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Understanding productivity dynamics: a task taxonomy approach

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Abstract

It is a well known fact that firms are changing their labour inputs to reflect the increasing use of computers and computer-driven machines in the workplace that is thought to increase firms' productivity. In this paper we develop a taxonomy based on occupational data that classifies firms according to their labour inputs' task intensity. We propose three main categories: Abstract, Manual and Routine. Abstract firms are high-skilled labour intensive, Manual firms are low-skilled and Routine firms have most of its labour force performing repetitive work. We apply this taxonomy to study productivity and its dynamics for Portuguese firms. Our results show that Abstract firms are the most productive and their share has increased in the economy. The least productive firms are Manual and have had a stable share recently. Routine firms' productivity lies between the other two and its share has declined over time. By developing and applying an extended version of the dynamic Olley-Pakes decomposition method, we conclude that the Portuguese aggregate productivity has increased due to a sharp increase in Abstract firms productivity together with a decline in the share of low productivity Routine firms.

Jelcodes:D24,O33

1 Introduction

Computers and computer-driven machines, or computer capital, are reshaping the workplace significantly as well as how firms produce. Brynjolfsson and McAfee (2014) calls this period a second machine age in resemblance to the first machine age, associated with the invention of the steam machine in the industrial revolution. Productivity is increasing as computers, robots and artificial intelligence change the way we work and interact. As a consequence, middle-wage jobs (routine jobs) are disappearing, as those tasks are being performed by computer capital – consequence of a technology becoming cheaper over time. In addition, high-skilled workers increase their productivity because of complementarity between them and computer capital. This phenomenon is termed routinisation in the literature. (Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011).

The timing of routinisation, which has manifested since the 1990s, is coincident with a period of increasing productivity growth, in particular labour productivity, experienced by most western countries. Research has identified ICT capital (or computer capital) as one of the main drivers for the increase in the output per worker or labour productivity (Jorgenson and Stiroh, 2000; Jorgenson, 2005; Timmer et al., 2013). Several other studies also attribute to ICT inputs the increase of firm productivity, along with the necessary changes in the organisation to accommodate ICT use and complementary assets (e.g. Bresnahan, Brynjolfsson and Hitt 2002; Brynjolfsson and Hitt 2003). But research has not studied this connection between the increase in productivity growth and the effects felt in the labour market resulting from routinisation.

We approach routinisation through the lens of the firm. We propose a taxonomy that classifies firms according to the tasks performed by their employees. The classification uses firms' labour inputs based on occupational information, which is frequently available in matched employer-employee datasets. By constructing a taxonomy based on inputs rather than idiosyncratic characteristics, we capture a wider range of dynamics, along with the implicit technology that firms use. With this taxonomy, we identify five categories of firms: focused Abstract, focused Routine, focused Manual, Polarised and Uniform. Focused categories refer to firms that use more intensively Abstract, Routine or

Manual tasks, respectively. Borrowing the term form labour economics we call Polarised to highly abstract and manual intensive firms, thus low routine intensive. Uniform firms are characterised by having similar levels of intensity in abstract, routine and manual tasks activities.

We apply the firm task-intensity taxonomy to the Portuguese firms to study productivity and productivity growth over the time frame of half a decade (from 2004 to 2009). The recent Portuguese productivity experience is thought to be similar to the Italian and the Spanish. Italy, in particular, has experienced total factor productivity losses due to misallocation of resources as Portugal did (Gopinath et al., 2015). Gopinath et al. (2015) finds similar patterns between Portuguese, Spanish and Italian firms in terms of factors' marginal revenue and total factor productivity dynamics. Blanchard (2007) also uses the specific case of Portugal to highlight the problem of stagnant or declining productivity of several euro area countries.

In a scenario where Abstract firms are increasing their prevalence in the economy and Routine firms declining, we estimate sector-based production functions using Levinsohn and Petrin (2003) methodology in order to compute firms' total factor productivity. The results show that for focused firms, Abstract are the most productive followed by Routine and Manual. For the overall period (5 years), Abstract firms show the largest productivity growth (38%), which is well above that of Manual (11%) and Routine (14%).

We further decompose the estimated productivity changes by applying an extended version of Melitz and Polanec (2015) dynamic decomposition where we include a novel term accounting for firms transitioning from one taxonomy category to another. Overall productivity growth is propelled by three factors: incumbents' market reallocations, that is, increasing market shares of most productive incumbents, exiting of the least productive routine firms and change in the task focus of firms from non-abstract to abstract.

This paper is structured as follows. Section 2 reviews the theoretical foundations of the taxonomy we propose. Section 3 presents de data used in the paper. In section 4 we develop and apply the task taxonomy. Section 5 estimates the total factor productivity followed by the study of the productivity dynamics in Section 6. Section 7 concludes.

2 Theoretical Background

2.1 Polarisation

Middle-wage jobs are disappearing in industrialised economies, while low and high-waged jobs employment shares increased over the past decades (Autor, Katz and Kearney, 2006; Acemoglu and Autor, 2011; Goos and Manning, 2007), a phenomenon termed as job polarisation (Goos and Manning, 2007). Job polarisation replaced the skilled biased technological change (SBTC) paradigm, which predicts that technology enhances high-skilled workers productivity, increasing the demand for skills along every dimension of skill. In this sense, as the use of technology increases in the workplace, the demand for high-skilled workers rise relative to the demand for middle and low-skilled workers (Krueger, 1993; Berman, Bound and Machin, 1998; Machin and Van Reenen, 1998; Acemoglu, 1998). The SBTC hypothesis can explain employment and wages until the 1990s, but it fails to explain the recent evolution of polarised employment and wages.

Searching for the sources of observable polarisation, scholars have settled in a technology driven hypothesis, the so-called routinisation hypothesis (Autor, Levy and Murnane, 2003) that, contrary to SBTC, predicts non-linear changes for three skill groups: low, middle and high. The routinisation model assumes that human workers perform a set of tasks in the workplace and some of those can be performed by computer-driven machinery or computer capital, while others cannot. In addition, some tasks are complemented, in the spirit of SBTC, by computer capital. Thus, as technology advances and becomes cheaper, firms change their labour and capital inputs to capture those effects and expanding their productivity.

The literature does not provide many clues on how firms' labor force dynamics are changing to accommodate advanced computer capital. Some have highlighted that through the use of information and communication technologies (ICT), firms can increase their productivity Brynjolfsson and Hitt (1996, 2003). More high-skilled intensive firms should benefit more from ICT adoption, because of the complementarity between high-skilled workers and ICT. While other studies have established the connection between skills that allow workers to master new technologies and productivity (e.g., Boothby, Dufour and

Tang 2010), we still know very little about how firms are reshaping their labour inputs to benefit from technology and how that is affecting productivity growth at the firm level.

2.2 Routinisation

Technology and skilled labour have been exhibiting complementarities at least since the 1910s and 1920s with the introduction of batch production and electric motors (Goldin and Katz, 1998). The concept of technology demanding workers' skills traces back to seminal works of Griliches (1957), Nelson and Phelps (1966) and Schultz (1975) and remains pervasive nowadays. As technology started to decrease its cost, mainly computers, firms massively adopted it in the workplace, thus leveraging productivity of the high-skilled workers due to their complementarity effect (Krueger, 1993; Autor, Katz and Krueger, 1998; Acemoglu, 1998).

Recently labour markets started to present a different relationship between wages, employment and skills. Contrasting with the idea that technology mainly benefits skilled labour, some authors started to observe that prices and quantities in labour markets are revealing different patterns than SBTC predicts. Markets started to polarize (Goos and Manning, 2007) – the most and the least skilled have increased their employment, while the employment of middle skilled workers is hollowing out. The most agreed hypothesis to explain polarised labour markets is routinisation (Autor, Katz and Kearney, 2006; Acemoglu and Autor, 2011), a technology based hypothesis that attempts to show that technology is progressively replacing human labour employed in jobs that consist mostly of routine tasks, easily replaced by technology.

The routinisation model (Autor, Levy and Murnane, 2003; Autor, Katz and Kearney, 2006) describes the workplace according to a task view, in which production is accomplished by executing a set of tasks. Tasks are performed by either human labour or computer capital (computer-driven machines or computers), and can be classified mainly into three groups: routine, manual and abstract. Routine tasks represent those that can be achieved by following a set of instructions, so they can be coded into machines and can be fully performed by either computer capital or human labour. Typical examples of occupations which are heavily routine include factory assemblers or office clerks. Manual tasks cannot be done by computer capital because they require more flexibility than computers can offer, though they are non-cognitive. Examples of occupations with high manual task intensity are cleaners or plumbers. Finally, Abstract tasks are cognitive, high-skilled and involve making complex decisions and engaging in interpersonal relations. Managers and physicians are examples of abstract intensive occupations.

The model assumes further that Abstract tasks benefit from technology as it increases the complementarity with high skills and cannot be routinised (performed by computer capital). The driving force behind the model is the exogenous secular declining price of computer capital (quality adjusted). Firms have an incentive to substitute computer capital for employees performing mostly routine tasks, as computer prices become lower than the wage paid to those employees. A simple example is a computer software replacing tasks that once were carried out by an office clerk, as an ATM or online banking services.

The incentive to replace human labour with computer capital is even stronger because of the complementaries between computer capital and workers performing abstract tasks. This complementarity between high-skilled workers (usually performing abstract tasks) and technology, is pervasive throughout the literature, not just on polarisation, but on SBTC as well. Examples include software that helps physicians to quickly access all information about patients, increasing their productivity. The literature provides empirical evidence supporting the routinisation hypothesis for several developed countries.[1] Although those studies consider routinisation when analysing labour markets, none have yet addressed firm labor force and productivity dynamics. The literature provides no indication about how firms change labour inputs or how their productivity is affected over time. To shed light on these questions, we propose a taxonomy which classifies firms based on their labour inputs.

[1]See for example, Autor, Katz and Kearney (2006) and Acemoglu and Autor (2011) for the US case, Goos and Manning (2007) for the UK, Goos, Manning and Salomons (2014) for Europe as a whole), including Portugal (Fonseca, Lima and Pereira (2014) and Centeno and Novo (2014).

3 Data

In this paper we use the Portuguese linked employer-employee dataset *Quadros de Pessoal* (QP), a dataset created by the Portuguese Ministry of Labour. It contains yearly information of all Portuguese firms with at least one employee, excluding agriculture, military, public administration and institutionalised or self-employed workers. Using QP, we have access to longitudinal information from 1986 to 2012 (except 1990 and 2001 that were not released at worker-level) containing several firm-level and worker-level characteristics. We match QP with another dataset named *Sistema de Contas Integradas das Empresas* (SCIE) from Statistics Portugal that contains information on firms' balance sheet and income statements. The dataset starts in 2004 and we have yearly information up to 2009. Using both datasets allows us to access accounting information, personal records, and firms' characteristics such as industry, region or age.

We restrict our analysis to full-time workers (30 hours per week or 130 per month) aged between 16 and 65, earning at least 90% of the minimum wage (sum of base wage plus regular and seniority related bonuses).[2] We restrict our sample to manufacturing (high-tech to low-tech) and services (knowledge intensive and less knowledge intensive) industries. After matching the two dataset we obtain more than 118 thousand firms in 2004 and 143 thousand in 2009, as shown in Table 1. The total workforce covered exceeds 1.8 million workers in 2009 and most firms are medium-low or low-tech manufacturing (23% in 2004 and 18% in 2009) or service based (74% in 2004 or 80% in 2009). Naturally, when we use QP alone the number of observations increases and the information extends from 1986 to 2012 rather than from 2004 to 2009.

4 Taxonomy

Grouping firms according to their characteristics is a widely used practice in research. Simple examples include aggregation by size or sector, but more complex aggregations have been successfully developed and used in the past. A widely known example is the

[2]We use 90% of minimum wage as a lower boundary, instead of the monthly minimum wage, to minimize loosing observations due to data errors and monthly wage variations.

Table 1: Number of observations

	2004		2009	
	Firms	**Employees**	**Firms**	**Employees**
High-Tech Manufacturing	0.4%	1.5%	0.1%	0.8%
Medium-High-Tech Manufacturing	2.5%	6.7%	1.7%	4.3%
Medium-Low-Tech Manufacturing	10.1%	15.5%	6.1%	8.3%
Low-Tech Manufacturing	12.6%	20.5%	11.7%	18.0%
Knowledge-Intensive Services	11.8%	14.5%	18.8%	20.4%
Less Knowledge-Intensive Services	62.5%	41.3%	61.5%	48.3%
Total	118 222	1 490 540	143 402	1 802 787

seminal Pavitt (1984) taxonomy. Pavitt (1984) taxonomy classifies firms based on their technology capabilities, in a successful attempt to describe firms' innovation practices and to aid policy analysis. Ever since Pavitt's taxonomy has been used and extended by several authors (e.g., Bogliacino and Pianta 2010), several other classifications are now available in the literature based on diverse characteristics of firms including regions, sectors or industries (e.g., Cooke, Uranga and Etxebarria 1997; Malerba 2002; Asheim and Coenen 2005; Von Nordenflycht 2010).

Few to no taxonomies incorporate firm level labour content or capture firm level information of which type of jobs are performed within firms. Recently, Consoli and Rentocchini (2015) proposed a taxonomy based on skill content of occupations for sectors. The authors use workers' occupations complemented with industry-level of U.S. labour productivity, number of firms and capital expenditures to construct a sector-based classification. Notwithstanding Consoli and Rentocchini (2015) classification captures part of the skills used by firms, but because it is sector-based, it fails to capture nuances among firms within the same sector and their dynamics.

Following from the routinisation hypothesis, we develop a taxonomy that captures firm's labour input in the form of tasks. We consider that the production of goods and services in the firm is accomplished by executing one or multiple tasks. Although a single worker can perform several tasks, for sake of simplicity we assign the worker to the most intensive task drawn from the worker's task set. To obtain a usable correspondence between tasks and the information available in most linked employee-employer datasets, we use tasks at the occupation level (ISCO 88, 2-digit level): each worker has an occupation and each occupation is associated with a task (the most intensive task for that particular occupation). The methodology is based on descriptors of O*NET database, which are then aggregated using principal components to form task measures (scales).[3] Because O*NET is based on US SOC codes, we convert it into ISCO 2-digits codes using U.S. employment data. The allocation of tasks to occupations is based on the most intensive task in each occupation. The tasks are abstract, routine cognitive, routine manual and manual. We aggregate routine cognitive and routine manual in a single category, termed routine. Appendix Table A1 summarises the correspondence between tasks and the ISCO-88 occupational codes.

We compute the share of employees performing each task within the firm. A firm is then described as having an abstract share, routine share and a manual share (the sum of shares is unitary). Some firms will have more employees performing abstract tasks (e.g., consultancy firms), while for others manual task are the main focus (e.g., cleaning services) and so on. Our taxonomy classifies firms according to their main task focus, thus boundaries are set for the tasks shares. To aid in defining these boundaries for the classification, we ran several clustering methods and performed extensive checks for randomly selected numbers of firms, which allowed us to fine-tune our categories. Table 2 presents the boundaries of each category.

Table 2: Taxonomy categories and boundaries

Firm Task Type	**Share of employees (%)**		
	Abstract (A_s)	**Manual** (M_s)	**Routine** (R_s)
Abstract (A)	>50	<36	<36
Manual (M)	<36	>50	<36
Routine (R)	<36	<36	>50
Polarized	>36	>36	<20
Uniform	$A_s - R_s < 18\%, A_s - M_s < 18\%, R_s - M_s < 18\%$		
Routine-Abstract	>36	<14	>36
Routine-Manual	<14	>36	>36

[3] We follow Fonseca, Lima and Pereira (2014). O*NET is the main project of the US Department of Labor's O*NET program. The dataset contains information at occupation level regarding the work activities and tasks measured by descriptors.

The intervals for the shares define four main groups of firm categories. First are the firms that are focused in just one task, when at least half of their employees' are employed in one of the three tasks. We identify three categories of focused firms – Abstract, Manual and Routine – corresponding to the most intensive task. The second group are the Polarised firms, a term which we borrow from the job polarisation literature. We call Polarised firms to those that use a small ratio of routine intensive labour and most of their employees perform abstract and manual tasks. Routine tasks are either not performed at all or are mostly likely to be performed by machines (computers or computer-driven machines). The third group is called Uniform. Uniform firms are those that present similar share of employees in abstract, manual and routine tasks. Uniform is basically our comparison group, the baseline, and thus along the paper sometimes is the omitted category. We have created two other groups of firms for tractability proposes – Routine-Abstract and Routine-Manual – which correspond to firms with a task composition on the boundaries of each pair of the task focused regions. The firm's classification is not clearcut for firms in these boundary regions and can be either included in one or in another task focus type. Thus, instead of excluding those firms, we consider those *out of focus* regions.

A two-dimensional representation of our classification can be found in Figure 1, where routine share is implicitly defined by abstract and manual shares (recall that the total sum of the shares is unitary). Figure 1 also illustrates the density of firms in each task in 2009, as each point is a firm. We have tested some modifications to the boundaries to force firms to change category, yet our categorisation is particularly robust to small changes in those limits. The robustness of our taxonomy comes at small cost of creating intervals where firms are not classified: in 2009 approximately 1.4% are not classified into any category (the grey squares in the graph around uniform firms from Figure 1) and approximately 7.5% of the total number of firms fall within the Routine-Abstract and Routine-Manual categories (out of focus regions). However, this guarantees that firms do not change category with just small changes in their task content and also ensures that there are substantial differences between each type of firms.

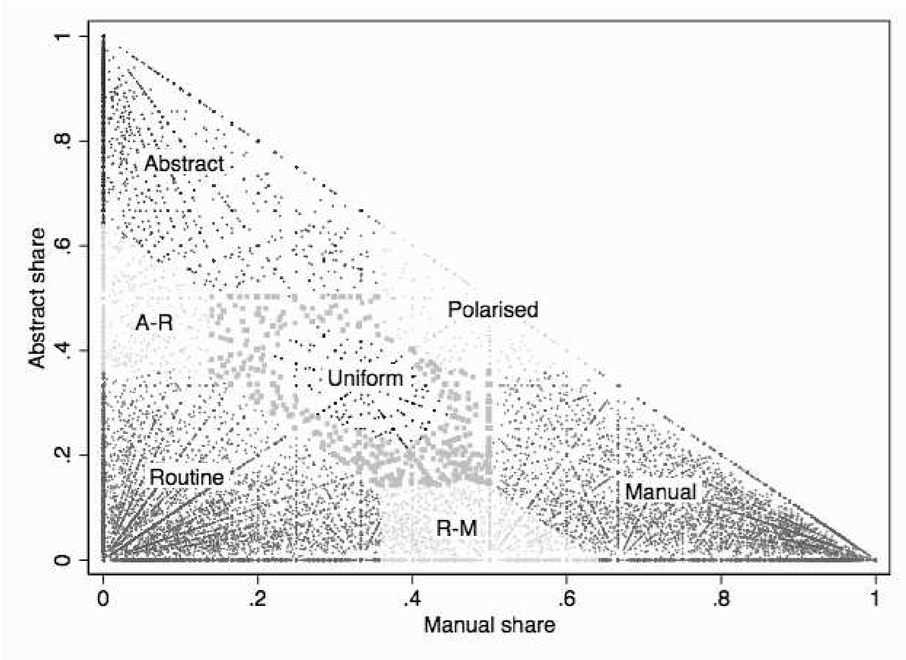

Figure 1: Taxonomy applied to 2009 Portuguese firms
Notes: Data from Quadros de Pessoal. Firms' density in 2009, industries include high-tech to low-tech manufacturing and knowledge-intensive and less knowledge-intensive services. Unlabelled grey squares around the uniform category correspond to the boundary zone which is not classified. The region A-R is Abstract-Routine and R-M is Routine-Manual.

4.1 Taxonomy application

We apply our taxonomy to the Portuguese firms in order to capture the effects of recent labour changes in the workplace on firm's task input and productivity. The taxonomy provides a dynamic view of firms based on their labour input, as firms can react by adjusting their inputs, mainly labour. A firm can be classified as Manual in one period and, and as Abstract in the next period. Conversely, taxonomies based on idiosyncratic characteristics of the firm, such as industry, remain static as only very few firms change from one category to another.

Because workers with high intensive routine tasks' occupations are being substituted by computers or computer driven-machines (Acemoglu and Autor, 2011), we can expect Routine Focused firms, that is firms employing mostly routine intensive labour, to decrease in importance. Figure 2 confirms that Routine Focused firms decrease their share between 1995 and 2011 both in terms of employment (49% to 40%) and in number of firms (37% to 32%). In contrast, Abstract Focused firms – the firm type that benefits the most from complementarities between abstract workers and technology – show an increase in their employment share (from 2% to 11%) and number of firms (from 3% to 12%). The Polarised firms shows a modest rise in importance, but its share in both dimensions is much smaller (less than 1.5%) than firms' focused in one task – for that reason in subsequent analyses we just consider the focused group: Abstract, Routine and Manual. We have omitted Uniform firms from figure 2 and from the remainder of our analysis, as their share is constant and relatively small over time (around 0.4

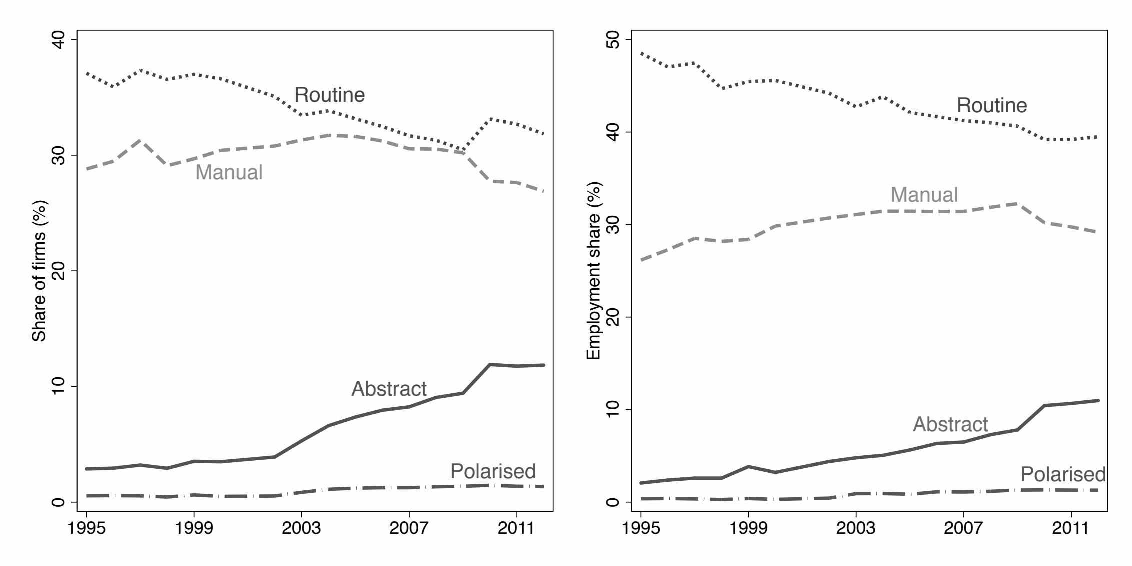

Figure 2: Share of firms and employment by firm type
Notes: Data from Quadros de Pessoal. For simplicity Uniform and boundary regions (Abstract-Routine and Routine-Manual) are omitted.

Table 3 presents summary statistics by firm type. Abstract firms are smaller, followed by Manual and Routine that are the largest. The largest distinction across the three types of firms is in terms of their employees' education. Abstract firms' share of college educated employees is 28% in 2004 and rises to 42% in 2009, while for Manual and Routine firms this share does not exceeds 5.3% in 2004 and 9.8% in 2009. Abstract firms are mostly concentrated in the knowledge-intensive services, whereas Routine and Manual are mostly in the less knowledge-intensive services. In manufacturing and by 2009, Abstract firms are mainly concentrated in medium high-tech and high-tech, while Routine firms dominate in low-tech and Manual firms in medium low-tech.

Figure 3 shows productivity statistics and capital use overtime for the three focused

Table 3: Summary statistics by firm type

	2004				2009			
	All	**Abstr**	**Rout**	**Man**	**All**	**Abstr**	**Rout**	**Man**
Firm size								
[1,9[	76.9	84.3	76.2	82.5	77.3	83.4	79.3	81.9
[10,49[	19.0	13.0	19.2	15.2	18.6	13.8	16.9	15.4
[50,99[	2.4	1.6	2.6	1.4	2.3	1.5	2.1	1.6
[100,249[	1.2	0.8	1.4	0.6	1.2	0.8	1.2	0.7
>=250	0.5	0.2	0.6	0.4	0.5	0.5	0.5	0.4
College	5.2	27.5	5.3	3.0	8.5	42.3	9.8	4.2
Manufacturing								
High-Tech	0.4	2.7	0.3	0.2	0.2	0.3	0.2	0.1
Medium-High-Tech	2.6	1.9	1.4	3.6	1.9	2.0	1.1	2.1
Medium-Low-Tech	11.4	1.1	10.4	11.8	7.4	1.4	3.0	11.0
Low-Tech	13.6	3.4	19.3	6.0	14.7	1.1	20.1	5.0
Services								
Knowl.-Intens.	10.2	59.6	8.7	7.5	11.9	69.3	15.7	7.3
Less Knowl.-Int.	61.7	31.3	59.9	70.9	63.9	26.0	60.0	74.5
Observations	118 222	5 725	45 206	52 899	143 402	12 638	52 031	61 346

Notes: All values are expressed as a share in percentage. Abstr is Abstract, Rout is Routine and Man is Manual. Firm size categories are measured by the number of employees. College refers to the share of college graduates in the firms' workforce.

task firm types and for all firms (total). The left panel shows labour productivity defined as value added (VA) divided by the number of employees (L). The right panel shows the evolution of capital (K), measured as the total gross value of fixed and intangibles assets per worker (L). Monetary values (VA and K) are in euros and have been deflated using Producer Price Index at 3-digits industry level.

Figure 3 shows that Abstracts firms' labour productivity is the highest, whereas Manual firms exhibit the lowest productivity. In addition to being the most productive firm type, Abstract firms' labour productivity also increases sharply until 2008. The remaining firm types follow the same increasing trend though with smaller slope, with the exception of Manual, which shows a slight productivity decline after 2007. Regarding capital per worker, the graph is rather similar: Abstract firms are more capital intensive and capital intensity is rising sharply until 2008, whereas Manual firms are the least capital intensive and the rate of growth in capital intensity is the smallest. Routine firms capital intensity and respective growth rate lies between the two other firm types.

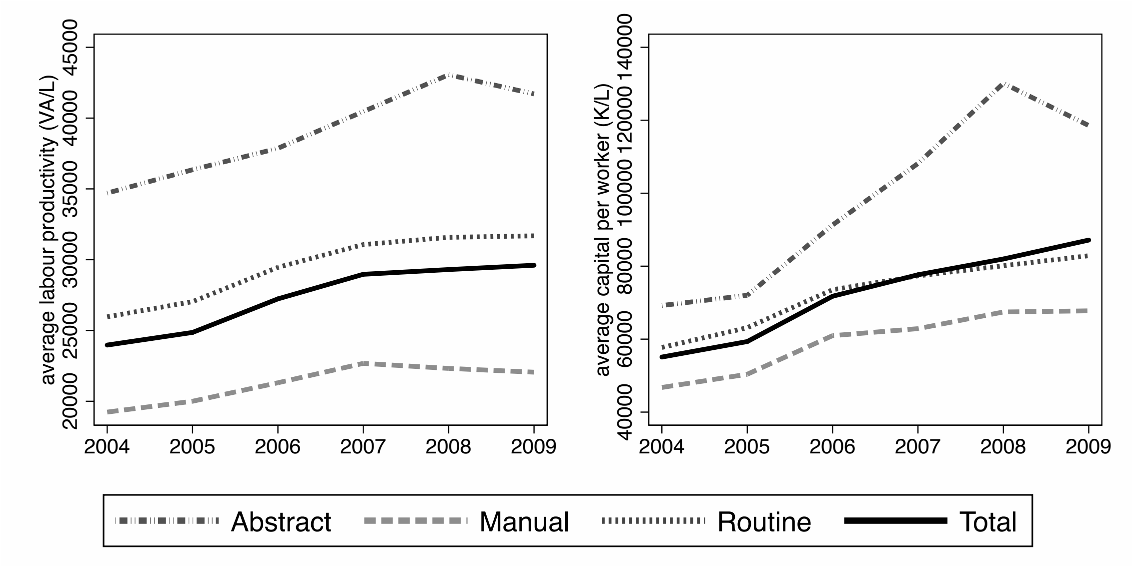

Figure 3: Labour productivity and capital use by firm type

5 Production functions

5.1 Methodology

Estimation of production functions have been extensively used to study productivity and productivity growth.[4] Productivity is the efficiency of how a firm converts its inputs in outputs. Typically, inputs of the production function, such as labour and capital, have being augment to accommodate several others inputs. An example is ICT input that has been associated with positive contribution to firm's productivity (Bresnahan, Brynjolfsson and Hitt 2002, Greenana and Mairesse 2000, Brynjolfsson and Hitt 2003 and Bloom et al. 2012).

Another commonly used measure of productivity is total factor productivity (TFP). TFP as measure of productivity has the advantage of being invariant to the factor inputs observed by the econometrician, usually capital and labour, thus it reflects the output of production given a set of fixed inputs (Syverson, 2011). As for the functional form of the production function, economic theory provides several options based on the economic conditions that firms face. The Cobb-Douglas specification is perhaps the most widely used form for the study of the impact of technology on productivity (Tambe, Hitt and

[4] See for example Bloom and Van Reenen (2007), Haskel, Pereira and Slaughter (2007), Chun, Kim and Lee (2014), Venturini (2015) and Bertschek and Kaiser (2004).

Brynjolfsson, 2012). The TFP can be computed by estimating the production function elasticities and then computing the residual that is idiosyncratic to the firm. Several others covariates can be estimated as well, usually to capture the variance among groups of firms, for example at sector-level, or random shocks that some firms (or particular groups of firms) suffer.

Several methodologies can be used to estimate the production function but, as Syverson (2011) argues, a high-productivity firm will tend to be measured as high-productivity despite the method used. The most conventional methodology is to estimate the production function parameters using Least Squares, which raises the issues of simultaneity and selection. Simultaneity occurs because firms set their inputs conditional on their expected productivity, in essence presenting an endogeneity problem. The problem of selection is particularly important in panel data, as less efficient firms (lower TFP) are more likely to exit the sample (shutdown) than high efficiency firms.

Olley and Pakes (1996) propose a structural approach that accounts for both self-selection by firm's closure and simultaneity caused by endogenous inputs, which is controlled using investment as an instrumental variable. However, as Olley and Pakes (1996) (hereafter OP) approach assumes that firms that commit to invest are unlikely to exit the market, investment has to be strictly positive, thus generating a truncation bias by not taking into account firms with zero investment. Lumpy investment is not accounted as well, as it does not lead to an even response to productivity shocks. In order to overcome these problems, Levinsohn and Petrin (2003) (hereafter LP) propose to use the intermediate inputs instead of investment as instrumental variables. Intermediate inputs are less prone to be associated with adjustment costs, reacting better to productivity shocks, and are typically used in production functions and strictly positive. Additionally, intermediate inputs as energy and materials tend always to be reported and positive, whereas investment is not.

The literature still provides several other models and estimation methods. For instance, Ackerberg, Caves and Frazer (2006) building on Olley and Pakes (1996) and Levinsohn and Petrin (2003) proposes a refined structural model. Wooldridge (2009) suggests a more efficient method to estimate Olley and Pakes (1996). However, none of those are exempt from making assumptions. Dynamic panel estimators such as those propose by Arellano and Bond (1991) and Blundell and Bond (1998) can also be used to estimate the production function. Dynamic panel estimators are more flexible towards the functional form of the production function, yet some problems arise, as loss of variability due to differencing (Wooldridge, 2009), or simultaneity bias. Consequently, as Syverson (2011) notes, choosing the most appropriate method just depends on what assumptions the researcher is comfortable with.

We approach the estimation problem using LP methodology, but for comparability we also estimate the production functions using the OP methodology. Following LP, we consider a production function with Cobb-Douglas technology. Denoting in lower case the logarithms of Y, L and K, we write the production function of firm i in time t as:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \epsilon_{it} \tag{1}$$

At time t, the output y_t is measured by the value added, labour l_t is the number of employees, and k_t is the capital. Productivity (TFP) is what cannot be explained by the observable inputs, thus the residual ϵ_{it}.

Both LP and OP consider that the residual can be decomposed into two parts. The first part is the productivity shock Ω_{it} that is observed by the firm and an unexpected productivity shock η_{it} that is not observed by the firm. The econometrician only observes the total residual ϵ_{it}. Thus, the production function can be written as:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \Omega_{it} + \eta_{it} \tag{2}$$

At this point the approaches of LP and OP diverge. While OP uses investment as an instrumental variable for endogeneity, LP uses the intermediate inputs m_{it}. In OP the unobserved productivity Ω_{it} depends on the investment demand function, whereas in LP Ω_{it} is measured by the inverse demand for intermediate inputs. Formally, the demand function for intermediate inputs is expressed as:

$$m_{it} = m_{it}(k_{it}, \Omega_{it}) \tag{3}$$

Assuming that the demand is strictly increasing in Ω_{it}, the function can be inverted:

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

Pluging in the production function, such that the unobserved productivity Ω_{it} depends now on the intermediate inputs m_{it} and capital k_{it}, give us:

$$y_{it} = \beta_l l_{it} + \phi(m_{it}, k_{it}) + \eta_{it} \tag{5}$$

with

$$\phi(m_{it}, k_{it}) = \beta_0 + \beta_k k_{it} + \Omega(m_{it}, k_{it}) \tag{6}$$

The unobserved productivity is expressed as a function of the observed inputs and follows a first-order Markov process as in OP.[5] Following Petrin, Poi and Levinsohn (2004), we first obtain the OLS estimation of production function with a third-order polynomial approximation of ϕ_{it} to identify β_l and ϕ_t. We then compute $\hat{\phi}_{it} = \hat{y}_{it} - \hat{\beta}_l$. With the estimates $\hat{\beta}_l$ and $\hat{\phi}_{it}$ the next step is to compute $\hat{\Omega}_{it} = \hat{\phi}_{it} - \beta_k^* k_{it}$ for any candidate β_k^*. An approximation of $E[\Omega_{it}|\Omega_{i,t-1}]$ is given by the regression predictions and computed values of $\hat{\Omega}_{it}$:

$$E[\widehat{\Omega_{it}|\Omega_{i,t-1}}] = \hat{\Omega}_{it} = \gamma_0 + \gamma_1 \Omega_{t-1} + \gamma_2 \Omega_{t-1}^2 + \gamma_3 \Omega_{t-1}^3 + \epsilon_{it} \tag{7}$$

LP wrote the sample residual of the production function using $\hat{\beta}_l$, β_k^* and $E[\widehat{\Omega_{it}|\Omega_{i,t-1}}]$ as:

$$\widehat{\eta_{it} + \xi_{it}} = y_{it} - \hat{\beta}_l l_{it} - \beta_k^* k_{it} - E[\widehat{\Omega_{it}|\Omega_{i,t-1}}] \tag{8}$$

To obtain the estimate of capital β_k, Petrin, Poi and Levinsohn (2004) propose to

[5]First-order Markov process $\Omega_{it} = E[\Omega_{it}|\Omega_{i,t-1}] + \xi_{it}$

solve the following minimization problem (Equation 9) using grid search algorithm and bootstrapping to construct standard errors for $\hat{\beta}_l$ and $\hat{\beta}_k$.

$$\min_{\beta_k^*} \sum_t (y_{it} - \hat{\beta}_l l_{it} - \beta_k^* k_{it} - E[\widehat{\Omega_{it}|\Omega_{i,t-1}}])^2 \tag{9}$$

We use both estimation methods in order to obtain productivity estimates for each firm in the sample. LP estimation is performed using the method proposed by Petrin, Poi and Levinsohn (2004) OP the one proposed by Yasar and Raciborski (2008) method. However, as we have underlined before, we only use the TFP estimated by LP method in subsequent analysis.

5.2 Production functions – results

For the estimation of the production function, we consider the usual inputs labour and capital used in OP and LP methods. As output variable we use value added. Some debate exists around the use of the value added, revenues or, when available, quantities as output measures. When a firm innovates on an existing product or service, the quantity output may not necessarily increase, but the price can increase (Syverson, 2011). The effect is then captured by revenue or value added, and productivity measures based on either will capture the price changes. Moreover, value added can be a better option because revenues will not capture productivity increases due to process innovation. Conversely, some of these practices to enhance productivity may require a temporary time window where current costs surpass previous costs (Holmes, Levine and Schmitz, 2012). Thus, choosing value added or revenues has both advantages and downsides. Acknowledging Basu and Fernald (1995) criticisms to the value added use, LP developed their methodology based on value added as it uses intermediate inputs, thus the choice of the value added is more appropriate in our case.

Table 4 presents the descriptive statistics for output and inputs of the production function by industry. The full estimable sample consists of more than 800 thousand firms, mostly from services (78%), followed by low-tech and medium-low-tech manufacturing (20% combined). High- and medium-high-tech manufacturing firms have, on average, the larger value added (12.42 and 12.24 log points, respectively). Also, manufacturing firms have, on average, more capital and labour, and invest more than services firms.

Table 4: Production function descriptive statistics by firm type

		Manufacturing				Services	
	All	**High**	**Med-High**	**Med-Low**	**Low**	**KIS**	**LKIS**
log VA	11.20	12.42	12.24	11.73	11.66	11.24	10.99
log capital	11.74	12.74	12.78	12.21	12.28	11.69	11.54
log labour	1.41	2.18	2.16	1.97	2.06	1.22	1.23
log intermediate	11.06	12.06	12.29	11.39	11.50	8.54	11.59
log investment	8.74	10.06	9.81	9.13	9.11	8.89	8.53
Observations	814594	2298	16493	63323	98595	137720	496165

Notes: Intermediate inputs are the sum of goods and energy. All values, except labour, are in euros, deflated using producers' price index at 3-digits industry level. Labour refers to the number of employees. High corresponds to high-tech manufacturing, Med-High is medium-high-tech manufacturing, Med-Low is medium-low-tech manufacturing, Low is low-tech manufacturing; KIS stands for knowledge-intensive services and LKIS for less knowledge-intensive services.

By using these variables we can estimate the production function by both methods. The OP method uses investment as the control for endogeneity and LP uses intermediated inputs. We estimate the production functions by industry aggregation according to their technological intensity of OECD and Eurostat (Hatzichronoglou, 1997). This approach of estimating the production functions by industry allow us to better isolate differences in technology across firms, a practice that has been standard in the literature (Syverson, 2011). Table 5 presents the estimated coefficients from the LP method (OP estimates can be found in Appendix Table A2). The estimated capital elasticity ranges from 0.252 in low-tech to 0.316 in high-tech and 0.324 in medium-low tech firms. The labour elasticity ranges from 0.567 in high-tech firms to 0.669 in knowledge intensive services.

From the production function estimations we retrieve TFP, which is our productivity measure. In Figure 4 we plot the aggregate log productivity (aggregated using the value added) for the LP method by firm type. The results show that the overall productivity has grown over 2004 to 2009, with Abstract firms being the top performers. Moreover, Abstract firms are the most productive firms, followed by Polarised, with Manual firms being the least productive.

The distance between Abstract, Routine and Manual productivity estimates is relatively high. Overall there is an increase in the aggregate productivity across all firm

Table 5: Production function estimates

	Manufacturing				Services	
	High	**Med-High**	**Med-Low**	**Low**	**KIS**	**LKIS**
log k	0.316***	0.276***	0.324***	0.252***	0.278***	0.298***
	(0.036)	(0.025)	(0.013)	(0.010)	(0.009)	(0.005)
log l	0.567***	0.563***	0.618***	0.623***	0.669***	0.572***
	(0.035)	(0.012)	(0.005)	(0.004)	(0.003)	(0.002)
Obs.	2298	16493	63323	98595	137720	496165

Notes: The dependent variable is the log value added. Estimation performed separately by industry type using LP estimation method. * 10% significant, ** 5% significant and *** 1% significant.

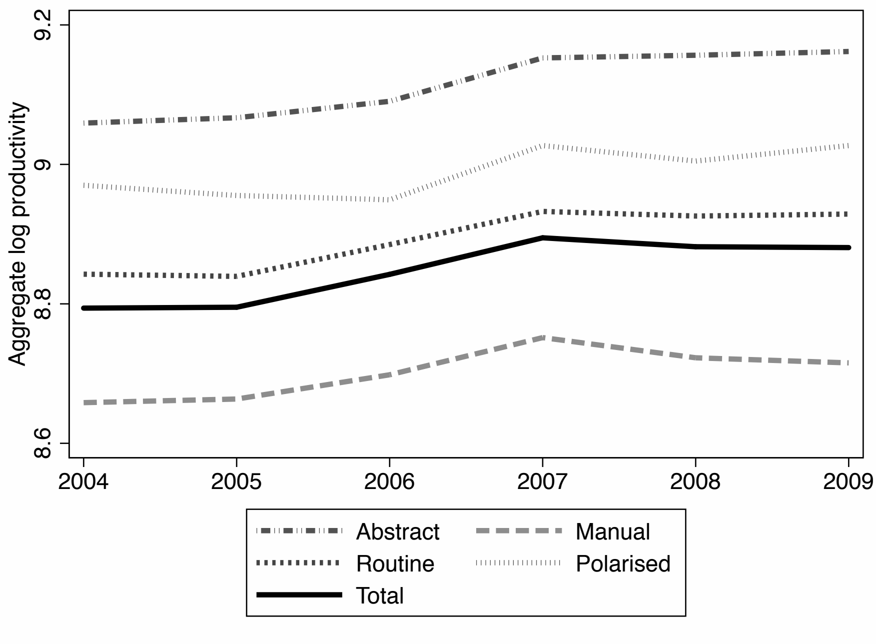

Figure 4: Aggregate productivity by firm type

Notes: Aggregate productivity is computed by averaging productivity $\hat{\Omega}_{it}$, with value added share as weights. The estimates of $\hat{\Omega}_{it}$ are obtained from estimating production function using Levinsohn and Petrin (2003) (LP) method. Estimation results from Table 5.

types. However, LP methodology highlights the effects of the recession by capturing the slowdown of productivity growth or even decrease in the case of Manual firms. Nevertheless, Abstract firms' productivity growth is positive from 2007 onwards, while the remaining firms' productivity decrease or present nil growth.

It is not surprising that Abstract firms are the top performers and that the distance between these and the other focused task groups of firms grows as technological progress continues. First, Abstract firms should be, by definition, associated with higher ICT inputs, and as the literature points out there is an association between ICT use and firm's productivity (Bresnahan, Brynjolfsson and Hitt, 2002; Greenana and Mairesse, 2000; Brynjolfsson and Hitt, 2003; Bloom et al., 2012). Second, while ICT may impact all firm types, Abstract firms have arguably a better organisational structure and the complementary assets required to fully benefit from those technologies (Brynjolfsson and Hitt, 1996, 2003). Moreover, Abstract firms have more skilled human capital that is required to obtain the complementary effect of ICT. As research points out, human capital is critical in order to properly implement ICT investments (Bresnahan, Brynjolfsson and Hitt, 2002).

6 Productivity dynamics

Although we are able to characterise productivity change by firm type, the sources of its dynamics are unknown. Growth can be due to a general shift in the productivity distribution that affect all firms equally or at least each firm type equally. Alternatively it can be due to market reallocation of incumbent firms' shares. To disentangle the importance of these elements in productivity growth, Olley and Pakes (1996) proposes a methodology that decomposes the aggregate productivity in a given year Φ_t into two parts:

$$\Phi_t = \bar{\phi}_t + \sum_i (s_{it} - \bar{s}_t)(\phi_{it} - \bar{\phi}_t) \tag{10}$$

The first $\bar{\phi}_t$ corresponds to the total productivity distribution, a within change in productivity. The within productivity is measured by an unweighted mean of firms' productivity. The second term is a summation between market share s_{it} and firm's productivity

ϕ (both demeaned), thus measuring the reallocation of market shares between firms. For simplicity we label the summation as cov_S, knowing that is not a true covariance between s and ϕ as it lacks the denominator. Market shares are measured by using the value added and the log TFP - obtained from the production functions' estimation.

While the decomposition presented in Equation 10 is useful to disentangle productivity dynamics, it does not account for market entry and exit, which may play an important role in productivity changes. It may be the case that Abstract firms' productivity is rising because new technologies enable young firms to compete with established firms (Greenwood and Jovanovic, 2001), or because smaller firms are now more viable due to the use of ICT (Brynjolfsson et al., 1994). In order to understand if this is the case, we apply and extend the Melitz and Polanec (2015) dynamic version of Olley and Pakes (1996) decomposition.

Melitz and Polanec (2015) augments Olley and Pakes (1996) decomposition by including three groups of firms: survivors, exitors and entrants. We add to their decomposition by incorporating transition firms, that is, firms that changed their task focus (for instance from Routine to Manual). Thus, we include two additional movements: entrance through transition and exit through transition between task focus. A firm is considered to enter through transition when it is observed in both periods but transited from one firm type to another. The same reasoning applies to exit through transition.

Extending Melitz and Polanec (2015), we write the decomposition for period 1 and 2 as:

$$\Phi_1 = s_{S1}\Phi_{S1} + s_{X1}\Phi_{X1} = \Phi_{S1} + s_{X1}(\Phi_{X1} - \Phi_{S1}) + s_{X_{tr}1}(\Phi_{X_{tr}1} - \Phi_{S1}) \tag{11}$$

$$\Phi_2 = s_{S2}\Phi_{S2} + s_{E1}\Phi_{E1} = \Phi_{S2} + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{E_{tr}2}(\Phi_{E_{tr}2} - \Phi_{S2}) \tag{12}$$

Where the index S represents the survivors, X the exitors and E the entrants. The transitioning group is denoted by X_{tr} for exit through transition and E_{tr} for entrance through transition. So, the change between two periods $\Delta\Phi = \Phi_2 - \Phi_1$ is given by:

$$\Delta\Phi = (\Phi_{S2} - \Phi_{S1}) + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}) + s_{E_{tr}2}(\Phi_{E_{tr}2} - \Phi_{S2}) + s_{X_{tr}1}(\Phi_{S1} - \Phi_{X_{tr}1})$$

or

$$\Delta\Phi = \Delta\bar{\phi}_S + \Delta cov_S + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}) + s_{E_{tr}2}(\Phi_{E_{tr}2} - \Phi_{S2}) + s_{X_{tr}1}(\Phi_{S1} - \Phi_{X_{tr}1}) \quad (13)$$

The first two components are the same as in Olley and Pakes (1996) decomposition (Equation 10). The within component $\Delta\bar{\phi}_S$ measures the change in survivors productivity distribution. The between term Δcov_S captures the change due to market reallocations of surviving firms. As Melitz and Polanec (2015) propose, the measure of change due to firms' entry into the market is captured by $s_{E2}(\Phi_{E2} - \Phi_{S2})$ and the change attributable to firms' exit by $s_{X1}(\Phi_{S1} - \Phi_{X1})$.

We introduce the new term $s_{E_{tr}2}(\Phi_{E_{tr}2} - \Phi_{S2})$, which measures the entries through transition by comparing these firms' productivity with the surviving firms that maintain their task focus. Similarly, exit through transition is computed by $s_{X_{tr}1}(\Phi_{S1} - \Phi_{X_{tr}1})$, in which we compare the firms that exit through change in task focus with the surviving firms group.

The results for all firms from the above decomposition can be found in Table 6 using the productivity results from LP estimation (Table 7 shows detailed results by firm type). Entry and exit through transitions can only be computed by firm type, and therefore they are not included in this table. The market shares s are computed based on value added of each firm. We present the results setting 2004 as the base year (period 1) and then varying the end year (period 2) from 2005 to 2009. Growth (0.067 log points for 2004-2009) comes mostly from market reallocations (changes in market shares) and the least productive firms leaving the market (117% combined contribution). The contribution from new firms entering the market to the increase in aggregate productivity is smaller but substantial

(36% contribution), while the within component pushes productivity growth down. The relative contribution of the various components does not change significantly when we look at the other time periods: the between component (market reallocations) and exit of least productive firms dominate productivity growth; firm entry has a positive effect on aggregate productivity growth; and the within component has a negative contribution.[6]

Table 6: Productivity growth decomposition

	Total	**Survivors**		**Entrants**	**Exitors**
	Change	**Within**	**Between**		
2005	-0.010	-0.005	-0.015	0.002	0.009
2006	0.018	-0.011	0.006	0.010	0.013
2007	0.062	0.009	0.022	0.015	0.016
2008	0.064	-0.014	0.032	0.017	0.029
2009	0.067	-0.035	0.035	0.024	0.043

Notes: Decomposition performed using LP TFP results for all firms (the estimation results are in Table 5). The base year is 2004. Within component refers to $\Delta\bar{\phi}_S$ and the between component is Δcov_S, where $cov_S = \sum_i (s_{it} - \bar{s}_t)(\phi_{it} - \bar{\phi}_t)$. Entry is computed by $s_{E2}(\Phi_{E2} - \Phi_{S2})$ and exit by $s_{X1}(\Phi_{S1} - \Phi_{X1})$.

Table 7 breaks down the decomposition by the three main firm types (Abstract, Manual and Routine), including the transitions.[7] Total productivity growth is much higher for Abstract firms (0.415 log points) than Routine (0.055) and Manual (0.045) confirming the TFP changes presented in Figure 4. For all firm types the within component is negative, that is, the average productivity of surviving firms contributes negatively to the aggregate productivity growth. However, this component is dampened by market reallocations (between term), leading to a positive productivity growth among surviving firms. This between effect (market reallocation) is the larger main driver of productivity growth between 2004 and 2009 for Routine and Manual firms.

New entrants or entrants through transition are the main contributors to productivity growth for Abstract firms (30% and 38% contribution in 2009, respectively). Firms leaving the Abstract category also contribute positively to growth, as their productivity is lower than surviving firms that remain abstract. For Routine and Manual firms, entry and exit through transition has a marginal contribution to growth. The same can be said of market

[6] Note that the exitors term is constructed so that when the coefficient is positive firms that are leaving the market are least productive than survivors.

[7] For simplicity we present the decomposition for focused firms. Together focused firms represent more than 87% of the pooled sample.

entry. However, in the case of Routine, exitors play a large contribution to growth, where the least productive firms leave the market. In sum, the aggregate productivity growth in the Portuguese economy has three main drivers: market reallocations, firms entering to or transitioning into the Abstract type and finally the least productive firms exiting the market (mostly Routine).

Table 7: Productivity growth decomposition by firm type

	Total	**Survivors**				**Transitions**	
	Change	**Within**	**Between**	**Entrants**	**Exitors**	**Entrants**	**Exitors**
Abstract							
2005	0.062	-0.024	0.042	-0.010	-0.011	0.044	0.021
2006	0.192	-0.035	0.016	0.062	-0.023	0.134	0.038
2007	0.366	-0.008	0.035	0.048	-0.014	0.260	0.044
2008	0.403	-0.003	0.146	0.015	-0.010	0.199	0.056
2009	0.415	-0.012	0.079	0.125	0.012	0.158	0.053
Manual							
2005	-0.006	-0.004	0.007	-0.002	-0.007	-0.002	0.002
2006	0.013	-0.006	0.030	-0.003	0.000	-0.004	-0.005
2007	0.066	0.015	0.056	-0.003	-0.004	0.002	0.000
2008	0.079	-0.004	0.089	0.001	-0.010	0.007	-0.004
2009	0.049	-0.025	0.080	-0.004	0.000	0.004	-0.007
Routine							
2005	-0.017	-0.035	0.012	0.003	0.010	-0.006	-0.001
2006	0.018	-0.044	0.046	0.002	0.018	-0.005	0.001
2007	0.051	-0.026	0.073	-0.002	0.012	-0.003	-0.002
2008	0.043	-0.057	0.081	-0.002	0.024	0.001	-0.003
2009	0.055	-0.079	0.092	0.005	0.044	-0.007	0.000

Notes: Decomposition performed using LP TFP results by firm type. The base year is 2004. Within component refers to $\Delta\bar{\phi}_S$ and the between component is Δcov_S, where $cov_S = \sum_i (s_{it} - \bar{s}_t)(\phi_{it} - \bar{\phi}_t)$. Entry is computed by $s_{E2}(\Phi_{E2} - \Phi_{S2})$ and exit by $s_{X1}(\Phi_{S1} - \Phi_{X1})$. Transitions entrants corresponds to $s_{E_{tr}2}(\Phi_{E_{tr}2} - \Phi_{S2})$ and transitions exitors to $s_{X_{tr}1}(\Phi_{S1} - \Phi_{X_{tr}1})$.

The above analysis of the productivity dynamics provides a way to identify the contribution of each firm event – surviving, entry, exit or transitioning – to productivity growth. The proposed taxonomy categorizes firms according to the tasks performed by their workforce and implied technology. The analysis could be further extended to the characterization of firms in each duplet type-event. We provide a brief account of these characteristics in Table 8. A thorough analysis calls for modelling the decision to enter the market and the survival conditions, but that is beyond the scope of the present study.

Table 8 presents firms' characteristics by type and event, where we include the differences between the means and the respective t-test. Looking at surviving firms between 2004 and 2009, Abstract firms tend to became larger, while Routine and Manuel maintain their size. Entrants and exitors are smaller than surviving firms across the three firm types, though the difference is more pronounced for Routine firms. As we have shown before (Table 3), Abstract firms are by far the ones that hire more college graduates. In 2004, Abstract incumbents (survivors) firm had 25.8% of their workforce holding a college degree; which compares to 4.8% for Routine firms and 2.7% for Manual firms. Among surviving firms, Abstract firms increase their proportion to 31.1%. For Routine and Manual, the increase is 1.2 and 0.6 percentage points respectively. Even more noticeable is that almost half of the Abstract entrants' workforce has college degrees; a difference of 18 percentage points when compared with incumbents. Such difference suggests that these new firms are more likely to adopt the latest generation technologies, being more innovative and demanding more human capital. Conversely, Abstract firms transitioning to other firm types employ a lower proportion of college graduates (-4 percentage points). Firms transitioning into Abstract also have a lower proportion (-6 percentage points) of college graduates. These firms, however, invest more in human capital when compared with Routine or Manual firms, thus we may assume that they were already structurally close to the Abstract type even before transition. Overall there are significant differences across firm types and events, which points to the need for further research on how different firm types adopt different strategies and have different capacities resulting in different events.

Table 8: Firms' characteristics by firm type and state: exit, entry, survival and transitioning

	Survivor (S)			Exiting ($X1$)		Trans. Exit ($X_{tr}1$)		Entering ($E2$)		Trans. Enter ($E_{tr}2$)	
	2004 ($S1$)	**2009** ($S2$)	**Diff** ($S2-S1$)	**Mean**	**Diff** ($X1-S1$)	**Mean**	**Diff** ($X_{tr}1-S1$)	**Mean**	**Diff** ($E2-S2$)	**Mean**	**Diff** ($E_{tr}2-S2$)
Abstract											
Size [1,9[	77.0	73.4	-3.62***	86.8	9.74***	88.9	11.9***	89.3	15.85***	88.3	14.9***
Size [10,49[	18.3	21.1	2.75**	11.4	-6.9***	9.8	-8.53***	9.4	-11.66***	10.6	-10.45***
Size [50,99[	2.9	3.5	0.58	1.2	-1.69***	0.0	-2.9***	0.6	-2.84***	0.5	-2.95***
Size [100,249[	1.2	1.5	0.29	0.5	-0.73**	1.3	0.06	0.4	-1.11***	0.3	-1.15**
Size >=250	0.5	0.5	0	0.1	-0.43**	0.0	-0.53	0.3	-0.23	0.2	-0.36
College	25.8	31.1	5.26***	27.9	2.11*	21.7	-4.14*	48.7	17.59***	24.6	-6.49***
Routine											
Size [1,9[	67.2	67.6	0.36*	80.3	13.07***	91.0	23.83***	86.1	18.55***	87.1	19.59***
Size [10,49[	25.8	25.4	-0.36	16.3	-9.49***	8.1	-17.67***	12.2	-13.23***	12.1	-13.29***
Size [50,99[	3.9	3.9	0.06*	2.2	-1.67***	0.5	-3.36***	0.9	-2.98***	0.5	-3.46***
Size [100,249[	2.2	2.2	0.03	1.0	-1.22***	0.2	-1.94***	0.5	-1.66***	0.3	-1.95***
Size >=250	1.0	0.9	-0.09	0.3	-0.69***	0.1	-0.87***	0.2	-0.68***	0.0	-0.9***
College	4.8	6.0	1.22***	5.4	0.66***	5.9	1.11***	11.9	5.95***	6.9	0.87***
Manual											
Size [1,9[	75.7	75.0	-0.77	85.2	9.5***	88.6	12.83***	86.7	11.7***	87.2	12.29***
Size [10,49[	20.5	21.0	0.41	13.0	-7.54***	10.9	-9.62***	11.7	-9.21***	11.6	-9.38***
Size [50,99[	2.2	2.5	0.27	1.0	-1.15***	0.4	-1.8***	1.0	-1.51***	1.0	-1.51***
Size [100,249[	0.9	1.0	0.05	0.5	-0.43***	0.1	-0.8***	0.5	-0.53***	0.1	-0.84***
Size >=250	0.6	0.6	0.04	0.2	-0.38***	0.0	-0.61***	0.2	-0.46***	0.1	-0.57***
College	2.7	3.2	0.59***	3.3	0.62***	4.3	1.64***	5.2	1.98***	4.5	1.25**

Notes: All values are expressed as percentages. Size categories are firms' number of employees. College refers to the share of college graduates in the firms' workforce. Exit are firms exiting the market, Survivors refers to firms that survived the entire period (incumbents) and Entering are firms that enter the market during time period considered and have more than one year. Trans. refers to transitions from other firm types through entering or exiting to a different firm type. Diff refers to the difference between the group and survivors in 2004 for exits and 2009 for entries. The difference includes a t-test where * is 10% significant, ** is 5% significant and *** is 1% significant.

7 Conclusion

In this paper we propose a new taxonomy based on the tasks performed by firms' workforce. This taxonomy aims to capture the recent trends in technological change, which are visibly substituting human labour for computer capital - the so called routinisation hypothesis. Our taxonomy divides firms into mainly three categories – Abstract, Routine and Manual – according to firms focus in either abstract, routine or manual task intensive labour.

We apply this taxonomy to study productivity and its dynamics in Portugal. Portugal has been extensively compared to other southern European economies in terms of productivity growth, thus our conclusions may apply to a wider set of economies. Our descriptive statistics show that Abstract firms are rising in importance both in terms of employment and number of firms, though they are still relatively less prevalent than both Routine or Manual firms. Abstract firms are appearing in sectors associated with high value added as high-tech and medium-tech manufacturing and knowledge intensive services. The rise of Abstract, decline of Routine and a stable share of Manual firms, suggests that labour market polarisation is not due to polarisation within firms, but rather to firms specialising in one task.

Productivity estimates show that Abstract firms are top performers, while Manual firms are at the bottom of the productivity ranking. The results are not surprising since Abstract firms are more technological intensive - as suggested by their large capital to labour ratio. This is consistent with the fact that abstract labour (high-skilled) and capital are complementary.

The Portuguese aggregate productivity has grown by 7% between 2004 and 2009. Our taxonomy enables us to understand that focused Abstract firms are the main drivers of productivity growth, accounting for 88% of total productivity growth. Because productivity has a large stake in a country's competitiveness and by extension economic growth, policy makers should design policies targeted at fostering the development of new technological firms, which are endowed with high-skilled workers. Also, promoting enterprises to re-organise their labour inputs so they can become Abstract firms can lead to increases in aggregate productivity.

It is not surprising that Portugal is associated with low productivity, as its levels of capital are still well bellow the European average and bellow other southern European countries. Policy makers must be aware that promoting the growth and creation of Abstract firms, and in turn productivity growth, requires higher levels of capital stock, as well as investments in human capital. Those are the pillars of Abstract firms. Our analysis of firm productivity dynamics enables us to identify the contribution of each firm event – surviving, entry, exit or transitioning – to productivity growth. The results show that Abstract firms invest more in human capital and are increasing in size more than Routine or Manual firms. Abstract firms entering the market are even more intensive in high-skilled workers, which suggests those firms can adopt the latest technologies, perform more innovation and demand more human capital than incumbents and other firm types. Further research is needed to understand what additional firm characteristics within each firm type are related with these firm events such as capital use, R&D intensity and exporting and innovation strategies.

We have opened a new avenue for studying productivity growth by proposing a firm taxonomy which characterises firms according to the task make up of their workforce. Our taxonomy suggests that a possible dichotomous relationship of internal activities are leading firms to become more task focused, thus specialising in just one type of task. It could be the case that the increased complexity of processes and specialisation in innovation activities are leading firms to opt for organisational separation in order to become more productive by either being exploitive or explorative. These questions provide an exciting ground for further research.

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Appendix A Tables

Table A1: Allocation between occupations and tasks

Abstract		Routine		Manual	
21	Physical, mathematical and eng. science prof.	34	Other associate professionals	51	Personal and protective services workers
24	Other professionals	41	Office clerks	91	Sales and services elementary occupations
23	Teaching professionals	42	Customer services clerks	71	Extraction and building trades workers
31	Physical and eng. science associate prof.	52	Models, salespersons and demonstrators	72	Metal, machinery and related trades workers
33	Teaching associate professionals	73	Precision, handicraft, print. and rel. trades work.	83	Drivers and mobile-plant operators
12+13	Small enterprises & corporate managers	74	Other craft and related trades workers	93	Laborers in mining, const., manuf. and transp.
22	Life science and health professionals	81	Stationary-plant and related operators		
32	Life science and health associate prof.	82	Machine operators and assemblers		

Notes: Occupational codes are ISCO-88. Adapted from Fonseca, Lima and Pereira (2014). To construct the categories, O*NET measures are aggregated into task intensity indexes using principal components and then attributed to ISCO 2-digits occupations using U.S. employment data and a detailed cross-walk. Task allocation is based on the most intensive task in a given occupation.

Table A2: Production function estimates (OP)

	Manufacturing				Services	
	High	Med-high	Med-low	Low	KIS	LKIS
log k	0.222**	0.267***	0.400***	0.324***	0.298***	0.340***
	(0.067)	(0.029)	(0.015)	(0.021)	(0.011)	(0.024)
log l	0.692***	0.667***	0.616***	0.622***	0.662***	0.645***
	(0.044)	(0.012)	(0.006)	(0.005)	(0.004)	(0.003)
Obs.	1897	13831	51545	80323	119947	396790

Notes: The dependant variable is the log value added. Estimation performed separately by industry type using OP estimation method. * 10% significant, ** 5% significant and *** 1% significant.