Gabinete de Estratégia e Estudos

GEE Paper

149

Abril de 2020

The Determinants of Total Factor Productivity in the Portuguese Quaternary Sector

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www.gee.gov.pt
ISSN (online): 1647-6212

The Determinants of Total Factor Productivity in the Portuguese Quaternary Sector[1]

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Abstract:

Quaternary activities have been on the rise, as a consequence of the increasing technological developments and work automation, as they are expected to have an impact on both the future of the job market and the overall economy. As such, and considering that Total Factor Productivity (TFP) constitutes a main driver of output growth, we propose to study its determinants for the quaternary sector. First, we establish several criteria to build our own definition of quaternary activities, as they are not acknowledged in national accounts or other statistics. For such purpose, our empirical assessment is based on a firm level panel dataset, comprising Portuguese firms, between 2006 and 2017. Secondly, we employ the Levinsohn and Petrin (2003)'s methodology to estimate TFP at the firm level. Finally, through a second stage estimation, we build a fixed effects model based on several determinants said to impact firms' TFP, and establish a comparison with the remainder sectors of economic activity. Both descriptive statistics of the database and the final regression outputs provide evidence that quaternary activities differ from the remainder in several characteristics. Our results show that innovation, wage premium and international openness rise the level of TFP, while indebtedness presents an opposite correlation. The age and size of the firm show a non linear relationship with TFP.

JEL Classification Codes: C33; D22; D24; O31; O47

Keywords: Total Factor Productivity; LEVPET; Fixed effects; Quaternary 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]We wish to express our deepest gratitude to Ana Martins (GEE), whose assistance and availability was essential for the completion of this study. Ana believed in the potential of this project since the first day and provided us all the help and conditions to make it possible. We also enhance the help and feedback from Ana Gouveia (Prime-Minister's Advisory), Tiago Domingues (GEE) and Nuno Tavares (GEE). Finally, we would like to pay our special regards to Diogo Monteiro (Nova SBE) and José Santos (Nova SBE) for all the unending hours of debate and enjoyable company during the completion of this project. All errors and omissions are due to the authors' responsibility.

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1. Introduction

Productivity growth has slowed down around the world prior to the 2007 recession (Cette et al., 2016). This slowdown, and even stagnation, happening in advanced economies such as the U.S., Europe and Japan, had already started prior to the 2007 recession (IMF, 2015). This led the definition of “secular stagnation” to be revisited among several economists. The term was first introduced in the 1930s when Alvin Hansen proposed that a demographic change – lower population growth rate – in the U.S. would discourage investment and therefore lower the natural rate of interest. It now refers to “the proposition that periods … when even zero policy interest rates are not enough to restore full employment, are going to be much more common in the future than in the past” (Krugman, 2014). Summers (2016) proposed that a decreasing propensity to invest results in higher saving rates than investment rates, which ultimately leads to excessive savings dragging down demand, lower real interest rates and a reduction in growth and inflation.

Hawksworth et al. (2018) argues that this productivity slump can be battled with the adoption of the most recent technological developments, such as Artificial Intelligence, robotics and other forms of smart automation. However, the adoption of these technologies is said to trigger structural shifts in the labor market. Frey and Osborne (2017) estimate that 47% of job positions in the U.S. are at high risk of computerization within 20 years at most. On the other hand, Manyika et al. (2018) suggests that if “businesses and governments … seize opportunities to boost job creation and for labor markets to function well”, job growth could offset the computerized jobs. They argue that, until 2030, Occupational Groups “Care Providers”, “Educators”, “Managers and Executives”, “Professionals”, “Technology Professionals”, “Builders and Creators” will increase, meanwhile occupancies in “Costumer interaction” and “Office support” will decline[4]. When looking at Occupational Categories, one can notice that knowledge and socio-emotional occupations (such as engineers, childcare workers, etc)[5] are the ones that will see employment rise, contrasting with more routine tasks (such as production workers, dishwashers, etc). This goes hand in hand with Frey and Osborne (2017)’s conclusions, where they oppose routinely tasks to occupations requiring knowledge, in the spectrum of the probability of computerization. These knowledge occupations can be more broadly and commonly referred to as knowledge based activities. Peneder et al. (2003) and Kenessey (1987) show KB (Knowledge Based) activities rose quickly in the last century and call for the need to study it separately.

Motivated by the global productivity slowdown and a predictable shift in the labor market towards knowledge based activities, the purpose of this paper is to analyze what determinants can boost productivity on this sector. For this purpose, we rely on Total Factor Productivity, as it is a key measure when explaining cross country’s differences in income per capita. The classical combination of labor,

[4] Occupational Groups, as defined in Manyika et al. (2018), include ”Care Providers”, ”Educators”, ”Managers and Executives”, ”Professionals”, ”Technology Professionals”, ”Builders”, ”Creatives”, ”Customer Interaction”, ”Office Support”, ”Other jobs, predictable environment”, and ”Other jobs, unpredictable environment”

[5] Occupational Categories, as defined by Manyika et al. (2018), are the occupations within the Occupational Groups, which include ”Doctors”, ”School teachers”, ”Executives”, etc

capital, and intermediate inputs does not entirely explain output creation, as the remaining part of output variation consists in measurement of technical efficiency (or residual) and provides insights on economic growth and business cycles. Thus, it is important to study the components of this residual, which is a driver of economic growth, to provide policy implications that promote the increase of firms' technological efficiency and optimal production.

Considering the growth of knowledge based activities and their importance on the future of the labor market, often associated with the jobs of the future, we aim to evaluate the determinants of total factor productivity growth in the Portuguese knowledge based (also referred as quaternary) sector, providing insights for public policy on how to increase these firms efficiency levels. In view of the sectoral approach to TFP on the manufacturing and services sector, covered respectively by Gonçalves et al. (2016) and Martins et al. (2018), this work will focus on a new and understudied sector in order to complement the assessment on the productivity of the Portuguese economy. This industry differs from the others in several aspects, mainly in the low amount of intermediate inputs used and the quantity of skilled labor employed. Furthermore, the definition of the sector itself is arguably ambiguous, as even with the global acceptance of the emergence of a quaternary sector in the economy, national accounts and statistics do not explicit it, often focusing on the three sectoral approach (Agriculture, Manufacturing and Services). As such, our contribution is twofold. First, based on the available literature, bound our own definition of knowledge based activities or quaternary sector. Secondly, having built the sector itself based on several criteria, study which determinants contribute to its TFP standards.

The remainder of this paper is organized as follows. Section 2 covers the main literature on the topic, both regarding the emergence of quaternary activities and the main productivity determinants. Section 3 explores the main characteristics of our database and provides our final definition of knowledge based activities, that will be further used in the research. Section 4 resumes the main methodological issues when estimating TFP at the firm level, as well as detailing the chosen methodology for the purpose of this study. Section 5 details the final output and analyses the main results of our approach. Section 6 concludes.

2. Literature Review

There is an extensive literature on productivity and its determinants. Most of the henceforth mentioned papers analyzing TFP at the firm level are performed per sector/industry. One of the arguments that supports this sectoral approach is based on the fact that studying productivity implies analyzing the evolution of a residual Martins et al. (2018). Furthermore, the heterogeneity among economic sectors suggests that such separation ought to be appropriate, as several determinants are expected to have different impacts on firms' productivity depending on the considered sector. For instance, Biatour et al. (2011) argues about the importance of considering such heterogeneity on the robustness of the results. They mainly point to the distinction between manufacturing and services firms regarding the components for TFP, as they find substantial differences among both industries.

Kenessey (1987) exploits this sectorial partition, finding substantial differences between economic sectors and arguing regarding the importance of such classification. Most empirical studies on TFP at the firm level are focused on the manufacturing sector (Fernandes (2006); and Yean (1997)), as recently several studies emerged on the service sector to complement the overall assessment on the TFP (Martins et al. (2018)). Empirical research on productivity in different areas other than the aforementioned is scarce.

2.1. Knowledge Based Sector

The sectorial division of the economic activity is far from being consensual, although the classical three sector partition years (Fisher (1939); Clark (1951)) remained somehow consistent through the years. The ascendancy of the so called quaternary activities and the increasing digitalization of economic tasks led to a strong debate on how this sectorial classification should be conducted. The concept of the quaternary sector emerged in the second half of the twentieth century and there is no consensual way to define it, as national accounting codes design do not account for it. Gottmann (1962) defines the Quaternary Sector as “services that require research, analysis, judgment, in brief, brainwork, and responsibility”. Selstad (1990) includes in it specifically R&D (Research and Development), Higher education and consultancy activities. Turečková et al. (2015), using NACE’s Economic Activities codes, considers “Information and communication”, “Financial and insurance activities”, “Professional”, scientific and technical activities”, “Administrative and support service activities”, “Education” and “Human health and social work activities”. Kenessey (1987) extended the work of Kuznets and Murphy (1966) on sectorial analysis by highlighting the emergence of the quaternary sector in the economy. He shows that this sector is sufficiently different from the remainder and thus ought to be studied separately. More precisely, he establishes several criteria and indicators to sustain such partition: Sectorial revenue as a percentage of GDP; Sectorial employment as a percentage of the employed labor force; Input-Output Relations Among the Four Sectors; Value Added and Intermediate Inputs as a percentage of revenue.

Peneder et al. (2003) calls out for a broader definition of the quaternary sector by calling out “the need to define a more focused sub-class of phenomena, which deals explicitly with the rise of knowledge based services, already referred to as ‘quaternization’ ”. This definition is the most agreed in the literature, bridging quaternary industries to KB activities.

Other studies point these activities as being the jobs of the future. Recent concerns with the possible consequences of automation on jobs created a wave of theories and research about the future of employment. Several literature points towards these KB jobs as the ones that will not be robotized in the near future. Frey and Osborne (2017) addressed the topic of the future of employment by studying how several jobs are alike to be computerized. By developing an algorithm for that matter, they conclude on a probability that every single task (according to SOC codes) has of being automated. They find that KB activities are the ones more susceptible to survive computerization. According to the authors “generalist occupations of human heuristics, and specialist occupations involving the development of novel ideas and artifacts, are the least susceptible to computerization". Thus, tasks requiring social and creative intelligence are considered as "low risk of automation" jobs. As such, occupations in certain areas, like management, computer, engineering and science or education, to a certain extent are said to be automation free. On the other hand, tasks involving other occupations, such as transportation or logistics, are likely to be substituted by computer capital in the future. They find that high skill occupations are less susceptible to the burden of computerization. Hawksworth et al. (2018) performed similar research estimating automation rates across industries. Even achieving more optimistic results, they conclude on similar occupations as being the ones less likely to be automatized. These outcomes are again in line with Manyika et al. (2018), stating that "Automation will have a lesser effect on jobs that involve managing people, applying expertise, and social interactions, where machines are unable to match human performance for now". All in all, literature points to the emergence of quaternary activities in the economy, linked with knowledge and social/creative intelligence. Such occupations are said to be less likely to be automated due to their human heuristics requirements.

2.2. Determinants of Productivity

Due to the scarcity of literature on the KB activities and its determinants, this section will more generally revisit literature of determinants of either other sectors or the aggregate economy. Based on extensive literature, we have acknowledged several determinants that are said to be crucial when explaining TFP at the firm level. Most studies concerning components for productivity point to several factors such as: Trade, Innovation, R&D investment, Skilled labor, Financial and internal characteristics, etc. The choice of these determinants is mostly agreed in the literature for every study of this kind. As already stated, results are expected to differ with the sector considered (services, manufacturing or, in this case, KB activities, etc.)

Neoclassical models used to account for productivity as an exogenous variable, determined outside of the model Solow (1956). More recently, modern economic growth models Romer (1990) aim to explain technological development by accounting for knowledge creation as its main driver, enabling the possibility of perpetual economic growth. Prescott (1998) argued that differences in technology among countries (partly explained by the knowledge component) explain inequalities in output growth between countries. As stated in Isaksson (2007), knowledge is not a measurable variable and it must be accurately proxied by a quantifiable indicator. For instance, Hall (2011) uses R&D expenses and patent counts as measures for innovation activity. He argues that the former has the advantage of being denominated in a currency and "represents a (costly) decision variable on the part of the firm about its appropriate level of innovative activity". However, being an input variable to innovation, it tells nothing about innovation success. Patent counts, on the other hand, are said to be a measure of innovation output, partially linked to innovation success. Abdih and Joutz (2006) used time series data for the U.S to conclude on a long run relationship between TFP and the stock of knowledge, proxied by patent counts. Greenhalgh and Longland (2005) point towards a positive correlation between TFP and patents and trademarks registrations. Also, Guellec and De La Potterie (2002) studied the impact of R&D on TPF growth with three different measures of R&D for the purpose: foreign sourced R&D, domestic business research and public research, all of which successfully explained TFP growth with foreign research having the most notable effect. Pianta and Vaona (2007) and Hall (2011) stressed the importance of product and process innovation on productivity, finding that product innovation has a substantial impact on TFP while process innovation impact is ambiguous. Other literature suggests ICT investment as a proxy for Innovation and as a crucial component for productivity growth. Spiezia (2013) studied the impact of three different categories of ICT investment – computer, software and communication- in 18 different OECD countries from 1995 to 2007, across 26 industries. He found a heterogeneous effect of these three components across countries but an overall contribution to their productivity levels. Seo et al. (2009) also analyzed the relationship between ICT investment and the evolution of productivity growth path. Apart from the positive contribution to TFP growth, they pointed to the existence of ICT externalities (knowledge spillovers) towards developing countries.

Trade openness and easiness are also seen as a crucial determinant of productivity growth, mainly as it is considered as a mean of exchange of knowledge. Coe and Helpman (1995) and Coe et al. (1997) promote trade as a measure of technological transfer. According to these authors, productivity patterns ought to increase if firms import from countries that have strong stocks of knowledge and advanced technology. Isaksson (2007) highlights the contribution of Mayer and Mayer (2001) work to Coe et al. (1997) approach, by combining it with the human capital factor. According to the author, this component is vital, as qualified labor ensures the implementation of foreign technology. Nataraj (2011) exploited the 1991 liberalization episode in India - massive reduction of tariffs on inputs and final goods - to determine the effects of trade reform on a firm's productivity. They found that this reform had a positive contribution to productivity. Not only lower tariffs on final products caused firms to be more efficient, but also the fact that the reduction on inputs tariffs led to a raise on its imports, enabling firms to access cheaper and more sophisticated inputs. Similar results regarding trade liberalization and firms TFP are concluded in Njikam and Cockburn (2011), with evidence from Cameroon. Also, some authors argue about the existence of learn-by-exporting effects, i.e. firms become more productive by their participation in the exports market, due to the gains they have by getting access to new knowledge and resources (Arvas and Uyar (2014); Fernandes (2006)), or in other words, due to knowledge spillovers. Banco de Portugal (2019) finds both evidence of the benefits of exporting or importing on productivity, highlighting that the most productive firms benefit more from this effect.

The adoption of advanced technology and knowledge (being it through investment in R&D and ICT, or by the adoption of foreign skills) is highlighted in the literature as being one of the most important determinants of productivity growth. However, skilled human capital is essential for the embracement of such elements. Romer (1990) defends the importance of skilled labor as a crucial determinant of innovation and implementation of foreign technology. Jajri (2007) analyses the TFP of Malaysia during 1971-2004 and argues regarding its determinants. He finds that the number of skilled workers highly contributes to productivity by managing to operate sophisticated technology and knowledge. Such results are in line with Fernandes (2006). While neoclassical models tended to account for the accumulation of physical capital, more recent models already account for human capital and knowledge accumulation to explain differences between countries (Jones, 2008). De La Fuente et al. (2011) (pointing to this upgrade in recent models) recalls that empirical evidence regarding this relationship is ambiguous, as several studies in the second half of the twentieth century did not find robust results of educational variables on growth and even negative relationships were deducted (Filmer and Pritchett, 2001). De La Fuente et al. (2011) argues that such results might arise due to the difficulty of measuring human capital correctly. He finds evidence that the impact of investment in education (human capital) on productivity is not only positive but higher than those in physical capital for most European countries.

Foster et al. (2008) shows that even within homogeneous goods industries TFP largely varies. Bloom and Van Reenen (2010) by conducting surveys to firms conclude that "one important explanation for the large differences in productivity between firms and countries - differences that cannot be readily explained by other factors - is variations in management practices.", uncovering that "imperfectly competitive markets, family ownership of firms, regulations restricting management practices, and informational barriers allow bad management to persist." Caselli and Gennaioli (2013) focus on dynastic family firms (this is, management of firms are passed through generations within the same family, rather than a meritocratic selection of managers), and point out dynastic family firms have lower TFP. Bloom et al. (2013) make an experiment and provide free consulting to manufacturing firms in India and conclude that firms that adopted the better managerial practices saw their TFP increase by 17% in the first year alone.

Financial structure is also approached in the literature as a relevant component for productivity, as it might determine a firm´s ability to invest in RD, sophisticated technology and knowledge. The role of capital structure on TFP at the firm level has been studied through the years and several different conclusions were taken. Nickell et al. (1996) covered this relationship empirically using a sample of U.K. firms. Their results and argumentation were in line with Jensen (1986), who proposed a positive relationship between firms' leverage and its productivity, arguing that high debt levels increase manager's productivity due to the pressure of bankruptcy caused by such leverage. This way, financial pressure ends up having a positive impact on productivity growth. Other studies point towards a different correlation between these two variables. Nucci et al. (2005) concludes on a non-linear negative relationship among productivity and leverage, using data from Italian companies. Ghosh (2006) finds similar results using similar arguments for the Indian case. Coricelli et al. (2009) shows that we can indeed find both effects of leverage in TFP, arguing that it has a positive impact until it reaches a critical threshold from which onwards has a negative impact. He argues that low levels of debt have a disciplining role due to the reduction in free cash flows in accordance with the theory of the firm's financial structure, meanwhile, highly-levered firms see their incentives to invest in productive investment reduced and rather invest in quick cash flows[6]. The easiness of a firm to get internal (or external) finance is also approached in the literature as a crucial factor. The availability of internal funds and access to credit in credit markets help to promote investment in productivity-enhancement

[6]The theory of a firm's financial structure is based on bankruptcy costs, conflicts of interests between equityholders and debtholders and control rights.

projects (Fazzari et al., 1989). Commission et al. (2014) also stresses the importance of internal funding on productivity growth.

Internal characteristics of the firm are said to influence its productivity levels. Among others, the size of the company (usually measured by the number of employees or its amount of total assets) constitutes a crucial feature when considering the TFP. However, the sign of the relation between these two indicators is far from being unanimous in the literature. Satpathy et al. (2017) finds a positive relationship between the size of Indian manufacturing firms and its productivity, proxying size with the (logarithm of) total assets of the firm for that purpose[7]. Leung et al. (2008) found similar results for manufacturing and non-manufacturing firms in Canada and the U.S. Opposite results were deducted by Tornatzky et al. (1990), who concludes smaller firms are more productivity due to their leaner organizational structure. Brouwer et al. (2005) suggested a non-linear relation among both indicators, pointing to an initial gain in productivity with size until a certain threshold, from which onwards the impact becomes negative.

On what regards age, there is a strong debate in the literature regarding the impact of a firm's age on productivity. Jovanovic and Nyarko (1996) argue about a positive effect, highlighting the learn-by-doing effects. Older firms have more experience and consequently more knowledge, which implies more advanced technology when compared to small firms. However, several authors suggest an inverse U-shaped connection among these two variables (Brouwer et al. (2005); and Fernandes (2006)). According to these authors, firms start at relatively low TFP values, as they learn and invest in new opportunities that increase their productivity levels (economies of scale also play a role here). They get to a point where their technology gets outdated as they start having decreasing returns to age.

3. Dataset and Sector definition

3.1. Data

Our Dataset constitutes a harmonized version of IES[8] by BdP (Bank of Portugal), a firm-level dataset containing yearly data on accounting and descriptive information for all non-financial firms (excluding sole proprietorships) in Portugal. Our initial dataset comprises 4,574,014 observations, over the period of 2006 to 2017. The firms' economic activity sector is provided in accordance with CAE codes[9]. Figures 5 and 6 in the appendix provide a summary per CAE-L and district.

We performed several data mining techniques to get a more comprehensive understanding of our data and ensure its validity. Several inconsistencies were reported. Firstly, we observed that several

[7]According to Castany et al. (2005), such a positive relationship can be explained by scale economies effects, the scope economies effects, the experience effects, and organization effects.

[8]Portuguese firm level data.

[9]CAE codes correspond to the Portuguese economic sector accounting codes, defined by The national Statistics Institute (INE), following the E.U NACE classification. We used the 3^{rd} and most recent revision of this classification - CAE Rev. 3 - available at https://www.ine.pt/ine_novidades/semin/cae/CAE_REV_3.pdf.

observations did not report values that comply with the Fundamental Accounting Equation[10]. To avoid misreporting bias we decided to dismiss the firms whose Assets deviate over 1% of its sum of Liabilities and Equity[11] We also observed several firms that report operating in different economic sectors in different years[12]. Moreover, the dataset contained firms with inconsistent values for Turnover and Cost of Goods Sold/Supply and External Services. Thus, we computed a GVA (Gross Value Added) [13] to turnover ratio and dismissed the outliers of this indicator[14]. To compute the Levinsohn and Petrin (2003)'s algorithm we dismissed the observations presenting non-positive values for our key variables in the estimation, as detailed further in section 4.2.

After treated, our sample consisted of 2,696,316 observations, along 12 years. Sector G (Wholesale and retail trade; repair of motor vehicles and motorcycles) comprise almost 30% of the total observations, as observed in figure 1. Micro firms dominate, corresponding to 83% of total observations, proceeded by small firms (14%), median firms (2%) and large firms (less than 1%)[15]. Younger firms prevail, with a median age of 9 years. The sector with the lowest average is R (Arts, entertainment and recreation) as shown in Figure 10 with a median age of 5. In Figure 2 we can notice that the number of firms is relatively constant over time, with a small dive in the time span of 2009-2013, which can be associated with the recession lived in this period. Sectors C (Manufacturing), G (Wholesale and retail trade; repair of motor vehicles and motorcycles) and M (Professional, scientific and technical activities) account for over 50% of the GVA and 60% of Turnover, being clearly the most relevant sectors in terms of economic activity. Lastly, sectors T, K, and U were dropped completely after our filters were applied.

Should be enhance that no qualitative information on employees is available on our dataset. Education level, years of experience or skills are important indicators to measure labour quality and human capital. As pointed in the literature, such variables are said to be crucial determinants of TFP at the firm level. Thus, several proxies are applied in order to capture the effects of those components, which are further detailed in section 5.

3.2. Knowledge Based sector definition

A crucial step of this paper is based on the definition of the working sector. As already referred, the quaternary activities group is not explicit in national accounts and, as such, in this paper, it is defined solely based on our interpretation of the literature. We consider diverse criteria to classify the KB sector. Firstly, we mainly rely on Frey and Osborne (2017) and Hawksworth et al. (2018) works on the

[10] Assets= Liabilities + Equity

[11] We decided to provide an error margin as small deviations might not imply a significant misreport. A visual analysis is shown in figure 7 in the appendix.

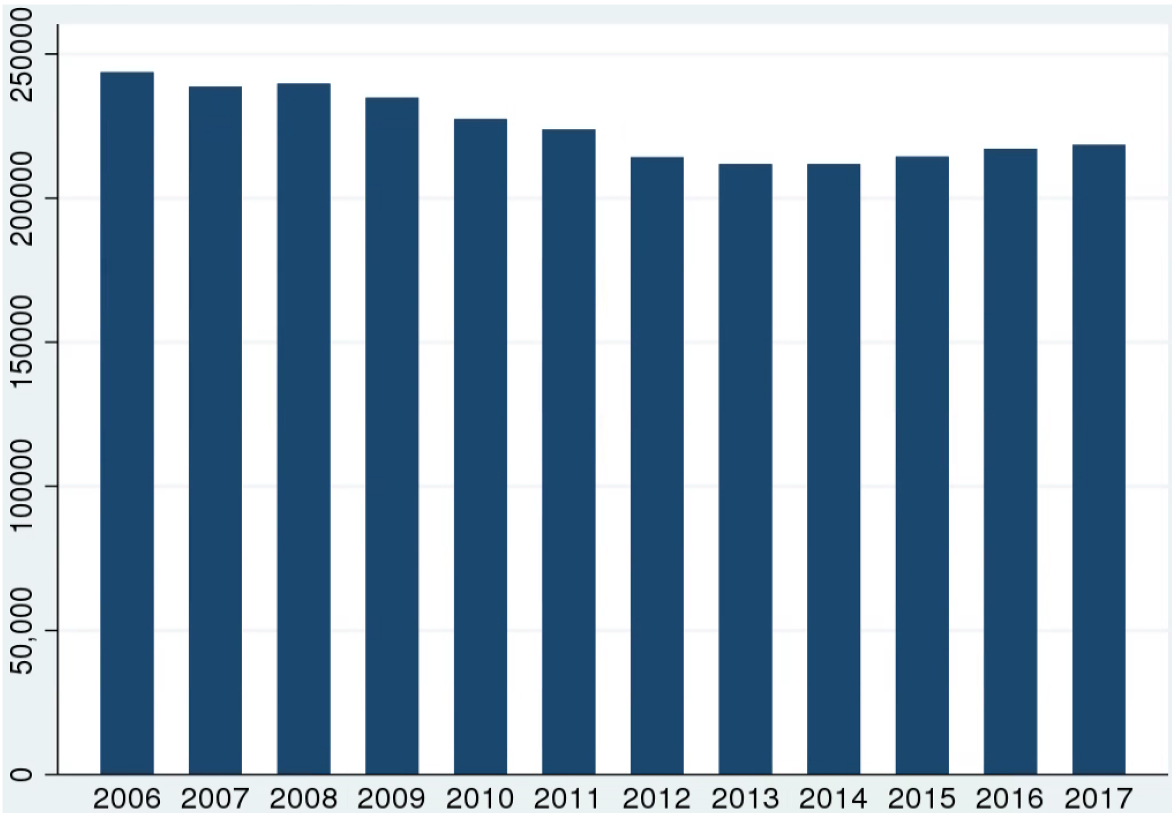
[12] CAE Rev.3 has been in place since 2008 and firms reporting before this year had their CAE converted. We ensured the change in CAE was not due to this change. The number of firms that change the reported CAE over the years is similar to when the years 2006 and 2007 are not included.

[13] GVA was computed in accordance to INE methodology.

[14] A more in depth analysis on the distribution of the GVA ratio can be found in figure 8 in the appendix.

[15] We rely on the Eurostat classification to aggregate firms regarding their size: Micro firms (1 to 9 workers), Small firms (10 to 49 workers), Medium firms (50 to 249 workers) and Large firms (250+ workers)

Figure 1: **Number of firms per year**



Source: authors computations based on IES database

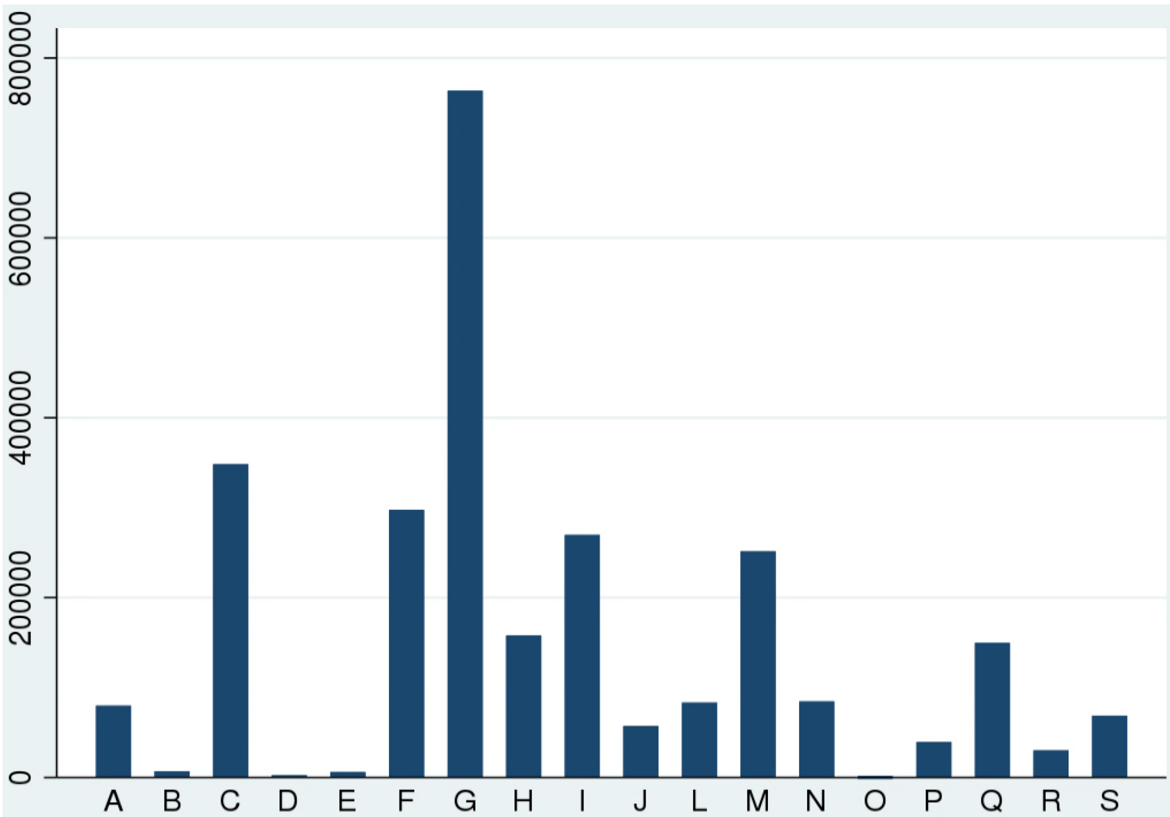
future of employment and automation. These papers point to routine tasks as being easily substituted by computer capital, while distinguishing KB activities as the ones with less susceptibility of being robotized in the future, highlighting the following sectors: "Management, Business and Financial", "Computer, Engineering and Science", "Education, Legal, Community Service, Arts and Media" and "Healthcare Practitioners and Technical" (see Figure 11 and 12 in the appendix)[16]. Given this, we excluded from the KB industry all CAE activities that are not linked to these sectors. Afterward, on a second step, we analyze the probabilities of computerization for each occupation[17] out of the ones that we had previously selected, and link them to every CAE (at a 3 digit level) in order to withdraw activities with high prospects of being robotized that are included in the referred sectors[18]. A full list of the CAE sectors included in our approach can be found in figure 9 in the appendix.

[16]Note that all these industries are included in the Services sector, from a classical three sector partition view

[17]Obtained from Frey and Osborne (2017)

[18]For instance, we include CAE-M (69-75 digits) activities: "Consulting, Scientific, Technical and Similar", as they are included in the "Management, Business and Financial" category. However, CAE-692 activities: "Accounting and auditing activities and Fiscal Consulting", included in the previous group, are removed from our list as, according to Frey and Osborne (2017), they are likely to be robotized in the future.

Figure 2: **Number of observations per CAE-L**



Source: authors computations based on IES database

Several descriptive statistics and tests prove that, as argued by Kenessey (1987), firms included in the quaternary sector differ from the remainder in various indicators. Figure 13 compares the average age of firms by economic sector (Agriculture, Manufacturing, Services and KB activities). Results go in line with the idea of the recent emergence of quaternary activities defended by Peneder et al. (2003), as KB firms are substantially younger than the ones in other sectors (average of 10 years against 13). Also, supporting Kenessey (1987) argumentation, our data suggests that the share of GVA is higher among quaternary activities (16.22%) when compared to the remaining sectors (11.53%). Other variables also exemplify this difference, such as the low amount of capital per worker employed (Figure 14).

KB activities account for a total 526,997 observations (note that these can be seen as a subgroup of the service sector), while the Agriculture sector has a total of 79,804, 661,137 in Manufacturing and 1,428,378 correspond to services industry. Contrary to the pattern previously observed (when all firms were being considered), there has been an increase in the number of firms in the KB sector, as Figure 15 illustrates; even during the sovereign debt crisis period. Regarding the entry and exit of firms in the market, there is a clear disparity among sectors. Both the services and manufacturing sectors have a clear decreasing trend over the years, reflecting the effects of the financial crisis. The agriculture and KB sectors; however, had the opposite tendency, with the number of firms growing over the years, more intensively on the latter. In line with Frey and Osborne (2017) findings, out data suggests that quaternary activities have higher average wage levels than the remainder industries, as it can be observed in Figure 16. The big majority of the firms in our sample are not considered to be exporters (94%), as most of the exporter firms are included in the manufacturing and services sector.[19]

4. TFP Estimation

There is a wide discussion in the literature regarding TFP estimation. Several parametric, semi-parametric and non-parametric processes have been proposed and agreement about the most effective technique is far from being consensual.[20] This section summarizes the most popular methodologies, highlighting some methodological issues and explaining the chosen method to compute TFP at the firm level.

4.1. Parametric Approaches - Methodological Issues

The standard procedure for a parametric approach consists on the estimation of a classical Cobb-Douglas production function, proposed in Solow (1956) when explaining output creation:

$$Y_{it} = A_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} M_{it}^{\beta_M} \tag{1}$$

Y_{it} corresponds to the physical output of firm i in period t, K_{it} is the input from capital, L_{it} the input from labor, M_{it} the input from intermediate materials and A_{it} is an Hicksian neutral efficiency level. A linear, and thus econometrically estimable, form of the production function can be obtained by applying logarithms (a monotonical transformation) in both sides of the equation, obtaining:

$$Y_{it} = \beta_0 + \beta_K K_{it} + \beta_L L_{it} + \beta_M M_{it} + \epsilon_{it} \tag{2}$$

where $ln(A_{it}) = \beta_0 + \epsilon_{it}$. β_0 measures the mean efficiency level across firms over time and ϵ_{it} represents the time and producer specific deviation from that mean.

Estimating the previous equation by standard OLS (Ordinary Least Squares) procedure, a parametric approach, incurs in several biases. Van Beveren (2012) highlighted all the issues related to the estimation of production functions by standard methods, pointing to concerns regarding selection bias, simultaneity bias, omitted input/output price bias, and multi-product firms' bias.

[19] We follow the Bank of Portugal definition and consider a firm as 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 is due to exports and its value overpasses 150 000€.

[20] An overview of nonparametric approaches can be found in Schreyer and Pilat (2001). Briefly, as discussed in Førsund et al. (1980) and Murillo-Zamorano and Vega-Cervera (2001), these methods have some disadvantages, such as its deterministic nature and the assumption of constant returns to scale.

Usually, the estimation of production functions was performed under a balanced panel, omitting firms that enter and exit over the sample period (Olley and Pakes, 1992). But the probability of a firm exiting the market is highly influenced by its productivity levels, incurring thus in a **selection bias** by the omission of those firms (Jovanovic and Nyarko, 1996). Also, even if an unbalanced panel is considered, not accounting for the exit decision of firms will incur in selection bias and negative bias on the capital coefficient (Ackerberg et al., 2015), as firms with a higher capital stock are more likely to survive when facing inferior productivity levels.

Standard OLS assumptions require the endogeneity of inputs to get unbiased coefficients. In reality, the choice of inputs is partly determined by firms' individual choices (Griliches and Mairesse, 1995). Positive productivity shocks result in an increase of inputs used (De Loecker, 2007). Thus **simultaneity bias** is a concern in standard estimation.

Lastly, **Omitted output/input price bias** results from the correlation of inputs and price deflators (both input and output). Also, **multi-product firms bias** occurs when firms produces multiple products with different demands and production techniques, resulting in bias estimates of TFP.

Figure 3 summarizes methodological biases when estimating production functions. For a more detailed explanation of each issue, see Van Beveren (2012).

Figure 3: **Summary of methodological issues on TFP estimation**

Origin of the bias	Definition	Direction of the bias	References
Selection bias	Endogeneity of attrition: Correlation between ε_{it} and K_{it} (the quasi-fixed input), conditional on being in the data set.	downward bias in β_k	Wedervang (1965) Olley and Pakes (1996) ABBP (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 and Andrews (1944) Olley and Pakes (1996) Levinsohn and Petrin (2003) ABBP (2007) Ackerberg et al. (2006)
Omitted output price bias	Imperfect competition in output markets: Correlation between firm-level deviation of output price deflator $(p_{it} - \overline{p}_{it})$ and inputs x_{it}.	downward bias in β_l downward bias in β_m upward bias in β_k	Klette and Griliches (1996) Levinsohn and Melitz (2002) De Loecker (2007)
Omitted input price bias	Imperfect competition in input markets: Correlation between firm-level deviation of input price deflators $\left(p_{it}^{k,m} - \overline{p}_{it}^{k,m}\right)$ and inputs x_{it}.	downward bias in β_l downward bias in β_m upward bias in β_k	Levinsohn and Melitz (2002) Katayama et al. (2005) De Loecker (2007)
Multi-product firms	Endogenous product choice: Differences in production technologies across products produced by single firm.	undetermined	Bernard, Redding, Schott (2005) Bernard, Redding, Schott (2006b) De Loecker (2007)

Source: Van Beveren (2012)

4.1.1. Alternatives to OLS estimation

Several classical methods to tackle endogeneity can be applied, being the most famous using an IV (Instrumental Variable) or FE (Fixed Effects) estimation. Van Beveren (2012) questions the applicability of these methods to the production function case. Finding a valid IV is a hard task by itself, i.e. correlated with the endogenous variable and not correlated with the error term. For such cases, using input prices (or variables that shift the demand for output or the supply of inputs) as an IV is a common choice (Ackerberg et al., 2007). Van Beveren (2012) states that using such IV is not appropriate. First, these prices are usually not reported by firms. Also, if the firm has some market power, input prices turn out to be invalid instruments, as firms will set prices partially based on input quantities and their productivity. Finally, the IV approach assumes that productivity evolves exogenously over time. A more detailed explanation of the problematic usage of IV in these situations can be found in Ackerberg et al. (2015).

FE estimation is a common way to overcome simultaneity bias (Ackerberg et al., 2007). Despite its popularity, FE assumes unobserved productivity has a time-invariant nature (Van Beveren, 2012), which can be a strong assumption.[21] Also, as noted by Wooldridge (2009), FE requires strict exogeneity of inputs conditional on firms' heterogeneity, which, in practice, is likely to not be verified.

4.2. Semi-Parametric Estimation

The Semi-parametric approach presents a new take on the parametric and corrects for some of its biases. It is as well the most widely used on recent literature, in particular the Olley and Pakes (1992) (OP) and the Levinsohn and Petrin (2003) (LP) methodologies. This section provides a brief description of the LP method, as well as detailing the choice of proxies for the chosen variables and some descriptive statistics. Taking a look to Olley and Pakes (1992) and Levinsohn and Petrin (2003) is highly desirable for a deeper understanding of both methodologies.

Both algorithms are very similar on its two-step procedure to compute TFP. The main difference between both estimators consists on the proxy chosen for unobserved productivity, as OP uses investment for the purpose, while LP uses intermediate inputs.[22] The OP method requires that investment is strictly increasing in productivity, as only firms with positive investment can be considered. This can result in a considerable selection bias and loss of efficiency. On the other hand, firms usually report positive values for materials and energy, as the LP method enables to retain most observations in the sample, and so not suffering from the truncation bias induced by the OP estimator. As such, the choice between both highly depends on the information of the dataset. An advantage of OP over LP is that it allows for an unbalanced panel and the incorporation of a survival probability in the second stage of the estimation. As our dataset does not provide enough quality information to construct a good investment proxy, we opted for the LP algorithm. As a consequence, a considerable number of observations are preserved.

[21] Details in section 4.2

[22] Endogeneity is incorporated into the production function equation through an investment function

4.2.1. The Levinsohn-Petrin Algorithm

The LP methodology proposed by Levinsohn and Petrin (2003) starts by considering that the error term in equation 2 can be decomposed into an observable and unobservable component, resulting in the following equation:

$$Y_{it} = \beta_0 + \beta_K K_{it} + \beta_L L_{it} + \beta_M M_{it} + \omega_{it} + \eta_{it} \tag{3}$$

where ω_{it} represents the transmitted productivity component and η_{it} is an error term which is uncorrelated with the production function inputs. 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). ω_{it} corresponds to a state variable in the firms' decision problem. Levinsohn and Petrin (2003) specify the demand for intermediate input M_{it} as a function of the state variables K_{it} and ω_{it}:

$$M_{it} = M_{it}(K_{it}, \omega_{it}) \tag{4}$$

Where M_{it} is assumed to be monotonically increasing in ω_{it}. With this assumption a proxy for unobserved productivity can be obtained by inverting the intermediate input demand function:

$$\omega_{it} = \omega_{it}(K_{it}, M_{it}) \tag{5}$$

With this expression, one obtains the unobservable productivity expressed as a function of two observed inputs. In regards to the transmitted productivity component, Levinsohn and Petrin (2003) assume that it results in a first order Markov process:

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

where ε_{it} represents an innovation to productivity which is uncorrelated with L_{it}, but not necessarily with $L_{i,t}$

As a measure of output, we opted to use turnover as a proxy. A possible alternative would be to use value added and omit the materials component in the production function. As argued by Basu and Fernald (1997), this approach yields biased estimates when in the presence of imperfect competitive markets. As assuming perfect competition among Portuguese firms is an extremely strong assumption, we opted to use turnover instead. As for the input variables, we used Fixed Tangible assets to proxy Capital, the number of hours worked to proxy Labor and, lastly, the sum of Cost of Goods Sold and External Services to proxy intermediate inputs. Table 1 presents descriptive statistics on the variables included in the production function, for the knowledge based sector

Table 1. **Production function variables summary statistics**

	count	mean	sd	min	max
Turnover (Y)	526 942	622 056	14 000 000	.01	9 630 000 000
Labor (L)	522 426	14 263	190 518	1	30 700 000
Capital (K)	526 942	259 286	13 400 000	.01	2 960 000 000
Intermediate Goods (M)	526 942	377 045	8 176 305	.01	1 280 000 000

Source: authors computations

4.3. Comparing different methods

For a deeper analysis, we estimate the production function represented in equation 1 for knowledge based firms from three different approaches: Ordinary Least Squares (OLS), Fixed Effects estimation and the LP algorithm. Results are visible in table 2.

Table 2. **Production function estimation**

	LP	OLS	FE
Labor (L)	0.220***	0.222***	0.189***
	(0.00203)	(0.00272)	(0.00282)
Capital (K)	0.0264***	0.0332***	0.0201***
	(0.000897)	(0.000989)	(0.000907)
Intermediate Goods (M)	0.753***	0.777***	0.743***
	(0.00287)	(0.00179)	(0.00292)
Observations	522481	522481	522481

Standard errors in parentheses
Source: authors computations based on IES database
Variables in logs
For Knowledge Based firms
* $p < .1$, ** $p < .05$, *** $p < .01$

Going back to Van Beveren (2012) approach on the expected coefficients biases (recall Figure 3), we observe that most of our results are in line with the literature. The FE methodology is expected to correct for the simultaneity and selection bias. As such, one would expect that the coefficient for materials and labor would be lower when using the Levpet method than in the OLS case, whereas the coefficient on capital would be higher. Our estimation demonstrates that all three coefficients are lower in the FE example, contradicting the literature for the β_K coefficient. As for the LP method, the output shows that all the estimates have higher values than the ones computed by FE, but lower than the OLS example. This suggests that, for the capital component, the upward bias provoked by Omitted input and output price overcomes the downward bias motivated by selection and simultaneity bias (theoretically nonexistent in the FE estimator). The opposite occurs for Materials and Labor, the simultaneity bias appears to exceed the omitted price forces as both coefficients are positively biased with standard OLS estimation. Finally, we appear to reach the same conclusions as in Levinsohn and Petrin (2003) regarding the sum of elasticities, being it higher with OLS, followed by LP and FE. For robustness purposes we used alternative measures to proxy labor and materials in the production functions, as visible in tables 3, 4 and 5 in the appendix. Despite a difference in the coefficients, the main conclusions are not altered. Similar results, except for the capital component, were obtained by Gonçalves et al. (2016) for the manufacturing sector, and by Martins et al. (2018) for the services sector.

Firm level TFP is thus estimated by the LP methodology, computed for each CAE-2D to control for the heterogeneity among firms in the sample. Figure 17 in the appendix illustrate a graphical analysis on TFP estimates for each year of the sample for both the knowledge and non knowledge based group. Firms included in the quarternary sector increased their productivity, on average, over the years, even during the periods of the financial and sovereign debt crisis; while the remainder suffered from a slowdown on productivity during these periods. Moreover, the knowledge based sectors proves to be the sector with the highest level of productivity, followed by the manufacturing industry.

5. Model Estimation

5.1. Second stage regression and its Methodological Issues

Having extracted TFP at the firm level, the next stage consists on regressing these estimates, in logarithm, on several determinants pointed in the literature as being explanatory of productivity. Given this, there are some methodological issues one should be aware when pursuing this estimation. Wang and Schmidt (2002) warns that if the omitted variable bias problem in the first stage is not solved, second stage coefficients will be inefficient and downward-biased.

Following Harris et al. (2005) we first estimate the production function and secondly use its residual as being TFP. Considering X as a vector for observed variables for the determination of the TFP values, we hold the following equation:

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

We follow Harris and Moffat (2015) and estimate equation 7 without accounting for X and include it in ε_{it}. 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 estimates TFP as dependent variable.

5.2. Determinants regression

Our model consists of a fixed effects estimation aimed at explaining the within variation of the data, this is, over-time variation for each individual (firm, in this case); rather than inner-firms characteristics invariant over time. We include group specific characteristics expected to be correlated with the covariates. Determinants were chosen on the base of the literature provided and on the available dataset. Time effects were considered by the inclusion of year dummies, capturing this way the impact of trends, macro shocks or other time variant factors that might be correlated with the regressors. Given that our time range spans the period of the financial crisis, these variables are expected to be fundamental to avoid omitted variable bias. Non-linear impacts of the determinants were considered and all relevant significance tests can be consulted in Figure 18.

Descriptive statistics on the model variable's can be found in tables 6 and 7. We divide our analysis on the explanatory variables according to four different categories of determinants of TFP:

- **Internal Firm Characteristics:** Size and Age;
- **Innovation and Skilled labor:** Innovation and Wage Premium;
- **Financial Indicators:** Indebtedness Ratio;
- **Trade Openness:** Exporter Status;

As such, our final model can be expressed as:

$$\begin{aligned} \textbf{lnTFP}_{it} = \beta_0 + \beta_1 Innovation_{it} + \beta_2 Age_{it} + \beta_3 Size_{it} + \beta_4 ExporterStatus_{it} + \\ \beta_5 WagePremium_{it} + \beta_6 Indebtedness_{it} + \delta_t Year_t + \varepsilon_{it} \end{aligned} \tag{8}$$

5.3. Regression results

This section describes and discusses the main results of the model. Should be noted that comparisons of our results to the ones obtained in the literature is limited due to differences in the dataset; mainly on what regards the time span (that includes different economic shocks), the difference in firms (Portuguese firms do not necessarily behave like others), different variables (not all proxies behave nor reflect the determinants in the same way), the data treatment and even the TFP estimation. Contrast with other research studies has no means to contradict or refute the respective authors, but simply establish a parallel between the results.

Figure 4: **Estimated Model**

Variable		Coefficient	Std. Error	P - Value		Description
Year	2 - 2007	0.00139	0.00048	0.007	***	Dummy Variable
	3 - 2008	0.00163	0.00067	0.019	**	
	4 - 2009	0.0002	0.00113	0.86		Reference group is 2006
	5 - 2010	0.00081	0.0016	0.61		
	6 - 2011	-0.0027	0.00131	0.049	**	
	7 - 2012	-0.006	0.0013	0.00	***	
	8 - 2013	-0.0072	0.00177	0.00	***	
	9 - 2014	-0.0066	0.00158	0.00	***	
	10 - 2015	0.0049	0.00123	0.00	***	
	11 - 2016	-0.0027	0.00067	0.00	***	
	12 - 2017	0	(ommited)			
Size	2 - Small	0.02899	0.00788	0.001	***	Dummy Variable
	3 - Medium	0.0386447	0.019621	0.057	*	
	4 - Large	0.0275823	0.03067	0.37		Reference group is Micro firms
Age		0.0026734	0.0005	0.00	***	Company's Age
Age^2		-0.0000582	1.66E-05	0.002		
Innovation		0.0026	8.60E-04	0.005	***	Dummy Variable 1 - Firm has Fixed intangible Assets/Total Assets different from zero 0 - Otherwise
Wage Premia		0.0058313	0.002553	0.029	**	Ratio between average wages (personal expenses/number of hours worked) and the average mean wages (mean of thr average wage per industry).
Debt - Assets ratio		-5.66E-09	3.49E-10	0.00	***	Liabilities over Total Assets
Exporter Status		0.00311	0.0019	0.106	*	Dummy Variable 1 - Firm has Exporter Status 0 - Otherwise

Number of Observation	516 684
Numver of Firms	92 117
corr(Ui, Xb)	0.0607
R^2	0.9893

Std Errors adjusted for 30 clusters in CAE 2 digits
Controlled for heteroskedasticity and serial correlation with cluster robust standard errors
* ** *** Significance at 10%, 5% and 1% respectively
R^2 computed with STATA command areg, followed with absorb (CAE 2 digits)

Source: authors computations based on IES database

Figure 4 shows the final model estimates. For a comparison purpose, the same model was estimated for the Manufacturing and Services sector.[23] Table 8 in the appendix provides a summary of the coefficients for all sectors. Looking to the results, one can notice that, in general, the coefficients for the knowledge based sector demonstrate much higher levels of statistical significance when compared to the other sectors, both on the specified variables and on the yearly dummies. Such a result is particularly interesting when recalling the definition of Total Factor Productivity: the share of output that is not explained by the combination of inputs, namely capital, and labor. Considering the dependence that the manufacturing and, to a lesser extent, services have on the physical amount of capital and labor when compared to quaternary activities, is would be predictable that the TFP determinants were much more significant in the case of the knowledge based sector. The remainder of this section performs an in depth analysis of each determinants group.

[23]The Agriculture sector was disregarded, as it is common on TFP literature.

5.3.1. Internal Firm Characteristics

As pointed in the literature; in section 2.2, the internal characteristics of a firm can contribute to their productivity standards. To account for this fact, we include two different components in th regression: age and size.

On what regards firms **age**, we conclude on a non-linear effect of age on firms' TFP. This result is not surprising given the amount of authors arguing in favor of such conclusion. As stated by Brouwer et al. (2005) and Fernandes (2006), firms enter the market with low productivity levels, when compared to the remainder firms. Afterwards, over the years, surviving young firms gain experience, investing and taking advantage of economies of scale and learn-by-doing effects (Jovanovic and Nyarko, 1996), increasing their productivity until a maximum point, where technology gets outdated and the impact of age on TFP becomes negative over time. This reasoning goes in line with our results, that suggest an inverse U shaped relationship between age and TFP, getting its maximum return at 23 years of existence, in line with Martins et al. (2018) conclusions for the service sector. When comparing to the remaining sectors of activity, we observe that the knowledge based sector diverges from the manufacturing industry, where productivity does not respond non-linearly to age; but it is similar to the services sector, following the same inverse U shape form, but reaching its maximum return 7 years earlier (30 years for the services sector).

Another internal characteristic of firms' that is analyzed on productivity literature is **size**. As already stated, we rely on the Eurostat criteria to classify firms regarding their size.[24] As such, having micro firms as a reference group, we include in the regression three dummy variables, taking the value of 1 if the company corresponds to a small, medium and large firm, respectively, and zero otherwise. From the literature, we know that the impact of size on TFP is ambiguous, with several different conclusions being reached. Our output points to statistically significant increases in productivity from being a small and medium firm (when compared to a micro firm), as opposed to large firms, who do not exhibit a significant value. Being a small firm increases TFP, on average, 2.89% while being a medium firm increases 3.86%, ceteris paribus, in comparison to micro firms. This result is partially in line with Tornatzky et al. (1990), who states that smaller firms have leaner organizational structures and as such, tend to be more productive. It diverges, however, from Martins et al. (2018) conclusions for the services sector, as the authors only find gains from being a large firm, when compared to micro firms. In fact, our results for the services sector suggest that there are no statistically significant gains from increasing the size of a micro firm. This paradigm changes when observing the behavior of manufacturing firms, where TFP gains are higher as the size of the firm increases, in line with Satpathy et al. (2017) findings for the Indian manufacturing industry. All in all, medium knowledge based firms are the ones with more TFP gains when compared to the reference group, in contrast to the remaining sectors.

[24] Recall section 3.1

5.3.2. Innovation and Skilled Labor

Knowledge and **innovation** are considered as the main drivers of TFP growth in the literature, as they are included in most TFP studies. Furthermore, as stated in section 2.2, several endogenous TFP macroeconomic models already include measures of innovation as inputs for productivity (Moran and Queralto, 2018).The best proxies for Innovation and the stock of knowledge have been highly debated in the literature, being patent counts and R&D the most common variables used. Ideally, we would employ R&D expenses as a proxy for innovation, however, our dataset lacks information concerning investment on R&D. As such, we use the share of fixed intangible assets over total fixed assets as a measure of innovation, as we consider it to properly represent a firms' capacity to innovate and its intellectual property.[25] As approximately 80% of our observations have no intangible assets, we consider a dummy variable that takes the value of 1 if the ratio Fixed Intangible Assets/Total Assets is different from zero, and zero otherwise. As expected, the coefficient for knowledge based firms on innovation is positive and statistically significant, similarly to most productivity studies. The coefficient itself, however, is particularly small when compared to the remainder studies in the literature, such as Martins et al. (2018) and mainly Gonçalves et al. (2016), as the latter use a similar proxy. A reasonable explanation for this fact is that firms on the knowledge based sector already have higher standards of innovation and technology when compared to the remaining sectors. As such, the marginal gain of an increase in innovation appears not to be as large as on the remainder sectors.[26] Our results are in line with Greenhalgh and Longland (2005), who found a positive impact of patent counts and trademarks (both components of intangible assets) on TFP.

One of the biggest downsides of our database is that it does not include qualitative information on employees, i.e educational level, years of experience etc... The **quality of labor** and/or human capital is pointed out in the literature as an important TFP driver, mainly on what regards the managing to operate sophisticated technology and knowledge application. It is, thus, a complement to innovation. We follow Martins et al. (2018) approach and proxy skilled labor as the Wage Premia: the ratio between personal expenses per hour worked over the mean of the average wage per hour per industry. As proposed by Gehringer et al. (2013), more efficient employees are paid higher wages, as they are more productive; as well as industries that pay higher salaries will achieve higher TFP levels. As expected, the coefficient for this variable is positive and statistically significant, meaning that skilled labor, proxied by the wage premia, contributes positively to the firm's productivity levels. An increase in the wage premia ratio increases TFP in 0.0058%, on average ceteris paribus. Such reasoning does not apply to the remaining sectors, where there is no statistical significance that this ratio implies an increase in TFP, suggesting that workers from the manufacturing and services industry do not react by increasing productivity when faced with a wage raise.

[25] We purposely do not include fixed intangible assets in the production function, as we include them as a determinant in the second stage regression, this way avoiding bias on its coefficient

[26] Note that the coefficients for the manufacturing and services industry are not statistically significant, as opposed to Gonçalves et al. (2016) and Martins et al. (2018). As already referred, a direct comparison is not always linear, as the proxies used are different as well as the data treatment, time span, etc...

5.3.3. Financial Indicators

The **financial structure** of a firm is considered to be an important driver of its productivity levels. However, the literature on this topic is not clear, as several different conclusions are undertaken for different countries and sectors. Jensen (1986) argues that leverage contributes positively to TFP, as managers respond positively to financial pressure, and become more productive under higher probabilities of bankruptcy caused by high debt levels. Other authors, such as Nucci et al. (2005) and Coricelli et al. (2009), argue that there is a turning point on the benefits from leverage, up to where firms can be more productive if they become more indebted. As for a financial indicator that could capture these effects, we opted for the Debt-Assets ratio, the ratio between total liabilities and total assets, which measures the proportion of a company's assets which are financed through debt. Our results illustrate that the coefficient for this variable is statistically significant and positive, but considerably small. As such, knowledge based firms decrease their TFP levels when raising their debt standards.[27] An interesting feature of our results is that this coefficient is statistically significant and with an opposite sign for the remaining sectors, although with small coefficients as in the previous case. As such, for firms in the manufacturing and services sectors, increasing their debt leads to a rise in TFP, on average ceteris paribus. As suggested by Nucci et al. (2005), most productive firms, with higher TFP levels, are likely to generate higher profits and cash flows and thus rely less on debt to finance their projects and overall activity. As shown in figure 19 in the appendix, knowledge based firms are the most productive ones among all sectors; as accordingly to the previous reasoning, they do not benefit in terms of productivity from raising debt, as they can easily sustain their activity through their own funds.

5.3.4. Trade Openness

Lastly, **international openness** is approached in the literature as a strong factor contributing to productivity at the firm level, as it is seen as a measure of technological transfer and exchange of knowledge (Coe and Helpman, 1995). As such, we include a variable in the model to measure whether firms opened to the international market have productivity gains when compared to the remainder. We use a dummy variable that classifies firms according to their exporter status. As defined by the Bank of Portugal, 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 is due to exports and its value overpasses 150 000€. Results go in line with most of the literature, as our output points to a positive effect of being an exporter on productivity, in line with Banco de Portugal (2019). On average, knowledge based firms who have exporter status are 0.33% more productive than the remainder. Results are in line with Gonçalves et al. (2016) findings for the manufacturing sector. In fact, our output shows a similar coefficient for that same sector, while no statistical significance is obtained for the services sector. Manufacturing firms appear to have more gains from becoming exporters than knowledge based firms. As already referred, quaternary firms have higher TFP levels compared to the remainder

[27] When we refer to increasing debt levels, it is compared to the amount of equity used to finance the existing assets; as the ratio itself suggests.

firms, as opening to the foreign market appears to not induce as in many gains as in less productive firms.

5.4. Robustness Checks

Several robustness checks were performed to ensure the validity of the model. Following Hausman (1978) we have performed a Hausman test to guarantee that the choice for fixed effects estimation was the most appropriate.[28] Results show that, for all sectors, individual effects appear to be correlated with the explanatory variables, meaning that random effects (RE) would yield biased coefficient estimates. Furthermore, a variance covariance matrix of all the regressors is available in figure 21. The independent variables turn out to have a low correlation between them, proving that standard errors of our model are not underestimated, and we can trust on the t-statistics for significance purposes. Following Wooldridge (2009) we have considered cluster robust standards errors, grouping firms at each CAE-2 digit, as we believe heterogeneity is present amount each CAE. We thus correct for serial correlation and heteroskedasticity, reinforcing the validity of statistical inference. Serial correlation is not expected to be a major concern in this model, as argued in Wooldridge (2009), within estimators provides consistency in the presence of large datasets with a small number of periods. Finally, as already mentioned, when estimating the TFP equation, several alternative variables are used as inputs. The main conclusions were unaltered.

6. Discussion and Final Remarks

In light of the productivity slowdown observed on advanced economies in the recent decades, and of the likely upcoming structural changes on the labor market due to job computerization, this paper focused on analyzing the determinants of TFP for the knowledge based or quaternary sector of the Portuguese economy. As such, two important contributions to the literature were pursued.

First, we have built a precise definition of knowledge based activities, mostly based on Hawksworth et al. (2018), Manyika et al. (2018) and Frey and Osborne (2017) verdicts on the future of the job market. We thus conclude on a group of activities; which constitute a fraction of the services sector, grouped according to CAE codes; that is said to differ from the remainder in several aspects, mainly on what regards the amount of skilled labor and stock of knowledge employed. In line with the literature, descriptive statistics of our database illustrate that the knowledge based sector, compared to the remaining sectors, has a lower amount of capital per worker, higher wages, higher share of GVA and younger firms.

Secondly, having estimated TFP at the firm level using the Levinsohn and Petrin (2003)'s methodology, we regress TFP on several determinants said to impact productivity in the literature. We find that innovation, international openness, and wage premia influence positively the level of TFP, in line with the literature for the manufacturing and services sector. The indebtedness ratio impacts

[28] See figure 20

negatively knowledge based firms' productivity, contrary to the remainder sectors of economic activity. Furthermore, internal firm characteristics show a non linear relationship with TFP. For age, knowledge based firms exhibit an inverse U shaped curve, similarly to the services sector and in opposition to manufacturing, who does not provide statistical evidence of such a relation. On what regards size, our results show that quaternary activities have gains from increasing their size up to medium firms, with no evidence for large firms. Once again, this result diverges from the other sectors. All these conclusion enforce the fact that the knowledge based sector is sufficiently different from the remainder and deserves a separate analysis when studying the behavior of the economy.

The present study contributes to several literature that focuses on studying the determinants of TFP at the firm level, with the distinctiveness of doing so for a sector which, to the best of our knowledge, has not been subject to such an analysis. Our motivation is not only based on the study of productivity, but also on exploring and analyzing a sector that is said to promote structural changes on the labor market and is a primary contributor to technological developments - one of the prime long run growth drivers.

This papers points to a wide fruitful line of future research. A deeper study and characterization of the quaternary sector is highly recommendable. Under the possibility of exploring a richer firm level dataset, a possible contribution would be to explore more differences between sectors, for instance, regarding workers qualifications. Furthermore, extending the analysis to other countries would be desirable, in order to analyze whether the knowledge based sector prevails in big economies, such as the U.S or the Euro Area as a whole.

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8. Appendix

Figure 5: **Number of Firms for each year and CAE-L**

	Year												
CAEL	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
A	5,486	5,271	5,493	5,566	5,722	5,975	6,256	6,899	7,529	8,106	8,592	8,909	79,804
B	689	652	645	620	612	585	555	521	497	490	475	451	6,792
C	32,816	32,112	31,544	30,342	29,104	28,448	27,412	27,123	27,215	27,467	27,576	27,205	348,364
D	273	149	158	172	186	203	199	200	199	213	222	213	2,387
E	443	443	480	506	495	517	525	537	521	501	508	504	5,980
F	31,771	31,046	30,427	28,701	26,826	25,067	22,127	20,494	19,880	19,983	20,348	20,944	297,614
G	71,953	70,304	69,630	67,601	64,979	63,299	60,653	59,828	59,301	59,285	58,959	57,849	763,641
H	15,343	15,113	14,931	14,454	13,885	13,406	12,545	11,970	11,594	11,519	11,490	11,584	157,834
I	22,888	22,909	23,152	22,984	22,311	22,397	21,676	21,725	21,852	22,185	22,641	22,897	269,617
J	4,377	4,333	4,522	4,558	4,593	4,720	4,684	4,812	4,941	5,092	5,207	5,287	57,126
L	8,809	7,545	7,553	7,160	6,837	6,360	5,831	5,769	5,961	6,382	7,098	7,961	83,266
M	19,979	19,748	20,863	21,329	21,201	21,441	20,941	20,806	20,835	21,214	21,409	21,685	251,451
N	7,192	7,307	7,473	7,306	7,011	6,981	6,655	6,645	6,755	6,880	7,130	7,267	84,602
O	3	2	2	2	2	2	4	3	2	2	2	.	26
P	3,199	3,242	3,366	3,381	3,307	3,336	3,250	3,222	3,274	3,284	3,251	3,175	39,287
Q	10,802	10,586	11,206	11,617	11,962	12,701	12,943	13,333	13,406	13,587	13,731	13,817	149,691
R	2,108	2,075	2,219	2,373	2,393	2,400	2,332	2,428	2,590	2,795	3,052	3,335	30,100
S	5,617	5,857	6,066	6,168	6,035	6,047	5,639	5,523	5,471	5,438	5,468	5,405	68,734
Total	243,748	238,694	239,730	234,840	227,461	223,885	214,227	211,838	211,823	214,423	217,159	218,488	2696316

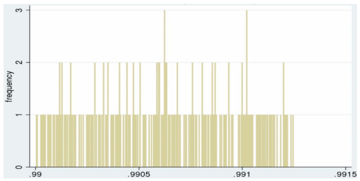
Source: authors computations based on IES database

Figure 6: **Number of Firms for each year and district**

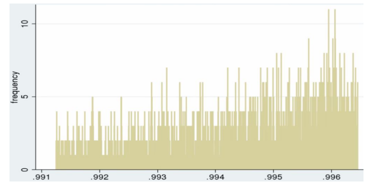
	Year												
District	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
Angra do Heroísmo	721	751	783	803	784	792	782	782	785	779	771	788	9,321
Aveiro	16,511	16,249	16,199	15,898	15,509	15,494	14,930	14,845	14,932	15,162	15,413	15,253	186,395
Beja	2,259	2,247	2,311	2,344	2,304	2,318	2,205	2,256	2,350	2,409	2,447	2,492	27,942
Braga	18,925	18,788	18,878	18,613	18,340	18,482	18,138	18,476	18,895	19,359	19,773	19,984	226,651
Bragança	2,033	2,012	2,096	2,116	2,120	2,161	2,140	2,149	2,182	2,188	2,244	2,205	25,646
Castelo Branco	3,612	3,520	3,553	3,464	3,363	3,364	3,252	3,214	3,215	3,264	3,293	3,278	40,392
Coimbra	8,930	8,772	8,840	8,665	8,466	8,357	8,038	7,874	7,903	8,025	8,010	7,954	99,834
Évora	3,389	3,283	3,328	3,299	3,187	3,165	3,080	3,057	3,100	3,199	3,230	3,228	38,545
Faro	10,989	11,139	11,421	11,113	10,521	10,170	9,611	9,425	9,539	9,799	10,125	10,417	124,269
Funchal	5,737	5,474	5,497	5,316	5,008	4,816	4,575	4,395	4,269	4,299	4,341	4,425	58,152
Guarda	2,790	2,731	2,762	2,724	2,694	2,705	2,631	2,643	2,629	2,657	2,685	2,663	32,314
Horta	334	348	358	376	378	387	401	422	439	470	498	529	4,940
Leiria	13,637	13,350	13,129	12,794	12,293	12,047	11,407	11,351	11,373	11,568	11,723	11,791	146,463
Lisboa	67,840	65,251	65,121	63,386	60,673	58,960	55,670	54,262	53,524	53,460	53,666	54,000	705,813
Ponta Delgada	1,619	1,598	1,671	1,696	1,649	1,645	1,609	1,620	1,670	1,712	1,727	1,769	19,985
Portalegre	1,972	1,943	1,982	1,928	1,940	1,970	1,924	1,913	1,918	1,920	1,947	1,913	23,270
Porto	43,055	42,376	42,714	41,945	40,888	40,440	38,929	38,869	38,950	39,622	40,227	40,545	488,560
Santarém	10,055	9,846	9,799	9,563	9,343	9,106	8,626	8,383	8,360	8,400	8,425	8,375	108,281
Setúbal	15,244	14,971	14,966	14,535	13,890	13,422	12,497	12,130	11,978	12,046	12,255	12,357	160,291
Viana do Castelo	4,258	4,274	4,398	4,374	4,274	4,246	4,133	4,162	4,216	4,292	4,386	4,465	51,478
Vila Real	3,087	3,102	3,187	3,186	3,210	3,165	3,123	3,113	3,076	3,152	3,205	3,262	37,868
Viseu	6,698	6,618	6,727	6,683	6,602	6,643	6,484	6,463	6,519	6,641	6,768	6,795	79,641
Total	243,695	238,643	239,720	234,821	227,436	223,855	214,185	211,804	211,822	214,423	217,159	218,488	2696051

Source: authors computations based on IES database

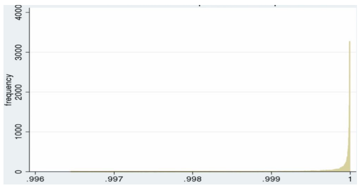
Figure 7: **Distribution of Current Assets/(Equity + Liabilities)**



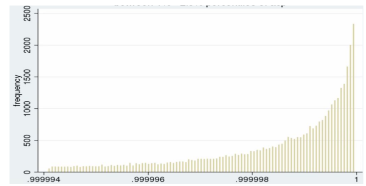
(a) **Below 0.01% percentile**



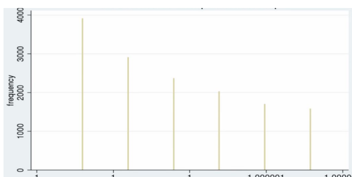
(b) **Between 0.01% and 0.1% percentiles**



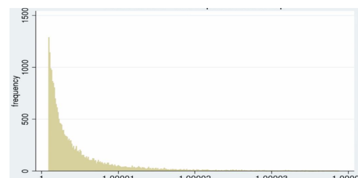
(c) **Between 0.1% and 1% percentiles**



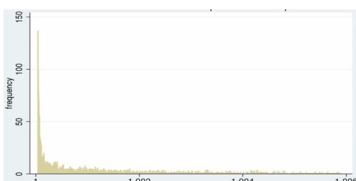
(d) **Between 1% and 2.5% percentiles**



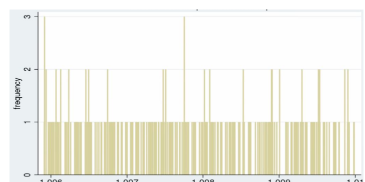
(e) **Between 97.5% and 99% percentiles**



(f) **Between 99% and 99.9% percentiles**

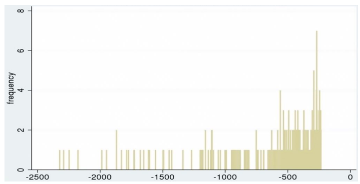


(g) **Between 99.9% and 99.99% percentiles**

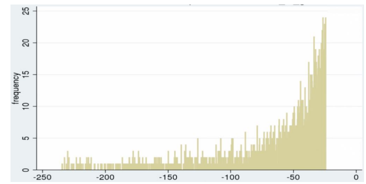


(h) **Above 99.99% percentile**

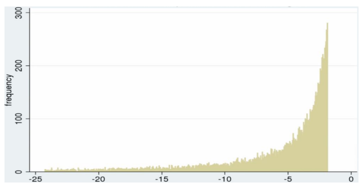
Figure 8: **Distribution of the share of GVA**



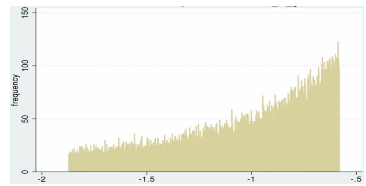
(a) **Below 0.01% percentile**



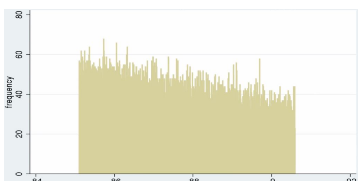
(b) **Between 0.01% and 0.1% percentiles**



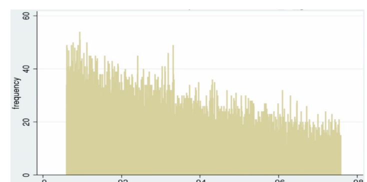
(c) **Between 0.1% and 1% percentiles**



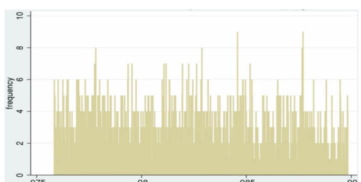
(d) **Between 1% and 2.5% percentiles**



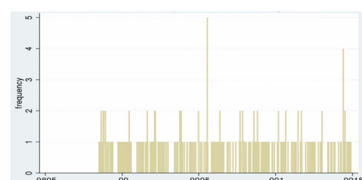
(e) **Between 97.5% and 99% percentiles**



(f) **Between 99% and 99.9% percentiles**



(g) **Between 99.9% and 99.99% percentiles**

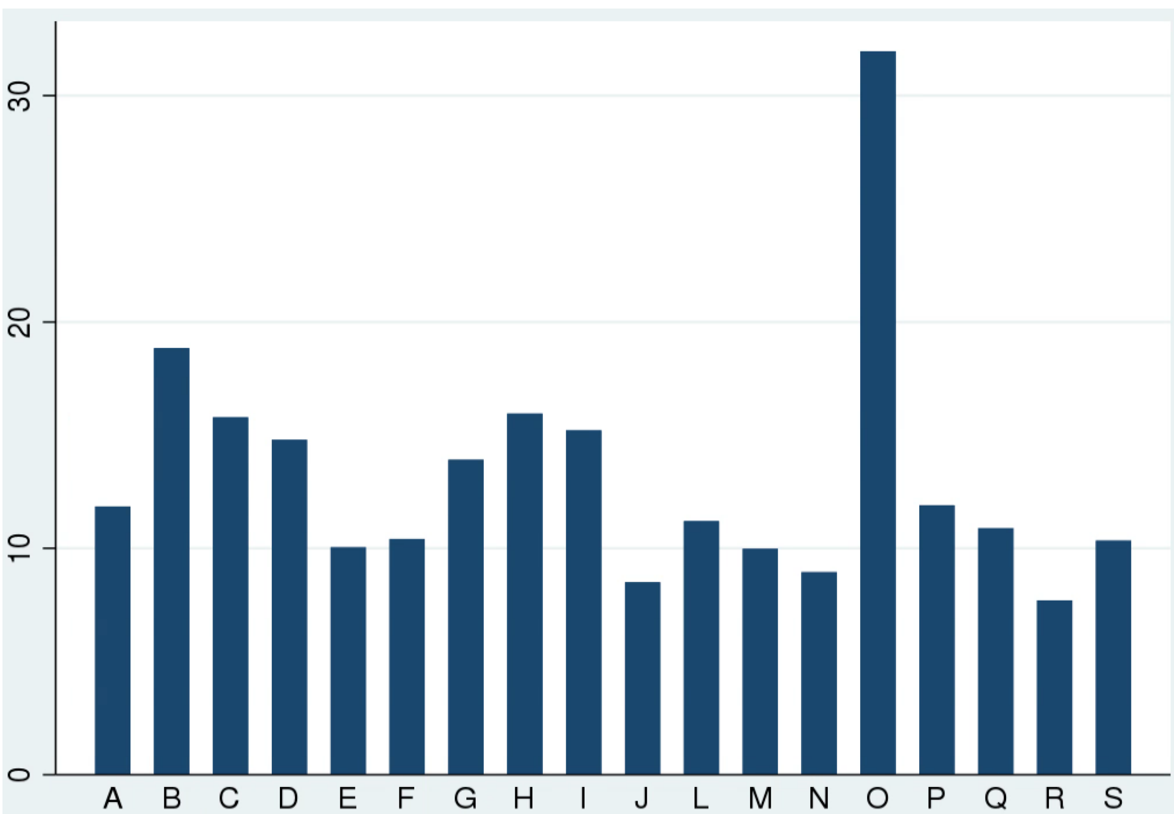


(h) **Above 99.99% percentile**

Figure 9: **List of CAE codes used on the Knowledge Based Sector**

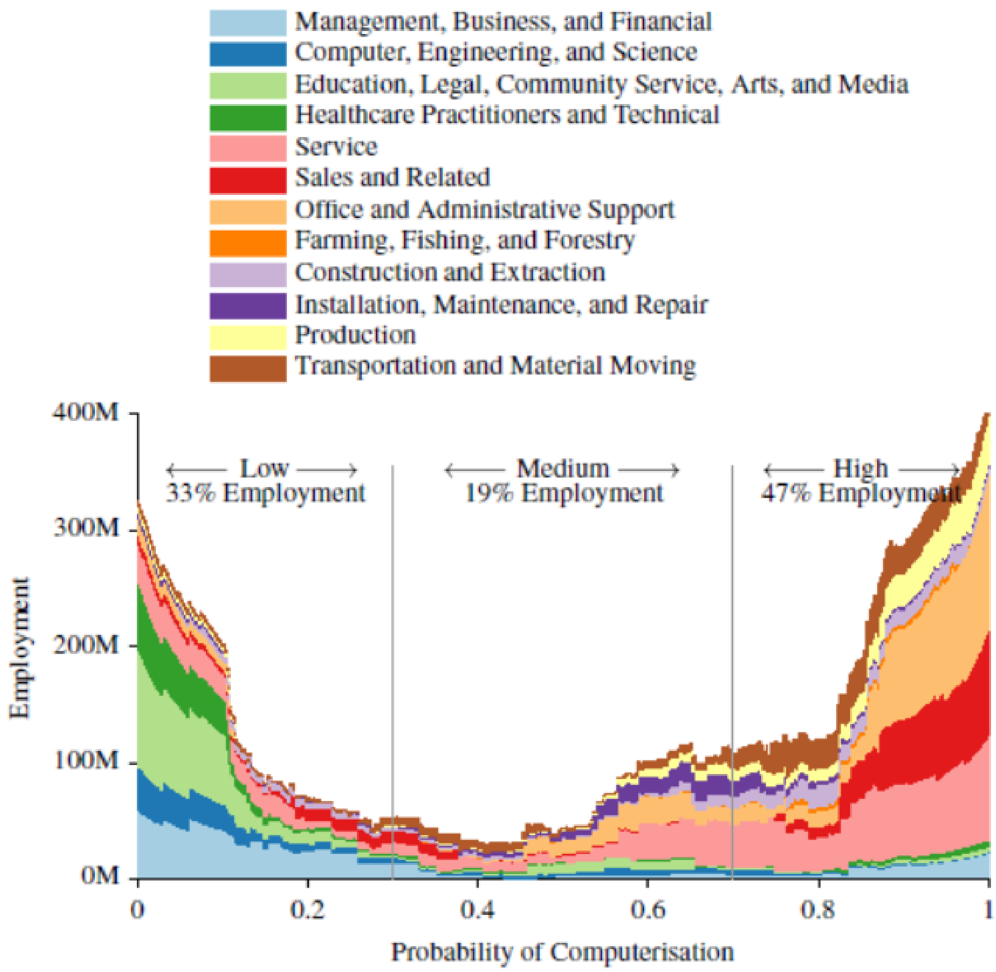
CAE-L	Description	CAE-3 Digits included
J	Information and Communication	All CAE-3d included
K	Financial and Insurance Activities	All CAE-3d included
M	Professional, Scientific and Technical Activities	691, 701, 702, 711, 712, 721, 722, 731, 732, 741, 742, 743, 743, 749, 750.
N	Administrative and Support Service Activities	774, 781, 782, 783, 891, 799, 803, 823.
O	Public Administration and Defence, Compulsory Social Security	All CAE-3d included
P	Education	All CAE-3d included
Q	Human Health and Social Work Activities	All CAE-3d included
R	Arts, entertainment and Recreation	All CAE-3d included
S	Other Services Activities	941, 942, 949
U	Activities of Extraterritorial Organisations and Bodies	All CAE-3d included

Figure 10: **Average firm age per sector**



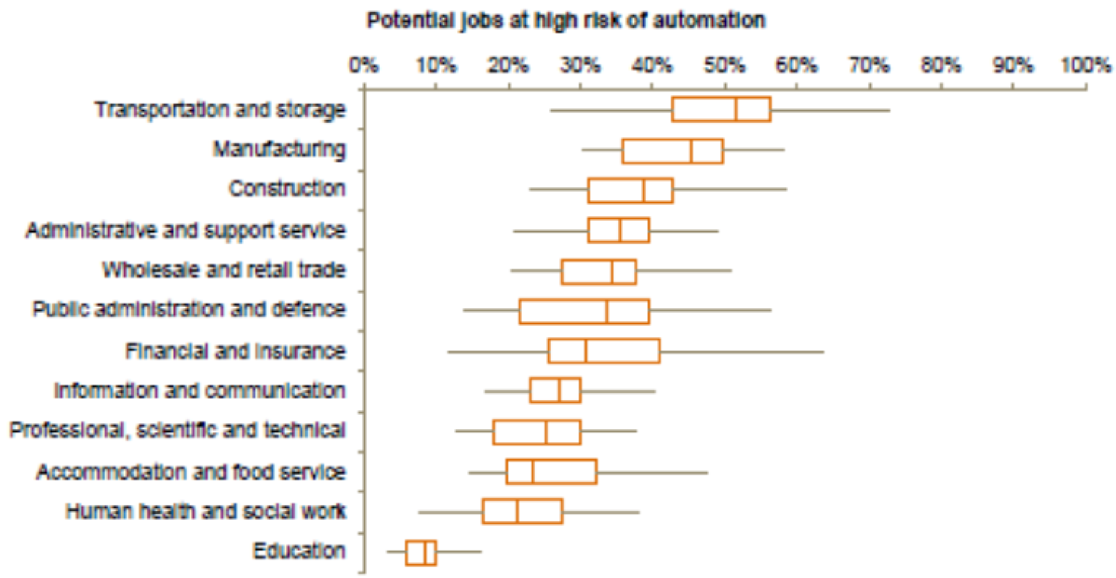
Source: authors computations based on IES database

Figure 11: **Jobs at risk of automation I**



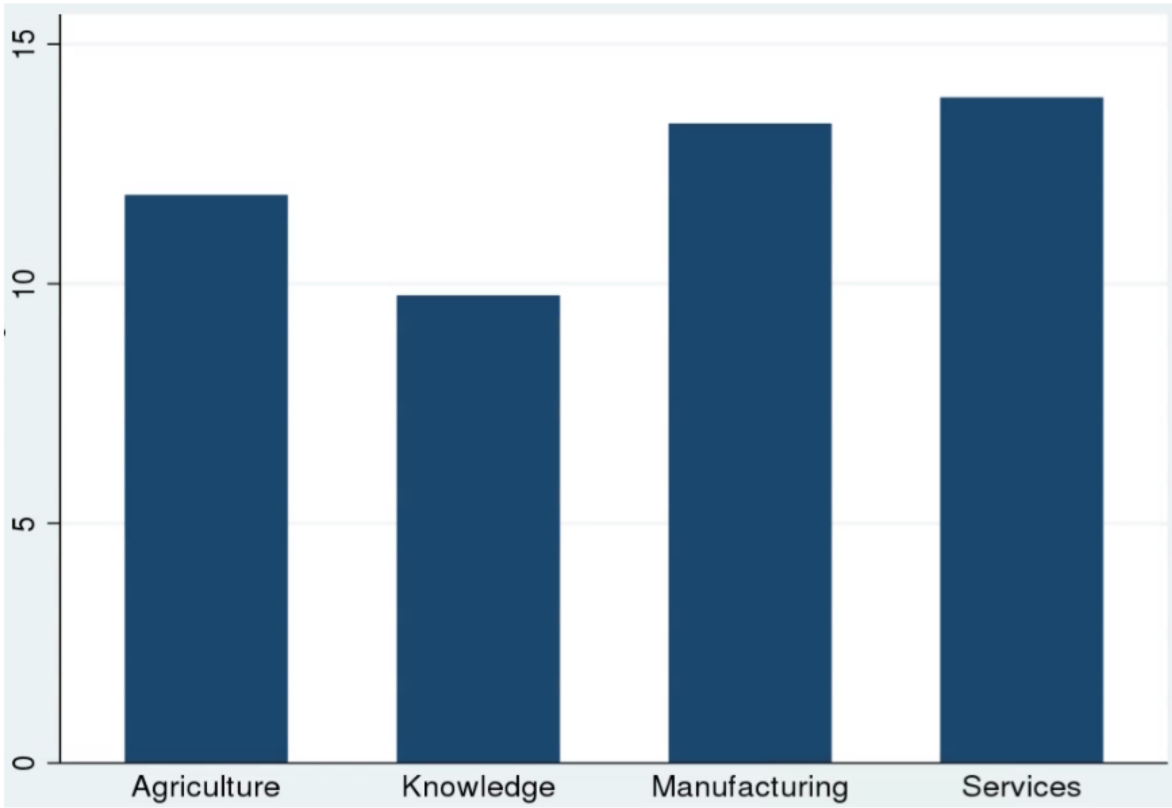
Source: Manyika et al. (2018)

Figure 12: **Jobs at risk of automation II**



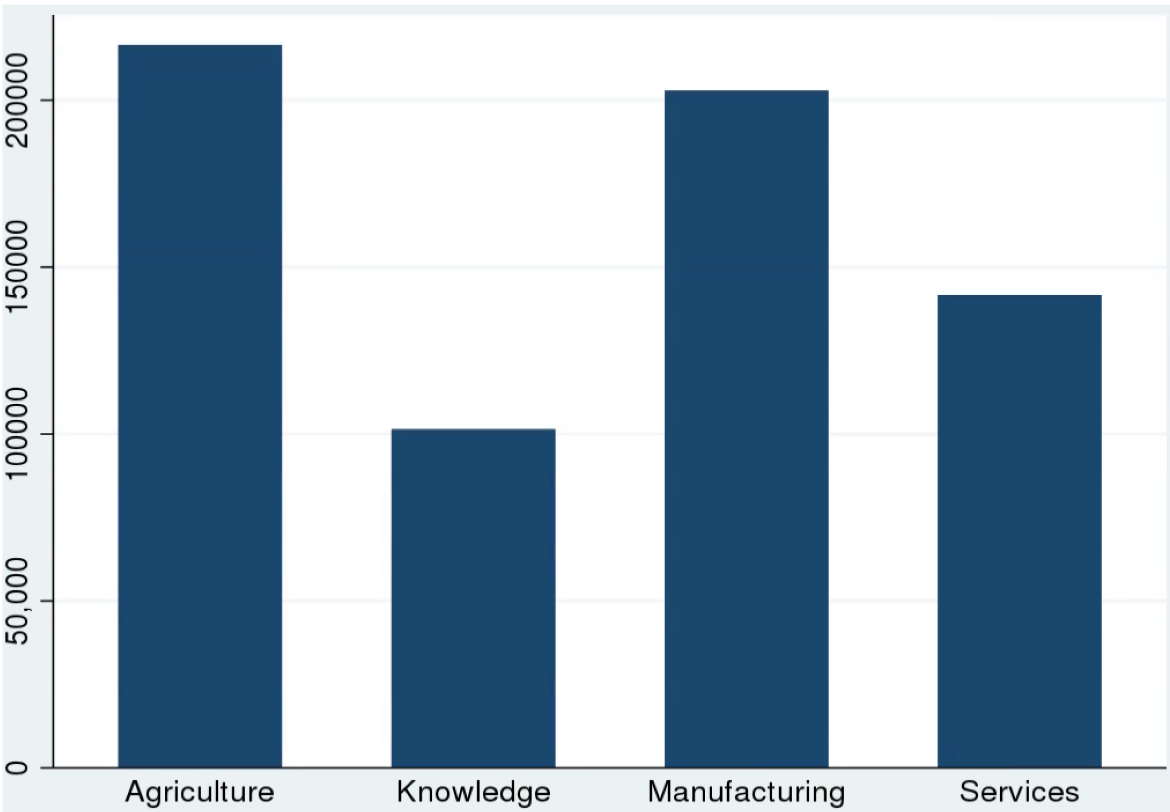
Source: Hawksworth et al. (2018)

Figure 13: **Average firm age per sector**



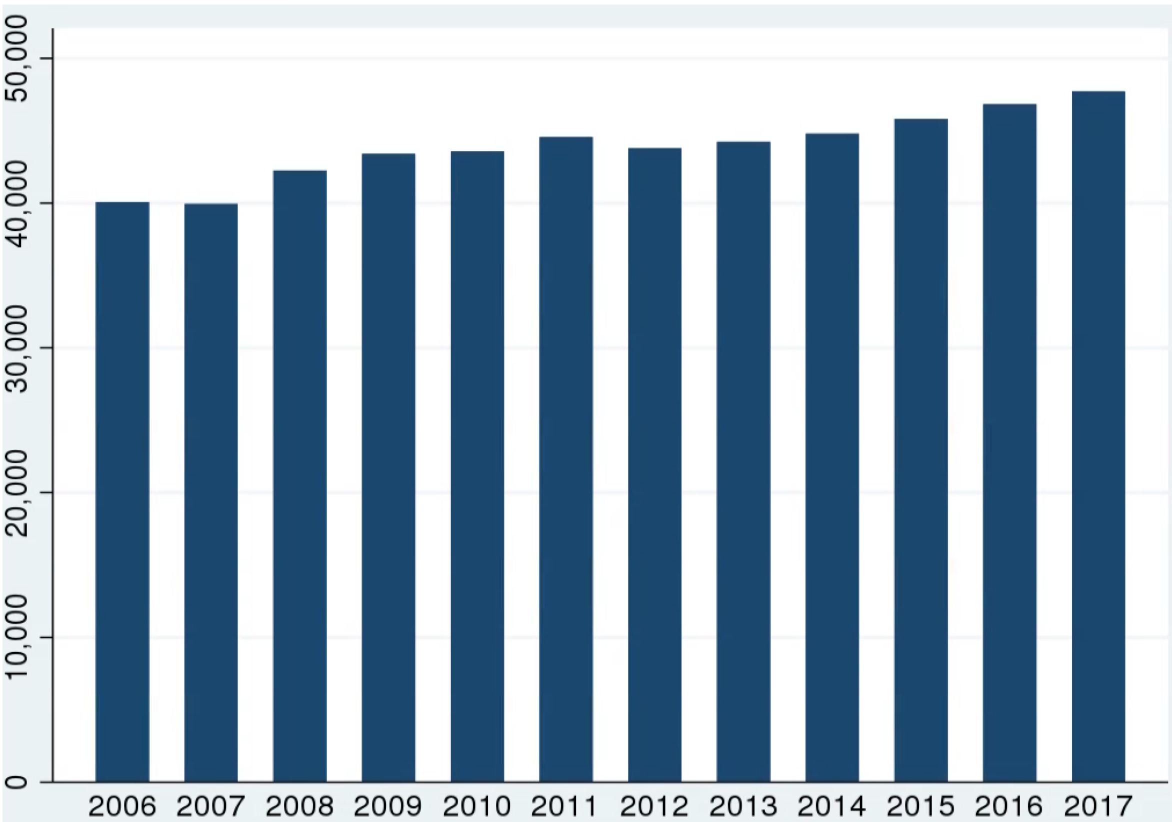
Source: authors computations based on IES database

Figure 14: **Average capital-per-worker ratio per sector**



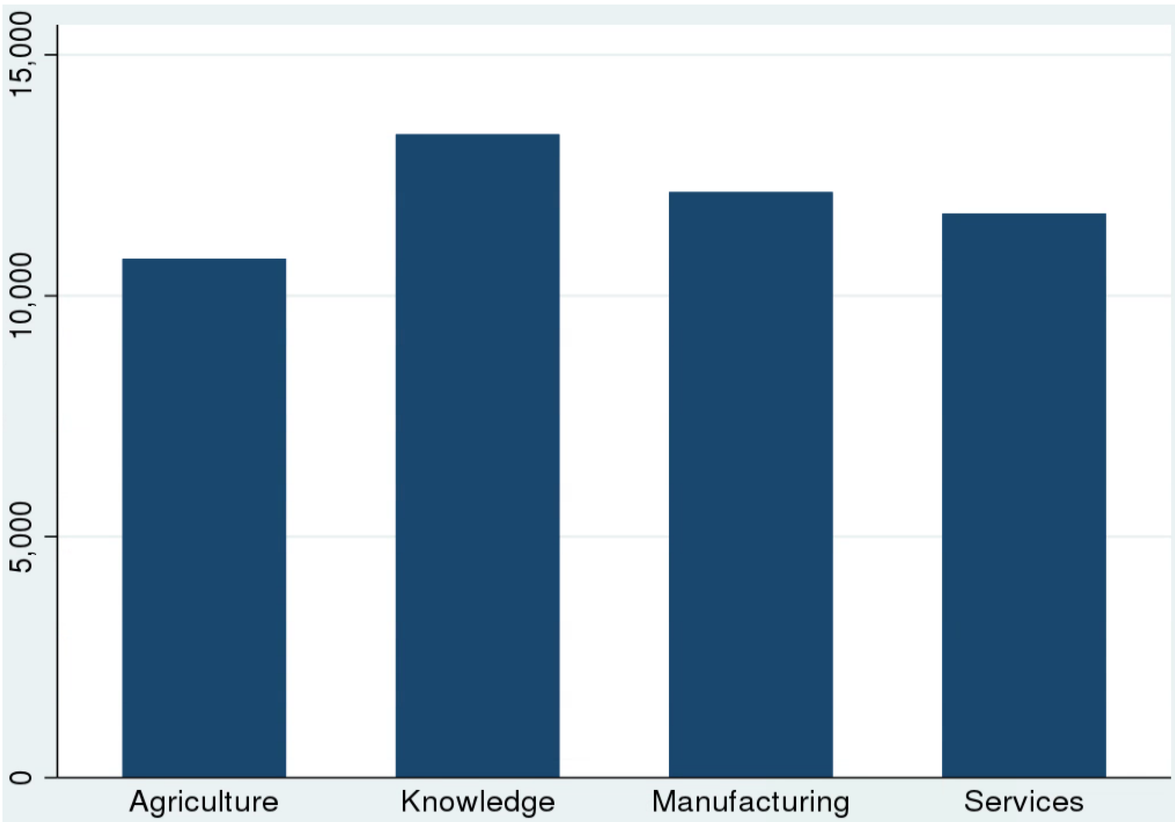
Source: authors computations based on IES database

Figure 15: **Number of Knowledge Based firms per year**



Source: authors computations based on IES database

Figure 16: **Average wage-per-worker ratio per sector**



Source: authors computations based on IES database

Table 3. **Production function estimation with alternative input variables I**

	LP	OLS	FE
Labor (L)	0.274***	0.276***	0.215***
	(0.00217)	(0.00271)	(0.00306)
Capital (K)	0.0309***	0.0383***	0.0251***
	(0.000959)	(0.00107)	(0.08096)
Intermediate Goods (M)	0.706***	0.721***	0.693***
	(0.00198)	(0.00187)	(0.00305)
Observations	522481	522481	522481

Same specifications as Table 2

Source: authors computations based on IES database

Inputs Changes: External Services and Utilities as the M input

Table 4. **Production function estimation with alternative input variables II**

	LP	OLS	FE
Labor (L)	0.294***	0.296***	0.268***
	(0.00224)	(0.00237)	(0.00275)
Capital (K)	0.0286***	0.0361***	0.0218***
	(0.000817)	(0.00183)	(0.000936)
Intermediate Goods (M)	0.655***	0.655***	0.648***
	(0.00185)	(0.00193)	(0.00288)

Same specifications as Table 2

Source: authors computations based on IES database

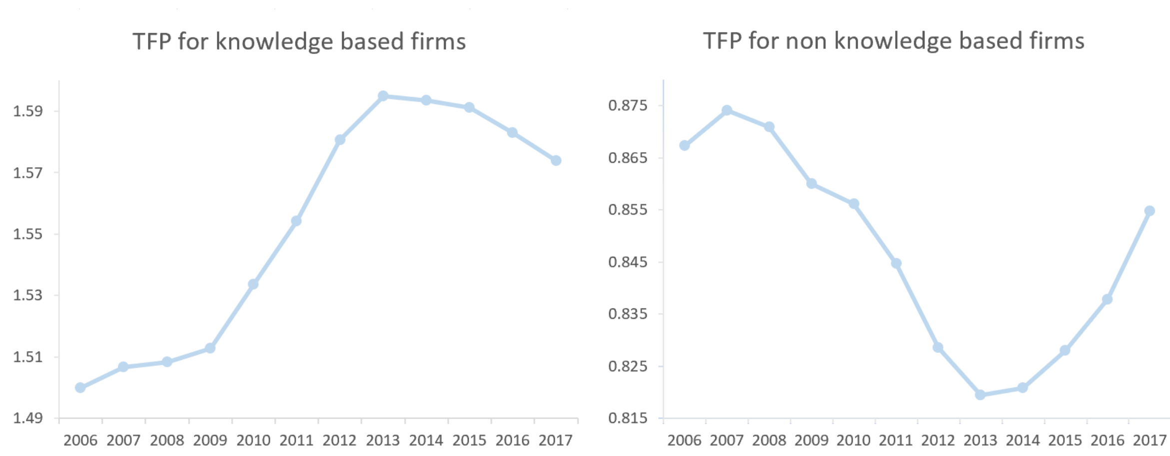
Inputs Changes: Personnel Expenses as the L input

Table 5. **Production function estimation with alternative input variables III**

	LP	OLS	FE
Labor (L)	0.257***	0.258***	0.240***
	(0.00311)	(0.00238)	(0.00257)
Capital (K)	0.0231***	0.0284***	0.0170***
	(0.000814)	(0.000934)	(0.00088)
Intermediate Goods (M)	0.705***	0.712***	0.702***
	(0.000722)	(0.00188)	(0.00282)

Same specifications as Table 2
Source: authors computations based on IES database
Inputs Changes: Personnel Expenses as the L input and
External Services and Utilities as the M input

Figure 17: **TFP level over time**



Source: authors computations based on IES database. ln(TFP) on the Y axis

Figure 18: **Joint significance tests**

Test(Age, Age^2)
F(2, 28)=19.77
Prob>F=0.000 ***

Test(Small, Medium, Large)
F(3, 28)=11.32
Prob>F=0.000 ***

Source: authors computations based on IES database.

Table 6. **Model variables summary statistics**

	count	mean	sd	min	max
Age	526 863	9.756	9.372	0	138
Wage Premium	516 763	1.0012	.8684	0	96.32
Indebtedness Ratio	526 942	-6.3582	5440.2	-3949060	1283.6

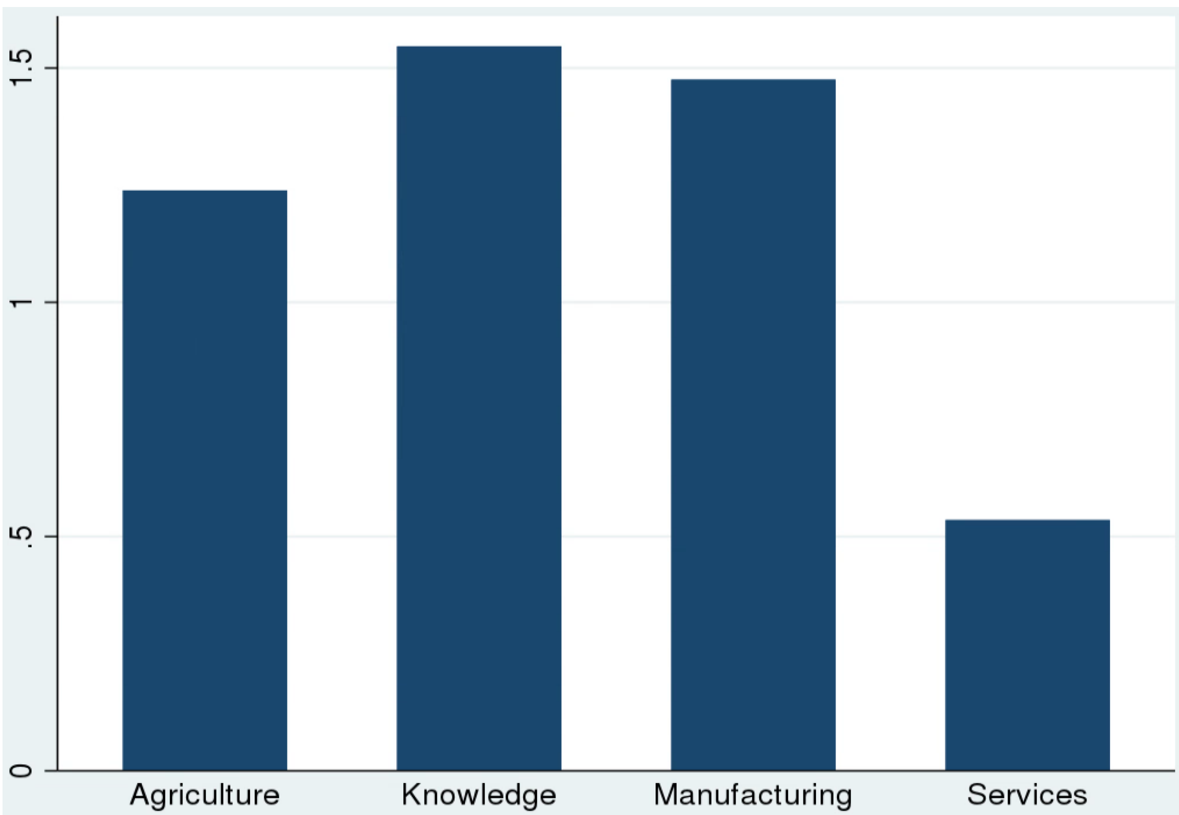
Source: authors computationsbased on IES database

Table 7. **Model dummy variables summary statistics**

Variable	Count	Count if = 0	Count if = 1
Innovation	526 942	411 359	115 583
Exporter Status	526 942	499 749	27 193
Small	522 510	476 883	45 787
Medium	522 510	515 438	7 872
Large	522 510	521 876	1 434

Source: authors computations based on IES database

Figure 19: **Average TFP per sector**



Source: authors computations based on IES database.

Table 8. **Determinants regression for each economic sector**

	Manufacturing	Services	Knowledge based
Innovation	0.000798	-0.000772	0.00259***
	(0.298)	(0.241)	(0.005)
Age	0.000190	0.000828**	0.00267***
	(0.548)	(0.032)	(0.000)
Age^2	-0.0000181	-0.0000138**	-0.0000582***
	(0.200)	(0.046)	(0.002)
Small firm	0.0256*	0.00900	0.0290***
	(0.087)	(0.187)	(0.001)
Medium firm	0.0598*	0.0105	0.0386*
	(0.074)	(0.434)	(0.059)
Large firm	0.0860*	-0.0235	0.0276
	(0.050)	(0.388)	(0.376)
Exporter Status	0.00651***	-0.000478	0.00310
	(0.009)	(0.808)	(0.107)
Wage Premium	0.00407	0.00295	0.00583**
	(0.329)	(0.284)	(0.030)
Indebtedness Ratio	0.0000526**	5.87e-08***	-5.66e-09***
	(0.024)	(0.000)	(0.000)
Year=2007	0.000903**	0.000374	0.00139***
	(0.021)	(0.381)	(0.007)
Year=2008	-0.000347	0.0000445	0.00163**
	(0.844)	(0.932)	(0.020)
Year=2009	-0.00523	-0.00107	0.000202
	(0.279)	(0.271)	(0.860)
Year=2010	-0.00454	-0.00137	0.000810
	(0.333)	(0.143)	(0.617)
Year=2011	-0.00590	-0.00322**	-0.00272**
	(0.348)	(0.033)	(0.047)
Year=2012	-0.00850	-0.00514**	-0.00601***
	(0.271)	(0.024)	(0.000)
Year=2013	-0.00803	-0.00544**	-0.00727***
	(0.284)	(0.020)	(0.000)
Year=2014	-0.00635	-0.00414**	-0.00662***
	(0.302)	(0.026)	(0.000)
Year=2015	-0.00440	-0.00306**	-0.00481***
	(0.361)	(0.038)	(0.000)
Year=2016	-0.00387	-0.00201**	-0.00266***
	(0.186)	(0.036)	(0.000)
Year=2017	0	0	0
	(.)	(.)	(.)
Constant	1.468***	0.528***	1.526***
	(0.000)	(0.000)	(0.000)
Observations	655174	1403864	516684

p-values in parentheses
Source: authors computations based on IES database
$^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$

Figure 20: **Hausman Tests**

Test Manufacturing(RE, FE)
$Chi^2(18)=25\,142$
$Prob>Chi^2=0.000$ ***

Test Services(RE, FE)
$Chi^2(17)=3\,302$
$Prob>Chi^2=0.000$ ***

Test Knowledge Based(RE, FE)
$Chi^2(17)=2\,695$
$Prob>Chi^2=0.000$ ***

Source: authors computations based on IES database.

Figure 21: **Variance-Covariance matrix of the regressors**

Variable	Innovation	Age	Small	Medium	Large	Exporter Status	Wage Premium	Indebtdness Ratio
Innovation	1							
Age	-0.0042	1						
Small	0.0043	0.1446	1					
Medium	0.0203	0.1246	-0.0599	1				
Large	0.263	0.0635	-0.023	-0.0083	1			
Exporter Status	-0.0029	0.0343	0.1339	0.1987	0.0818	1		
Wage Premium	0.0527	0.1279	0.1429	0.1064	0.0481	0.01501	1	
Indebtedness Ratio	-0.0001	-0.0002	-0.0002	-0.0001	0	-0.0001	-0.0002	1

Source: authors computations based on IES database.

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