varepsilon_{it} \tag{2}$$

Where lower-case letters represent the variables in log form and $ln(A_{it}) = B_0 + \epsilon_{it}$. The constant B_0 is a measure of the mean efficiency level across firms and over time, ϵ_{it} represents the time and producer specific deviation from that mean, which can be further decomposed into an observable (or at least despicable) and unobservable component (Van Beveren, 2012). This decomposition results in the following equation:

$$Y_{it} = B_0 + B_k k_{it} + B_l l_{it} + B_m m_{it} + \varpi_{it} + \eta_{it} \tag{3}$$

Where ϖ_{it} represents the transmitted productivity component and η_{it} is an error term which is uncorrelated with capital, labour and intermediate input decisions (Petrin et al., 2004). This error term η_{it} is an i.i.d. component that denotes unexpected deviations from the mean due to either measurement error, unexpected delays or other external circumstances (Van Beveren, 2012). The distinction between the two components, ϖ_{it} and η_{it} , is that ϖ_{it} is a state variable in the firm's decision problem (Petrin et al., 2004). Therefore it determines both liquidation and input demand decisions (Olley and Pakes, 1992).

Levinsohn and Petrin (2003) specify the demand for intermediate input m_{it} as a function of the state variables k_{it} and ϖ_{it}:

$$m_{it} = m_{it}(k_{it}, \omega_{it}) \tag{4}$$

Where m_{it} is assumed to be monotonically increasing in ω_{it} (Petrin et al., 2004). With this assumption a proxy for unobserved productivity can be obtained by inverting the intermediate input demand function (Eberhardt et al., 2010):

$$\omega_{it} = \omega_{it}(k_{it}, m_{it}) \tag{5}$$

With this expression, one obtains the unobservable productivity expressed as function of two observed inputs (Petrin et al., 2004). In regards to the transmitted productivity component, ω_{it} Levinsohn and Petrin (2003) assume that productivity is a result of a first-order Markov process:

$$\omega_{it} = E[\omega_{it} \mid \omega_{it-1}] + \varepsilon_{it} \tag{6}$$

Where ε_{it} represents an innovation to productivity which is uncorrelated with k_{it}, but not necessarily with l_{it} (Petrin et al., 2004).

For the purpose of this study, turnover was chosen to be the dependent variable, although LP also provides another approach using value-added instead. In the Cobb-Douglas framework, the gross output version of the production function includes the parameters of capital stock, labour and intermediate inputs, whilst the value-added version includes two parameters: capital stock and labour (Sulimierska et al., 2014). According to Basu and Fernald (1997), using value-added is appropriate when the focus is on the uses of output and not on the sources. The latter is more relevant when studying productivity growth. They demonstrate that the value-added approach yields biased estimates of returns to scale in the context of imperfect competition. As our main goal is to study TFP growth and we consider in our database imperfect competition markets, we relied instead on gross-output.

We estimated equation 2 where y_{it} denotes the log of turnover. The results of this estimation are presented and analyzed in Section 5.

4.5. Comparing Different Methods

For a more extensive analysis, we compare the results obtained from the different approaches mentioned previously: Ordinary-Least-Squares (OLS), Least Square Dummy Variable with fixed effects (LSDV) and the LP algorithm. ***Figure 6*** sums up the estimated coefficients attained for capital, labour and material inputs for the three approaches OLS, Fixed Effects and LP algorithm.

Variables	OLS	Fixed Effects	LP
Observations	282 516	282 516	282 516
Total Number of Firms	84 969	84 969	84 969
Capital (K)	0.0296 (0.0007107)	0.03 (0.0007105)	0.06 (0.0164429)
Labor (L)	0.466 (0.0022857)	0.463 (0.0022852)	0.464 (0.0036362)
Material (M)	0.403 (0.0015879)	0.402 (0.0015869)	0.02 (0.2458256)
Sum of Elasticities	0.899	0.895	0.544

Note: Standard errors in brackets
Source: Authors' computations based on IES database

Figure 6: **Comparison among alternative TFP estimations**

Going back to ***Figure 4***, retrieved from Van Beveren (2012), its third column shows the expected direction of the biases that originate from the different methodological issues. Since the fixed effects method theoretically corrects for simultaneity and selection bias, one should expect its estimated coefficients on labour and materials to be lower than the ones obtained from OLS. As for the coefficient on capital, one expects it to be higher in the FE estimation compared to the OLS result.

As presented in ***Figure 6***, the difference between the coefficients obtained from these two methods is very small. However, the coefficients attained using FE are in line with theoretical expectations. Similarly to Muendler (2004), the coefficient for intermediate inputs obtained from the LP approach is lower than the one from the OLS and the FE method. In comparison to Van Beveren (2012),we also obtain higher estimates for capital in LP compared to OLS. Nevertheless, we do not have higher estimates for material inputs and labour coefficients. On what concerns the returns to scale, our three estimates present decreasing returns to scale. As in Levinsohn and Petrin (2003), the sum of elasticities is highest in the OLS estimation.

Figure 7 shows a graphical representation of the productivity estimation through the LP algorithm, controlled for heteroscedasticity and serial autocorrelation with cluster-robust standard errors[7]. Considering the TFP aggregation for each of the 30 sectors of activity (CAE-L), ***Figure 7*** represents the weighted average of the TFP for the total economy. During the period 2010-2012, TFP growth slowed down in line with the period of crisis experienced in Portugal. Then, in the period 2012 - 2014, TFP recovered to its pre-2010 values. Despite a slight reduction in 2015, TFP growth of the Portuguese service companies showed an upward trend afterward.

5. Model Estimation

5.1. Second-Stage Regressions and its Methodological Issues

Having estimated firstly the TFP values, we now build our model using those estimates in logarithm as our dependent variable, as the second phase of the second-stage regression. On such terms, the researcher should be aware of the robustness and statistical issues that may exist from second-stage regressions. 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 si).

[7]After the drops described above, industry 51 (CAE 2-digit) had a very small number of observations, lower than that required to run the LP algorithm. Thus, in the final estimation we considered the remaining 30 industries.

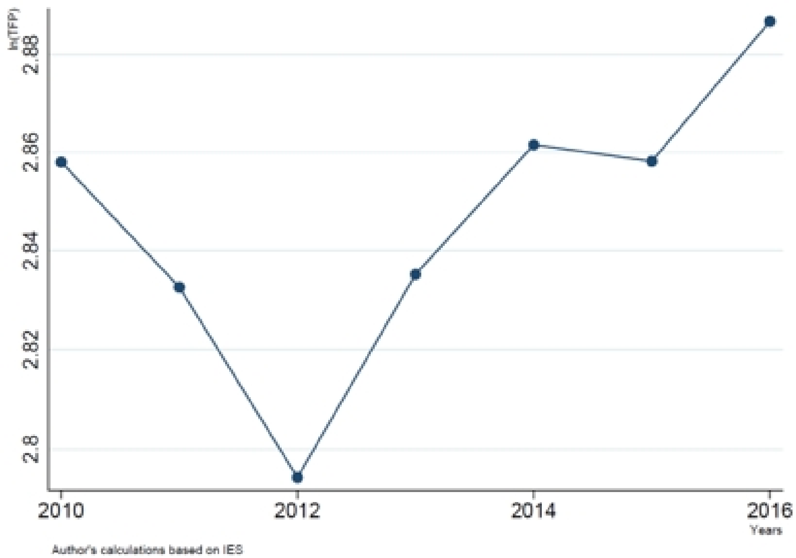

Figure 7: **Mean of TFP growth in the Portuguese service sector**

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 used the residual from the estimated production function as being TFP (the level of output that was not determined by inputs) . If we consider the matrix X as a vector for observed (proxy) variables for the determination of the TFP values, we hold the following equation:

$$ln\widehat{TFP}_{it} = y_{it} - \widehat{\alpha}_L l_{it} - \widehat{\alpha}_M m_{it} - \widehat{\alpha}_K k_{it} = \widehat{\alpha}_i - \widehat{\alpha}_X x_{it} + \widehat{\alpha}_T t + \varepsilon_{it} \tag{7}$$

According to Harris and Moffat (2015) it is quite common to estimate ***Equation 7*** without accounting for X and include it in ε_{it} and, therefore, we follow this method[8]. Several authors approach the econometric problematic from this issue, although Van Beveren (2012) showed that TFP estimated with different methods still present close results on the second-stage estimation, using the estimated TFP as dependent variable.

[8] For instance, Harris and Li (2008) rely on a system-GMM approach that allows for fixed effects and endogenous inputs, amid several other options.

On ***Figure 8*** 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 (0.9986) compared to van Van Beveren (2012) (that registered 0.684). The correlation between FE and LP is also higher in our results (0.6339 compared to 0.3672) and we present a lower, but indeed high, level of correlation between LP and OLS (0.6346 compared to 0.9262).

	Fixed Effects	OLS	LP
Fixed Effects	1		
OLS	0.9986	1	
LP	0.6339	0.6346	1

Source: Authors' computations based on IES database

Figure 8: **Correlation between alternative TFP estimations**

5.2. Robustness of the Model

Our estimated model for the TFP determinants (presented at ***Figure 6***) 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, 2010).

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, 2008). We found a correlation of 0 between the fixed effects and the explanatory variables, showing no correlation. While analyzing the robustness of our model we have not given strong emphasis on serial correlation of errors, following Wooldridge (2010) as the within estimators yield consistency with large datasets with a small number of periods. As suggested in Wooldridge (2010) and Bertrand et al. (2004) we have considered cluster-robust standard errors as the normal standard from the within estimator provide inconsistent values in the presence of serial correlation. 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 et al., 2007).

5.3. Estimated Model and Results

We present our final estimated fixed-effects model, with a set of determinants for the Total Factor Productivity growth. As it was showed previously in this work, we estimated our dependent variable through the LP algorithm. All descriptive statistics from the TFP growth determinants can be accessed on Appendix (***Figure 14***). We divide our analysis on the explanatory variables according to four different categories of determinants of TFP growth:

- ***Internal Firm Characteristics:*** Size and Age;
- ***R&D, Innovation and Human Capital:*** Innovation, Training and Wage Premium;
- ***Trade:*** Exporter status
- ***Financial Health:*** Capital Intensive and Equity ratio

The final model estimation can be expressed by ***Equation 8*** where $lnTFP$ is our dependent variable, β_j are the coefficients of the different regressors and ε_{it} is the error term.

$$\begin{aligned}\mathbf{lnTFP}_{it} = \beta_0 + \beta_1 Time_{it} + \beta_2 Size_{it} + \beta_3 Age_{it} + \beta_4 Training_{it} + \beta_5 Innovation_{it} + \\ + \beta_6 ExporterStatus_{it} + \beta_7 WagePremia_{it} + \beta_8 CapitalIntensity_{it} + \\ + \beta_9 Equityratio_{it} + \varepsilon_{it}\end{aligned} \tag{8}$$

Variable		Coefficient	(Std. Errors)	T-stat	P-value		Description
Year	2 - 2011	-0.044814	0.103811	-4.32	0.000	***	Dummy Variable
	3 - 2012	-0.102143	0.023670	-4.32	0.000	***	Reference Group is 2010
	4 - 2013	-0.712724	0.020969	-3.40	0.002	***	
	5 - 2014	-0.388586	0.158851	-2.45	0.021	**	
	6 - 2015	-0.113626	0.107483	-1.06	0.299		
	7 - 2016	0	(omitted)				
Size	2 - Small	0.009484	0.016086	0.59	0.560		Dummy Variable
	3 - Medium	0.029643	0.080675	0.37	0.716		Reference Group is Micro firms
	4 - Large	0.258941	0.791646	3.27	0.003	***	
Age		0.003517	0.003092	1.14	0.265	***	Company's age
Age ²		-0.000168	0.000047	-3.55	0.001		
Training		1.136145	0.514992	2.21	0.035	**	Share of Training Expenses on Personnel Global Costs
Training ²		-5.816394	2.418061	-2.41	0.023		
Innovation		0.010585	0.006201	1.71	0.099	*	Dummy Variable **1** - Firm increased intangible assets by more than 199€ [p(25)] or have assigned workers to R&D by more than 3 [p(75)] **0** - Otherwise
Exporter Status		0.044687	0.023317	1.93	0.064	*	Dummy Variable **1** - Firm has *Exporter Status* **2** - Otherwise
Wage *Premium*		0.000069	0.000036	1.90	0.067	*	Ratio between average wages (personal expenses/number of hours worked) and average mean wages (mean of the average wage per industry)
Capital Intensity		-1.33E-06	5.44E-07	-2.45	0.021	**	Fixed Tangible Assets per worker
Capital Intensity ²		1.35E-12	1.14E-11	1.18	0.248		
Equity ratio		0.003327	0.001205	2.76	0.010	***	Equity over Total Assets

Number of Observations	50 288
Number of Firms	21 457
corr (u_i,Xb)	-0.0366
R^2	0.9386

(Std. Errors adjusted for 30 clusters in *CAE 2-digit*)
Controlled for heteroscedasticity and serial autocorrelation with cluster-robust standard errors
* ** *** Significance at 10%, 5% and 1%
R^2 was calculated with STATA command *areg*, followed with *absorb (CAE 2-digit)*

Source: Authors' computations based on IES database

Figure 9: **Estimated model**

5.3.1. Internal Firm Characteristics

Regarding the effects of firm's internal characteristics, we have chosen to control our sample in three different dimensions: time, size and age. As it was discussed previously in this work, literature suggests different effects of firms' internal characteristics on TFP growth. We have found the existence of a non-linear effect of ***Age*** on TFP growth. As Brouwer et al. (2005) suggest, younger firms tend to enter in the market with relatively low productivity levels and therefore they are forced to catch up the existing firms, which results in considerably high productivity growth rates for the surviving young firms. Thereafter, these productivity growth rates then start declining with age until they converge to the incumbent firms' average rate. Our estimation showed the existence of a quadratic correlation between age and productivity, commonly designed as inverted U-shaped relationship. These results are in line with the ones from (Biggs, 1996). Fernandes (2008) suggest the existence of a robust inverse-U shaped relationship between firm age and TFP on which the most productive firms are the ones between 10-20 years old. The joint significance test of age on total factor productivity growth is available to check on the Appendix (***Figure 15***). This results contrast with the ones of manufacturing (see Gonçalves et al. (2016)) in which the relationship between age and productivity is negative.

Another important factor in explaining TFP growth at the firm level has to do with firms' size. As our previous literature suggests, there is no clear consensus regarding the effect of a firms ***Size*** on TFP growth. However, most of the literature concludes a non-linear relationship between size and TFP growth. If a smaller firm increases in size, it will initially experience a positive effect in its productivity, due to economies of scale. However, after growing beyond a certain threshold, diseconomies of scale may have a dominating effect, resulting in a negative impact from the firm size on productivity. We measured firms' size by the number of workers employed according to the Eurostat classification. Our dummy variable considers the micro firms as our reference group to assess the differences between micro firms and small, medium and large ones. According to our results, we have found that being a large firm impact, ceteris paribus, the growth rate of TFP by 25.9% on average (comparing to a micro firm).

5.3.2. Research & Development, Innovation and Human Capital

Innovation and R&D are commonly pointed out in the literature as drivers of TFP Growth. As our dataset does not have any information concerning investments on R&D, we have looked into alternative ways of measuring the impacts of innovation on TFP growth. We proxy Innovation and R&D with the dummy variable ***Innovation*** that assumes the value 1 if the company has increased its intangible assets by more than 199 (value of the percentile 25), or if it has assigned to R&D by more than 3 workers (value of the 75 percentile of this variable, when it is positive). Our results show that an innovative company, ceteris paribus, sees its TFP grow by more 1.1% than non-innovative companies. Differently from several studies in 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, avoiding bias on our model estimation. Our results are in line with Calligaris et al. (2016) that found evidence for a positive relationship between intangible assets (a proxy for innovation activities) and productivity. This result is similar to the one of Gonçalves et al. (2016) as the coefficient is positive and of similar magnitude.

We also consider the variable ***Training*** which measures the share of training expenses on personal global costs. Having skilled human capital is essential for the adoption and dissemination of new technologies and production processes (Kim and Loayza, 2017). Training increases marginal productivity of an employee more than it increases its wage and it has higher impacts in non-manufacturing sectors (Konings and Vanormelingen, 2015). Despite the positive effect of training in total factor productivity in the short-run, its long-run effects are not that evident. Our estimation evidences a positive relationship of training in total factor productivity growth, in the short-run. However, our results corroborate the idea of a non-linear correlation, that is, after a given threshold, the relationship between additional training and TFP growth becomes negative [9] . Since the training of workers at a firm-level entails significant costs for the company, it is reasonable to say that the company's decision to train its employees depends on its analysis of the costs and benefits associated with training activities. For initial values of training, the benefits are usually greater than the cost. However,

[9] The joint significance test of training on TFP growth is available to check on the Appendix (***Figure 15***).

following a normal S-Curve or Sigmoid learning curve [10], the improvement of proficiency starts slowly, then increases rapidly, and finally levels off. Corroborating the results of Konings and Vanormelingen (2015) the coefficient that relates the effect of training with TFP growth is higher than the one found in Gonçalves et al. (2016) for the manufacturing sector.

Despite the fact that we could not have access to any data concerning workers education, we choose to proxy human capital, skills or education levels by the variable ***Wage Premia***, which represents the ratio between personal expenses per hour worked over the mean of the average wage per hour per industry. Gehringer et al. (2013) suggest that this variable can be interpreted in two ways: firstly, more efficient employees get higher salaries, meaning they are more productive, and secondly, industries that pay higher wages will achieve higher levels of TFP. Our results go in line with our literature review, indicating that wages are a driver of TFP growth, despite the small coefficient (1% increase in wage premium is correlated with a 0.000073% increase in TFP growth). This coefficient seems to be higher for the Portuguese manufacturing sector.

5.3.3. Trade

Trade is often seen in the literature as a carrier of knowledge and foreign technology (Isaksson, 2007). In order to capture the impact of exporting, we used the Bank of Portugal Exporter status to build a dummy variable ***Export Status*** that takes the value 1 in case the company fulfills the criteria and 0 otherwise. In this regard, we have found that the exporter status is associated with, ceteris paribus, the growth rate of TFP by 4.6% on average (which compares to 5.9% in Gonçalves et al. (2016) for the Portuguese Manufacturing sector). Our results are in line with the theoretical explanation for the positive link between productivity and exporting. As previously mentioned, this may be explained by the self-selection hypothesis (ie, high-performing companies tend to self-select into the international environment) (Arvas and Uyar, 2014). Our results are in line with the theoretical explanation for the positive link between productivity and exporting (Baldwin and Hanel, 2000).

[10] The S-Curve or Sigmoid function is the idealized general form of all learning curves, with slowly accumulating small steps at first followed by larger steps and then successively smaller ones later, as the learning activity reaches its limit. That idealizes the normal progression from discovery to the limit of what learning about it.

5.3.4. Financial Health

In line with a great branch of the literature, we considered Financial Health as a main determinant of TFP growth at the firm level, influencing firm's ability to produce innovation based practices and investments. We considered the ***Equity ratio*** as our proxy for the financial health, indicating the relative proportion of equity used to finance a company's assets. Our results show that a 1% increase on the equity ratio is correlated, ceteris paribus, with a TFP growth of 0.3%, which corroborates the Commission et al. (2014) findings, that productivity growth and the availability of internal funds are positively correlated. In another perspective, Koke (2001) studied the relationship between financial pressure and TFP growth for Germany manufacturing firms and conclude that financial pressure has a positive effect on TFP growth and, in general, financial pressure is a cumulative result of hierarchical financing decisions overtime (see (Shyam-Sunder and Myers, 1999) and (Coricelli et al., 2012)). Gonçalves et al. (2016) also analyzed the importance of financial health in TFP growth in manufacturing sector and also found a positive association with firms capitalization.

We also include in our estimation a variable called ***Capital intensity***, which measures Fixed Tangible Assets per worker. In fact, this variable was introduced in order to capture both financial health and innovation dynamics. Capital intensity can be interpreted in two different ways; firstly, firms in better financial situation tend to be able to raise capital per worker to higher levels than those who are stuck in a less benignant financial situation; secondly, firms that innovate the most are used to have higher levels of capital per worker. From our estimation we found that capital intensity is negatively correlated with TFP growth until a certain threshold, after which this relationship become positive. The intuition behind this U-shaped correlation between capital intensity and TFP growth is that an increase in Fixed Tangible Assets produces negative effects on TFP until both capital and labour adjusts to benefit from it and generate enough value added to compensate the initial cost [11].

[11] The joint significance test of capital intensity on TFP growth is available to check on the Appendix (***Figure 15***).

6. Policy Implications and Concluding Remarks

Productivity slowdown in advanced economies has at its origin several factors such as weak demand, low levels of investment, poor management practices, excess capacity, economic, political, and regulatory uncertainty and measurement problems. Slowdown is also due to the increased weight of services in the economy and the fact that services have lower average productivity than manufacturing.

In an attempt to better understand the dynamics of productivity evolution, literature suggests a set of determinants of productivity, such as Age, Size, R&D, Innovation, Human Capital, Trade and Financial Health. The results we present intend to identify the most important factors for the service sector of the Portuguese economy, among those advanced in the literature, providing useful information for the policymakers and firms managers concerning measures and policies to improve efficiency and productivity. Based on our empirical analysis, we trace a set of conclusions allowing us to derive important policy targeted at the following areas:

- ***Promote market entrants and eliminate exit barriers:*** As it was discussed previously in this work, literature suggests different effects of firms' age on TFP growth. New entrants tend to enter in the market with relatively low productivity levels but higher productivity growth rates, and therefore they are forced to catch up with the existing firms. To support the creation of new firms, policies should focus on the elimination of existing policy distortions such as entry and exit barriers and heavy bankruptcy legislation. Equivalently, incentives aimed at access to alternative sources of finance for startups should be pursued as well as incentives to innovative companies with a digital character that bring disruptive benefits to the existing players. At that light, partnerships between universities, creative hubs, star-ups and businesses should be encouraged.

- ***Encourage exporters:*** Trade is often seen in the literature as a carrier of knowledge and foreign technology, mostly as a result of the learning effects of exporting and self-selection of high-performing companies into the international environment. According to our findings, policies that increase opportunities to export through the reduction of various trade costs (such as administrative, legal and bureaucratic costs and political uncertainty) and simultaneously promote firms' internationalization could result in important productivity gains. Regional trade agreements with different geographical partners may work as an effective internationalization policy.

- ***Improve human capital and digital skills:*** In a context of rapid technological change and increasing digital disruption, in order for companies to capitalize those new opportunities they have to pursuit workforce strategy and be able to invest in their workforce qualifications. This entails several major changes in how firms and the public administration views and manages skills. In this regard, companies should rethink the role of the human resources activities and, in general terms, be more agile in the way they think about managing people's work. Educational systems should support the catching up of digital transformation skills, as well as encourage lifelong learning and empower cross-industry, public-private and academia-business collaboration in order to obtain a more qualified and efficient workforce. Additionally, policies aimed at increase labour mobility have proven to be efficient ensuring an optimal allocation of skills.

- ***Empower firms' innovation and training activities:*** In order to provide firms an economic and financial environment keen to prompt its performance and achieve higher levels of technological efficiency, policies should encourage stronger links between business, academia and research centers, as well as foster investments in R&D and training, encourage the use of more skilled labour, specialized and efficient work and make a greater use of training. At that light, country-specific innovation policies can facilitate the diffusion of knowledge between firms, universities and the public administration. Public funding for job training programs, improving labour market dynamism and mobility, and providing income and transition support to workers are also recommended in this context. Investment in R&D is also important and, thus, unlocking private investment by decreasing uncertainty (a key barrier to investing) is also recommended.

- ***Encourage different sources of financing:*** Policies that encourage equity over debt such as the removal of tax incentives that favor debt over equity and the simplification of equity rules should be advocated. Since one of the main obstacles for startups to scale up and be financial sustainable has to do with the ability to finance new projects, different business financing alternatives should be encouraged, such as special bond issues, angel investors, venture capital and others.

7. References

Ackerberg, D., C. L. Benkard, S. Berry, and A. Pakes (2007). Econometric tools for analyzing market outcomes. *Handbook of econometrics 6*, 4171–4276.

Acs, Z. J., R. Morck, and B. Yeung (1999). Productivity growth and firm size distribution. *Z. J. Acs, B. Carlsson, and C. Karlsson (eds.), Entrepreneurship, Small and Medium-Sized Enterprises and the Macroeconomy*, 367–396.

Arvas, M. A. and B. Uyar (2014). Exports and firm productivity in turkish manufacturing: an olley-pakes estimation. *International Journal of Economics and Financial Issues 4*(2), 243–257.

Baldwin, J. and P. Hanel (2000). Multinationals and the canadian innovation process.

Baltagi, B. (2008). *Econometric analysis of panel data.* John Wiley & Sons.

Barrett, A. and P. J. O'Connell (2001). Does training generally work? the returns to in-company training. *ILR Review 54*(3), 647–662.

Bartelsman, E. J. and M. Doms (2000). Understanding productivity: Lessons from longitudinal microdata. *Journal of Economic literature 38*(3), 569–594.

Basu, S. and J. G. Fernald (1997). Returns to scale in us production: Estimates and implications. *Journal of political economy 105*(2), 249–283.

Becker, M., S. Klingner, and M. Böttcher (2011). Increasing service productivity by characteristics-driven recommendations for action. *Reser 2011 Proceedings. Hamburg. Google Scholar*.

Bernard, A. B., S. Redding, and P. K. Schott (2005). Multi-product firms and the dynamics of product mix. *Yale School of Management*.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics 119*(1), 249–275.

Biggs, J. (1996). Enhancing teaching through constructive alignment. *Higher education 32*(3), 347–364.

Bloom, N., C. Genakos, R. Sadun, and J. Van Reenen (2012). Management practices across firms and countries. *Academy of Management Perspectives 26*(1), 12–33.

Bloom, N., R. Lemos, R. Sadun, D. Scur, and J. Van Reenen (2014). Jeea-fbbva lecture 2013: The new empirical economics of management. *Journal of the European Economic Association 12*(4), 835–876.

Botrić, V., L. Božić, and T. Broz (2017). Explaining firm-level total factor productivity in post-transition: manufacturing vs. services sector. *Journal of International Studies 10*(3), 77–90.

Bravo-Ortega, C., J. M. Benavente, and Á. González (2014). Innovation, exports, and productivity: Learning and self-selection in chile. *Emerging Markets Finance and Trade 50*(sup1), 68–95.

Brouwer, P., J. De Kok, and P. Fris (2005). Can firm age account for productivity differences. *EIM SCALES-paper N 200421*, 1–49.

Brynjolfsson, E. and L. M. Hitt (2000). Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic perspectives 14*(4), 23–48.

Caliendo, L., F. Monte, and E. Rossi-Hansberg (2017). Exporting and organizational change. Technical report, National Bureau of Economic Research.

Calligaris, S., M. Del Gatto, F. Hassan, G. I. Ottaviano, F. Schivardi, et al. (2016). Italy's productivity conundrum. a study on resource misallocation in italy. Technical report, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Cardarelli, M. R. and L. Lusinyan (2015). *US Total factor productivity slowdown: Evidence from the US States.* Number 15-116. International Monetary Fund.

Commission, E. et al. (2014). Helping firms grow. *European Competitiveness Report*.

Coricelli, F., N. Driffield, S. Pal, and I. Roland (2012). When does leverage hurt productivity growth? a firm-level analysis. *Journal of international Money and Finance 31*(6), 1674–1694.

Correia, A. L. and A. F. Gouveia (2016). What determines firm-level export capacity? evidence from portuguese firms. *GEE Papers* (57).

Crass, D. and B. Peters (2014). Intangible assets and firm-level productivity.

Crespi, G. and P. Zuniga (2012). Innovation and productivity: evidence from six latin american countries. *World development 40*(2), 273–290.

Cucculelli, M., L. Mannarino, V. Pupo, and F. Ricotta (2014). Owner-management, firm age, and productivity in i talian family firms. *Journal of Small Business Management 52*(2), 325–343.

Dabla-Norris, E., E. K. Kersting, and G. Verdier (2012). Firm productivity, innovation, and financial development. *Southern Economic Journal 79*(2), 422–449.

De Loecker, J. (2007). Do exports generate higher productivity? evidence from slovenia. *Journal of international economics 73*(1), 69–98.

Dhawan, R. (2001). Firm size and productivity differential: theory and evidence from a panel of us firms. *Journal of economic behavior & organization 44*(3), 269–293.

Eberhardt, M., C. Helmers, et al. (2010). *Untested assumptions and data slicing: A critical review of firm-level production function estimators*. Department of Economics, University of Oxford.

Fazzari, S., R. G. Hubbard, and B. C. Petersen (1987). Financing constraints and corporate investment.

Fernandes, A. M. (2008). Firm productivity in bangladesh manufacturing industries. *World Development 36*(10), 1725–1744.

Gehringer, A., I. Martinez-Zarzoso, F. N. Danziger, et al. (2013). The determinants of total factor productivity in the eu: insights from sectoral data and common dynamic processes. *EcoMod2013 5343*.

Goedhuys, M. (2007). The impact of innovation activities on productivity and firm growth: evidence from brazil.

Gonçalves, D., A. Martins, et al. (2016). The determinants of tfp growth in the portuguese manufacturing sector. *GEE Papers 62*.

Griffith, R., E. Huergo, J. Mairesse, and B. Peters (2006). Innovation and productivity across four european countries. *Oxford review of economic policy 22*(4), 483–498.

Harris, R. and Q. C. Li (2008). Exporting, r&d, and absorptive capacity in uk establishments. *Oxford economic papers 61*(1), 74–103.

Harris, R. and J. Moffat (2015). Plant-level determinants of total factor productivity in great britain, 1997–2008. *Journal of Productivity Analysis 44*(1), 1–20.

Harris, R., D. S. Siegel, and M. Wright (2005). Assessing the impact of management buyouts on economic efficiency: Plant-level evidence from the united kingdom. *Review of Economics and Statistics 87*(1), 148–153.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, 1251–1271.

Hoechle, D. et al. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal 7*(3), 281.

Isaksson, A. (2007). Determinants of total factor productivity: a literature review. *Research and Statistics Branch, UNIDO*.

Kim, Y. E. and N. Loayza (2017). Productivity and its determinants: Innovation, education, efficiency, infrastructure, and institutions. *Unpublished Working Paper*.

Koke, J. (2001). Control transfers in corporate germany: Their frequency, causes, and consequences.

Konings, J. and S. Vanormelingen (2015). The impact of training on productivity and wages: firm-level evidence. *Review of Economics and Statistics 97*(2), 485–497.

Leung, D., C. Meh, and Y. Terajima (2008). Firm size and productivity. Technical report, Bank of Canada Working Paper.

Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies 70*(2), 317–341.

Majumdar, S. K. (1997). The impact of size and age on firm-level performance: some evidence from india. *Review of industrial organization 12*(2), 231–241.

Matteucci, N., M. O'Mahony, C. Robinson, and T. Zwick (2005). Productivity, workplace performance and ict: Industry and firm-level evidence for europe and the us. *Scottish Journal of Political Economy 52*(3), 359–386.

Mohnen, P. and B. H. Hall (2013). Innovation and productivity: An update. *Eurasian Business Review 3*(1), 47–65.

Mortensen, P. S., C. W. Bloch, et al. (2005). *Oslo Manual-Guidelines for Collecting and Interpreting Innovation Data: Proposed Guidelines for Collecting and Interpreting Innovation Data*. Organisation for Economic Cooporation and Development, OECD.

Muendler, M.-A. (2004). Estimating production functions when productivity change is endogenous.

Olley, G. S. and A. Pakes (1992). The dynamics of productivity in the telecommunications equipment industry. Technical report, National Bureau of Economic Research.

Petrin, A., B. P. Poi, J. Levinsohn, et al. (2004). Production function estimation in stata using inputs to control for unobservables. *Stata journal 4*, 113–123.

Pianta, M. and A. Vaona (2007). Innovation and productivity in european industries. *Economics of Innovation and New Technology 16*(7), 485–499.

Remes, J., J. Manyika, J. Bughin, J. Woetzel, J. Mischke, and M. Krishnan (2018). Solving the productivity puzzle: The role of demand and the promise of digitization. *McKinsey Global Institute*.

Rutkauskas, J. and E. Paulavičienė (2005). Concept of productivity in service sector. *Engineering Economics 43*(3), 35–41.

Shyam-Sunder, L. and S. C. Myers (1999). Testing static tradeoff against pecking order models of capital structure1. *Journal of financial economics 51*(2), 219–244.

Solow, R. M. (1987). We'd better watch out. *New York Times Book Review 36*.

Sorbe, S. S., P. Gal, and V. Millot (2018). Can productivity still grow in service-based economies? *OECD working papers*, 53.

Strauss, H. and B. Samkharadze (2011). Ict capital and productivity growth.

Sulimierska, M. et al. (2014). Total factor productivity estimation for polish manufacturing industry: A comparison of alternative methods. Technical report.

Townsend, Z., J. Buckley, M. Harada, and M. A. Scott (2013). The choice between fixed and random effects. *The SAGE Handbook of Multilevel Modeling. SAGE*.

Van Beveren, I. (2012). Total factor productivity estimation: A practical review. *Journal of economic surveys 26*(1), 98–128.

Wang, H.-J. and P. Schmidt (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *journal of Productivity Analysis 18*(2), 129–144.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Zwick, T. (2003). The impact of ict investment on establishment productivity. *National Institute Economic Review 184*(1), 99–110.

A. Appendix

CAE 2-digit	Sector	2010	2011	2012	2013	2014	2015	2016	Total variation
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	3 593	3 661	3 475	3 245	3 239	3 611	4 002	11%
46	Wholesale trade, except of motor vehicles and motorcycles	4 554	4 621	4 301	4 167	4 084	4 481	5 147	13%
47	Retail trade, except of motor vehicles and motorcycles	8 999	8 915	8 345	8 098	7 988	8 983	10 020	11%
49	Land transport and transport via pipelines	2 493	2 547	2 347	2 182	2 151	2 405	2 737	10%
50	Water transport	20	26	25	27	31	26	26	30%
52	Warehousing and support activities for transportation	257	265	251	246	249	273	285	11%
53	Postal and courier activities	77	73	64	66	73	87	76	-1%
55	Accommodation	665	677	689	717	786	911	1 104	66%
56	Food and beverage service activities	9 580	9 717	9 125	8 831	8 611	9 490	10 386	8%
58	Publishing activities	220	213	195	199	183	195	206	-6%
59	Motion picture, video and television programmer production, sound recording and music publishing activities	105	107	103	107	115	128	145	38%
60	Programming and broadcasting activities	77	72	72	61	55	59	56	-27%
61	Telecommunications	47	59	61	70	79	84	92	96%
62	Computer programming, consultancy and related activities	521	542	561	568	593	686	808	55%
63	Information service activities	46	52	53	47	59	75	86	87%
68	Real estate activities	1 269	1 197	1 064	984	1 032	1 202	1 464	15%
69	Legal and accounting activities	3 031	3 103	3 015	2 895	2 823	3 033	3 172	5%
70	Activities of head offices; management consultancy activities	622	642	633	611	609	776	905	45%
71	Architectural and engineering activities; technical testing and analysis	1 125	1 126	1 015	891	959	1 070	1 254	11%
72	Scientific research and development	24	28	23	21	27	35	43	79%
73	Advertising and market research	410	426	376	353	358	411	472	15%
74	Other professional, scientific and technical activities	507	511	475	456	480	526	632	25%
75	Veterinary activities	230	256	272	275	286	325	380	65%
77	Rental and leasing activities	207	223	201	184	182	237	284	37%
78	Employment activities	54	49	43	41	46	64	76	41%
79	Travel agency, tour operator and other reservation service and related activities	207	228	204	196	214	267	313	51%
80	Security and investigation activities	74	77	73	69	62	73	84	14%
81	Services to buildings and landscape activities	791	798	748	728	690	784	843	7%
82	Office administrative, office support and other business support activities	782	810	766	713	718	854	923	18%
95	Repair of computers and personal and household goods	210	201	185	167	170	198	200	-5%
Total		**40 797**	**41 222**	**38 760**	**37 215**	**36 952**	**41 349**	**46 221**	**28%**

Source: Authors' computations based on IES database

Figure 10: **Firms by *CAE 2-digit* (2010-2016)**

Sector	Number of Firms	Percentage
G	117 529	41.60%
H	19 385	6.86%
I	71 289	25.23%
J	7 862	2.78%
L	8 212	2.91%
M	41 928	14.84%
N	14 980	5.30%
S	1 331	0.47%
Total	**282 516**	**100%**

Source: Authors' computations based on IES database

Figure 11: **Firms by *CAE-L***

Size	Number of Firms	Percentage
Micro	262 660	92.97%
Small	19 623	6.95%
Medium	229	0.08%
Large	3	0.001%
Total	282 515	100%

Source: Authors' computations based on IES database

Figure 12: **Firms by dimension**

District	2010	2011	2012	2013	2014	2015	2016
Aveiro	63	86	85	90	86	101	119
Beja	9	13	8	3	5	4	7
Braga	93	109	122	129	141	175	185
Bragança	8	15	13	12	12	13	17
Castelo Branco	14	13	13	12	18	15	21
Coimbra	39	73	61	48	46	48	64
Évora	15	20	13	11	15	17	22
Faro	28	55	38	37	33	32	38
Guarda	27	41	21	22	24	27	21
Leiria	85	97	87	106	98	109	125
Lisboa	308	427	345	336	351	375	424
Portalegre	7	13	6	5	10	11	14
Porto	216	243	275	294	301	342	413
Santarém	46	45	46	39	38	55	67
Setúbal	45	86	76	60	71	76	83
Viana do Castelo	27	25	32	38	44	50	62
Vila Real	16	12	17	15	10	16	17
Viseu	46	54	49	50	47	49	58
Angra do Heroísmo	0	0	1	1	1	2	5
Horta	0	0	0	1	1	0	1
Ponta Delgada	2	1	2	1	0	1	4
Total	**1 094**	**1 428**	**1 310**	**1 310**	**1 352**	**1 518**	**1 767**

Source: Authors' computations based on IES database

Figure 13: **Exporters per district (2010-2016)**

Variable	Mean	Stand. Dev.	Min	Max	Observations
Age	15.490	13.401	1	117	272 084
Training	0.007	0.023	0	0.781	51 859
R&D workers	0.032	0.496	0	80	121 160
IFA	121.226	14 879.490	-394 304	1 586 402	51 886
Wage *Premium*	1	21.256	0	2 753 972	282 516
Capital Intensity	12 723.440	38 140.580	0.001	3 295 607	282 516
Equity ratio	-0.160	3.098	-580.475	4 232 576	282 516

Source: Authors' computations based on IES database

Figure 14: **Descriptive statistics for the second-stage estimation**

Test (Training, Training^2)
F(2.29)=2.89
Prob > F = 0.0714 *

Source: Authors' computations based on IES database

Test (Age, Age^2)
F(2.29)=10.32
Prob > F = 0.0004 ***

Source: Authors' computations based on IES database

Test (Capital Intensive, Capital Intensive^2)
F(1.29)=5.98
Prob > F = 0.0208 **

Source: Authors' computations based on IES database

Figure 15: **Joint significance tests**