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Abstract

As job markets have been polarizing, firms have been changing their labor inputs. By using matched employer-employee data for Portugal, we examine whether labor market polarization has occurred within or across firms and how labor input upgrades have contributed to overall productivity growth. We develop a firm taxonomy based on worker's occupational data. Firms can be focused on one task – Abstract, Manual or Routine – on a combination of tasks, or none. Results show that Abstract firms are the most productive and their share has increased over time. Manual firms, the least productive, have had a stable share throughout the period. Routine firms have seen their share decline over time. The dynamic decomposition of the estimated productivity reveal that productivity growth is propelled by increased market shares of the most productive incumbents and exiting of the least productive, especially for Abstract firms. Notwithstanding these productivity growth drivers, they fail to avert the productivity stagnation observed in Portugal between 2004 and 2009 due to the overall decline in productivity of incumbent firms, especially Routine. We discuss the policy implications of our results which are relevant to other European economies also lagging behind in terms of knowledge and innovation capabilities.

JEL Classification: D24, L23, O33

Keywords: **Taxonomy, productivity, routinization, technological change, polarization**

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1 Introduction

Computers and computer-driven machines, or computer capital, are reshaping the workplace significantly as well as how firms organize production. 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. In addition, high-skilled workers increase their productivity because of their complementarity with computer capital. The polarization of the job market – the simultaneous decline in middle-skilled jobs and the increase in low- and high-skilled jobs – has been linked to the adoption of computers and the consequent replacement of routine tasks – the routinization hypothesis (Acemoglu and Autor, 2011; Autor, Levy and Murnane, 2003).[1]

Although a vast body of literature that addresses polarization and routinization from the angle of the labor market exists, few studies have looked at how job market polarization has changed the distribution of skills inside firms.[2] We approach routinization through the lens of the firm, by using matched employer-employee Portuguese data to seek answers to two main questions. First, is job market polarization mainly taking place within or across firms? And second, how do these shifts within and across firms contribute to aggregate productivity growth?

In order to answer these two questions, we propose a taxonomy based on the task-approach followed by the routinization literature.[3] We classify firms according to the tasks

[1]Non-withstanding strong evidence supporting the routinization hypothesis, other factors may have also contributed to the labor market trends observed in the last few decades: shifts in international trade (Autor, Dorn and Hanson, 2015; Ebenstein et al., 2014), changes in the supply of skills (Bessen, 2012; Fodor, 2016; Vona and Consoli, 2015) and business cycles (Jaimovich and Siu, 2012), all may have played a role in labor market polarization.

[2]To our knowledge, only a few studies, all using Finnish data, have looked at within-between firm decomposition of job polarization patterns (see Böckerman and Maliranta, 2013; Hyytinen and Maliranta, 2013; Kerr, Maczuskij and Maliranta, 2015). However these studies have not looked at firm productivity dynamics nor have they used a task based firm taxonomy in their analysis. They have found a weak to moderate role for job polarization inside the firm with differences by occupation as well as a link between firm-level polarization and various international activities that the firms engage in.

[3]The task based approach has been criticized in recent works, in particular the focus on occupations instead of skills, and the robustness of the evidence of a polarizing labor market as well as the technological explanation for polarization (see Beaudry, Green and Sand, 2016; Castex and Kogan Dechter, 2014;

performed by their workforce identifying several categories of firms: three task-focused categories – Abstract, Routine, Manual – firms that use more intensively abstract, routine or manual tasks respectively; Polarized firms, borrowing the term from labor economics – firms highly intensive in abstract and manual tasks, but low in routine; two boundary categories, similar to Polarized, but intensive in either abstract and routine or manual and routine; and Uniform firms characterized by similar levels of intensity in abstract, routine and manual task activities. By constructing a taxonomy based on firms' labor inputs rather than idiosyncratic characteristics such as industry or size, we capture a wider range of changes in firm dynamics.

We apply this taxonomy to Portuguese firms to study the evolution in firm task intensity and its relationship with productivity and productivity growth. We show that Abstract firms are increasing their prevalence in the economy and Routine firms are declining. We further compute total factor productivity by estimating production functions using Ackerberg, Caves and Frazer (2015) methodology. The results show that among task-focused firms, Abstract are the most productive followed by Routine and Manual. In addition, for the overall period (2004-2009), Abstract firms show the largest productivity growth (22%), contrasting with the negative growth for Routine (-0.6%) and Manual (-1.5%).

We decompose the estimated productivity changes by applying a dynamic decomposition following Olley and Pakes (1996) and Melitz and Polanec (2015) and conclude that overall productivity growth is propelled by incumbents' market share reallocations, that is, increasing market shares of the most productive incumbents and exiting of the least productive firms. Despite these productivity growth drivers, which are stronger for Abstract firms, they fail to counterbalance the decline in the overall productivity of incumbents (mostly Routine and Manual) resulting in the productivity stagnation observed between 2004 and 2009.[4] Our results raise the question of how policy-makers should design policies

Hunt and Nunn, 2017; Mishel, Shierholz and Schmitt, 2013). Yet, most evidence still corroborates the routinization hypothesis.

[4]Portugal was not the only southern European country experiencing economic stagnation during this period. Gopinath et al. (2017) finds similar patterns between Portuguese, Spanish and Italian firms in terms of factors' marginal revenue and total factor productivity dynamics. Italy, in particular, has experienced total factor productivity losses due to misallocation of resources as Portugal did. Blanchard (2007) also uses the specific case of Portugal to highlight the problem of stagnant or declining productivity of several euro area countries.

to foster productivity and reduce the skill mismatch occurring in labor markets undergoing similar changes. If innovation policies, within a regional innovation system, should promote Abstract firms, education and training policies need to tackle the prevailing high long-term unemployment, an indicator of major structural imbalances in regions lacking innovation and knowledge capabilities.

This paper is structured as follows. Section 2 reviews the theoretical foundations on which our work is based, develops the new taxonomy, and presents the methodology behind the productivity estimation and its decomposition. Section 3 describes de data used. Section 4 applies the task taxonomy to our data. Section 5.1 estimates total factor productivity followed by the study of the productivity dynamics in Section 5.2. We perform several robustness checks in Section 5.3. Section 6 discusses the policy implications of our results and section 7 concludes.

2 Theoretical Framework

We begin this section by reviewing the literature on the relationship between technology and skills and on the routinization model. We then present and discuss the new firm task-based taxonomy. In the last two subsections, we delve into the estimation of firms' productivity and its dynamics.

2.1 Technology and skills

Technology and skilled labor 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 idea that technology demands workers' skills traces back to seminal works by Griliches (1957), Nelson and Phelps (1966) and Schultz (1975) and empirical research corroborates this hypothesis (see, for example, Acemoglu, 1998; Autor, Katz and Krueger, 1998; Bresnahan, 1999; Krueger, 1993; Krusell et al., 2000).[5] New technologies can be difficult to master and thus require more skills. Usually, more educated workers are

[5]Not all technologies are complementary to high skilled labor. As Acemoglu (2002) notes, during the nineteenth and early twentieth centuries, technology advances were directed at reducing the skills required in the workplace by simplifying work and breaking it into small tasks, replacing the work of skilled artisans.

more able to learn new technologies faster, which leads to employers hiring more skilled workers. In this sense, technology has been noted to be biased towards skilled workers, the so called skilled biased technological change (SBTC hereafter).

As technology started to decrease its cost, in particular computers, firms massively adopted it in the workplace, thus leveraging productivity of the high-skilled workers due to their complementarity effect (Acemoglu, 1998; Autor, Katz and Krueger, 1998; Krueger, 1993). When the adoption of microprocessor-based technologies occurred more intensively, in the 1980s, SBTC became more evident and pervasive throughout the developed world (Berman, Bound and Machin, 1998). Thus, the expanded use of computers and computer controlled machines in the workplace have led to a rise in the employment share of highly skilled labor (Autor, Katz and Krueger, 1998). Moreover, the investment in computers and R&D lead to an increase in the pace of skill upgrading (Autor, Katz and Krueger, 1998; Machin and Van Reenen, 1998). Thanks to robotics, few skilled workers can now perform more efficiently tasks that were previously performed by many unskilled workers (Johnson, 1997). The use of robots therefore increased the complexity of many tasks that were previously routine. Alongside with new technologies, new organizational practices such as Total Quality Management or Just-in-Time also require skilled workers, as complementarities arise from the interdependence of skills and those practices (Bresnahan, 1999; Caroli and Van Reenen, 2001; Piva, Santarelli and Vivarelli, 2005).

Although SBTC was a pervasive phenomenon, it does not fully explain the changes in wages and employment felt from the 1990s onwards. In the 1990s, contrary to the SBTC hypothesis, where the relative employment and wages grows monotonically with skills (or wages), low-waged jobs also increased their employment shares. In this sense, middle-waged jobs hollowed out, leading the labor market to become polarized towards low and high skilled jobs (Acemoglu and Autor, 2011; Autor, Katz and Kearney, 2006; Goos and Manning, 2007). Portugal was no exception, and both Centeno and Novo (2014) and Fonseca, Lima and Pereira (2014) find evidence of job market polarization, from the mid 1990s. In the search for the sources of observable polarization, most scholars have settled in a technology driven hypothesis. Routinization is mostly derived from a subtle variation of STBC based on Autor, Levy and Murnane (2003) routinization model. Contrasting with SBTC, the routinization model predicts non-linear employment changes for three skill groups – low, middle and high – that are consistent with the observable employment polarization of the labor market.

Despite its major importance, technological change is not the sole contributing factor to the recent observed employment trends. For example, Autor, Dorn and Hanson (2015) are able to identify the employment effects of international trade and technological change separately.[6] Ebenstein et al. (2014) also shows that trade and offshoring exerted a downward pressure on wages and employment, especially for routine occupations. Furthermore, the business cycle interacts with job polarization. Jaimovich and Siu (2012) show that the decline in middle-skill occupations concentrates in the depressing phase of the economic cycle. When the recovery occurs, jobs in those occupations are not recovered contributing to *jobless recoveries*.

The routinization and the task-approach literature has mainly dealt with the demand side the labor market, overlooking the changes occurred in the supply side, most notably the supply of skills which should be accounted for when analyzing long term trends in employment and wages. Vona and Consoli (2015) highlight the role of knowledge systematization in changing education and training to shape the supply of skills in response to the emergence of new technologies and radical innovations. Bessen (2012) suggests that historically, the increase in labor quality – higher skills – has contributed to investment in new (laborsaving) technologies and economic growth. Along the same lines, Fodor (2016) show that firms' investment in ICT is subject to reverse causality: firms' investment decisions depend on the supply of skills. These supply side considerations should not be neglected, especially when deriving policy recommendations, which have the power to affect the supply of skills directly.[7]

[6] Contrary to what is commonly assumed the two effects differ along several dimensions. In the US in particular, import competition (US imports from China) depresses employment in the tradable sector – manufacturing – affecting regions subject to trade shocks and mostly abstract intensive occupations, while routinization has mainly a compositional effect on employment. The timing of the effects also differ: trade competition has been increasing, while technological change has been experiencing a declining effect on manufacturing towards the 2000s, though with an uprising effect on services, especially those knowledge-intensive.

[7] It is also true that the routinization hypothesis is debatable. Castex and Kogan Dechter (2014) and Beaudry, Green and Sand (2016) contend that technological change decelerated after the 2000s and observe a decline in the cognitive skills wage premium. Some studies even go further and challenge the presence of polarization and argue against what they consider an excessive focus on an analysis based on occupations (Hunt and Nunn, 2017; Mishel, Shierholz and Schmitt, 2013).

2.2 A firm taxonomy based on tasks

The routinization model proposed by Autor, Levy and Murnane (2003) and extended by Autor, Katz and Kearney (2006) provides a task-based approach in which not only skilled labor and technology are complements, but it also assumes that technology, or more precisely computer capital, is a substitute for middle skilled labor. Computers (and computer-controlled machines) can perform a set of instructions, but are unable to deal with every single contingency. Thus, computers are not able to make complex decisions and be as flexible as humans are, though they are reliable and efficient at executing program codes. The model labels tasks that can be performed by computers as routine tasks, because those tasks can be done by following a set of well-determined rules and can therefore be programmed into a machine.

Routine tasks are the core part of many middle-skilled jobs, such as bookkeeping, clerical work, repetitive assembly, and monitoring jobs.[8] Because computer capital is a perfect substitute for routine tasks, as computer capital price declines, firms have an incentive to substitute computer capital for routine jobs. A simple example is a computer software replacing tasks that once were carried out by an office clerk, as is the case of ATMs or online banking services.

Following Autor, Katz and Kearney (2006), we consider that non-routine tasks can be abstract and manual. Abstract tasks are related with solving problems, managing, dealing with complex communications, designing and programming and other creative tasks that require cognitive skills. Examples of abstract intensive occupations include managers, physicians, engineers, economists and computer scientists. In contrast with routine workers, for whom technology is a substitute, abstract workers benefit from technology adoption as it increases the complementarity with their high skills, hence increasing their productivity. For example, the adoption of clinical software enables physicians to quickly access all information about patients including historical data, increasing their productivity and substituting part of the routine tasks previous performed by healthcare clerks.

[8] One might think that bookkeeping and repetitive assembly are not the same type of routine task. Certainly, bookkeeping requires more cognitive skills, by contrast assembly require more manual skills. Autor, Levy and Murnane (2003) makes the distinction between routine cognitive and routine manual tasks. For the sake of simplicity, we will call both types routine tasks, as does Autor, Katz and Kearney (2006). Also, when a job is mainly constituted by routine tasks, we call it a routine job.

Finally, manual tasks generally require few cognitive skills, but require more flexibility than computers can offer and cannot be automated. Examples of occupations with high manual task intensity are cleaners, gardeners and plumbers.

The task based approach has been used to explain job market polarization in several economies including Portugal (see, for example, Acemoglu and Autor, 2011 and Autor, Katz and Kearney, 2006 for the US case; Goos and Manning, 2007 for the UK; Goos, Manning and Salomons, 2014 for Europe; Fonseca, Lima and Pereira, 2014 for Portugal). However, this approach has not yet been applied at the firm level nor used to examine productivity growth. Several studies find that through the use of ICT, firms increase their productivity (Bresnahan, Brynjolfsson and Hitt, 2002; Brynjolfsson and Hitt, 1996, 2003), and more high-skilled intensive firms benefit more from ICT adoption, because of the complementarity effect between skills and ICT (Goldin and Katz, 1998). While some studies have established the connection between productivity and skills which allow workers to master new technologies (e.g., Boothby, Dufour and Tang, 2010), we still know little about how firms are reshaping their labor inputs to benefit from technology and how that is affecting productivity growth at the firm level.

We develop a taxonomy based on firm level task content, enabling us to characterize firms' behavior in the context of routinization and link two previously independent literatures: job market polarization and firm productivity. Grouping firms according to their characteristics is common in the literature.[9] Several classifications are now available based on multiple firm characteristics including regions, sectors and industries (e.g., Asheim and Coenen, 2005; Cooke et al., 1997; Malerba, 2002; Von Nordenflycht, 2010), but few to no taxonomies incorporate firm level labor content or capture firm level information on the type of jobs performed within firms. Recently, Consoli and Rentocchini (2015) proposed a sector level taxonomy based on the skill content of occupations. The authors use workers' occupations, industry-level US labor productivity, number of firms and capital expenditures to construct a sector-based classification. Though the classification captures a measure of the skills used by firms, because it is sector-based, it fails to capture firm-level

[9] Examples include simple aggregations by size or sector, as well as more complex taxonomies such as in the seminal work of Pavitt (1984), which classifies firms based on their technology capabilities and has been used and extended by several authors (e.g., Bogliacino and Pianta, 2010).

dynamics.

Our taxonomy assumes that the production of goods and services in the firm is accomplished by executing one or multiple tasks. While a single worker can perform several tasks, for sake of simplicity we assign each worker to the most intensive task drawn from the worker's task set: abstract, routine and manual. Tasks are determined by the workers' occupation (ISCO 88, 2-digit level) and each occupation is associated with a task (the most intensive task for that particular occupation). We follow Fonseca, Lima and Pereira (2014) methodology in assigning tasks to occupations, which is based on grouping descriptors from the O*NET database by using principal components to form task measures (scales).[10] Because O*NET is based on US SOC codes, a conversion to ISCO 2-digits codes is performed using a data crosswalk and US employment data. Appendix Table A4.1 summarizes the correspondence between tasks and the ISCO-88 occupational codes.

We next compute the share of employees performing each task within the firm: abstract, routine and manual (the sum of shares is unitary). For example, some firms will have more employees performing abstract tasks (e.g., consultancy firms), while others main focus are manual tasks (e.g., cleaning services). Moreover, different technologies lead to different task shares, even among firms that operate in the same industry. Informed by the routinization model, we define eight categories that represent how the firm's workforce is distributed across the three types of tasks. We only use task shares to determine each firm category, not including any other firm characteristics such as firm size, age or industry. The boundaries chosen for our classification were fine tuned by looking extensively at examples of different types of companies that we were able to track. We have also conducted several robustness tests by assigning different taxonomy boundaries. Section 5.3 presents the relevant part of those tests. Furthermore, we run different clustering techniques for aid in the construction of the category boundaries, yet since the taxonomy conceptualization is informed by the routinization model, we opt not to include possible explanatory variables in its definition (e.g., capital, size, age). Consequently, methodologies based on clusters will generate a purely geometric division of the space that fail in the connection with the

[10] 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.

theory.

Table 1: Taxonomy categories and boundaries

Firm Task Category	**Share of employees**		
	Abstract (A_s)	**Manual** (M_s)	**Routine** (R_s)
Abstract (A)	$\geq$1/2	<1/3	<1/3
Manual (M)	<1/3	$\geq$1/2	<1/3
Routine (R)	<1/3	<1/3	$\geq$1/2
Polarized	$\geq$1/3	$\geq$1/3	$\leq$1/6
Abstract-Routine	$\geq$1/3	$\leq$1/6	$\geq$1/3
Routine-Manual	$\leq$1/6	$\geq$1/3	$\geq$1/3
Uniform	$A_s - R_s \leq 1/6, A_s - M_s \leq 1/6, R_s - M_s \leq 1/6$		
Other	Not classified in the remaining categories		

Table 1 presents the shares of the three tasks that define each firm category. The first three categories – Abstract, Manual and Routine – consist of firms that are focused in just one task. They include firms with at least 50% of the workers assigned to one of the three tasks and less than one-third assigned to each of the other two. Abstract firms are conceptualized as highly knowledge intensive firms, focused on cognitive tasks (e.g., solving complex problems), and intensive on technology use as result of the complementarities between its abstract workers and technology. Conversely, Manual firms are low knowledge intensive firms, organized towards non-cognitive (physical) tasks that require flexibility (e.g., moving objects). Their technology use is low, as most of their activities do not benefit from complementarities between tasks and technology. Routine firms are mainly focused on performing repetitive tasks, which can be performed by (computer) capital.

The fact that our taxonomy distinguishes between Routine firms – technological laggards – and Abstract firms – technological adopters – raises the question: why are not all managers adopting technologies simultaneously as they become available? In some industries it can be the case that there is no superior technology to that currently in use, even in Routine firms. It can also be the case that mangers have a financial restriction to invest in new technologies and the capital markets do not offer a viable solution. In addition, the decision process Routine firms' managers face when considering to adopt a new technology is complex, subject to uncertainty and error.[11] Furthermore, the decision process is prone to failure and subject to imperfections of learning, *myopia of learning* in the words of Levinthal and March (1993). In particular, managers can focus on the short-term (*temporal myopia*) and be uninformed of existing technologies (*spatial myopia*) which may result in technology investment errors (Miller, 2002).

Firms are also subject to technological discontinuities where a new technological regime replaces the prevailing one, generating uncertain environments. Firms with superior organizational capabilities and more able to take managerial action to cope with this technological uncertainty, strive and survive whereas others are pushed out of the market (Anderson and Tushman, 2001). Routine firms that adopt a new technology, intensive in abstract tasks, may transit to the Abstract category, with a rise in productivity. Firms that could adopt the new technology but do not do so for any of the above mentioned reasons, will have lower productivity and, eventually, may exit from the market if competitors become more productive after adoption. The technology adoption decision process therefore impacts the firm's productivity growth as well as firm exit and firm transitions between categories. As such, in our empirical evaluation of productivity dynamics we consider both firm entry and exit and transition between firm categories.

The fourth firm category comprises Polarized firms, a term which we borrow from the job polarization literature. Polarized firms use a small ratio of routine intensive labor – less than one-sixth – and most of their employees perform abstract and manual tasks – more than one-third each. Routine tasks are either not performed at all or are mostly likely to be performed by machines (computers or computer-driven machines). The following two categories focus on two tasks: Abstract-Routine and Routine-Manual – which correspond to firms with a task composition on the boundaries of each pair of the task focused categories, and no clear focus on one single task. Their definition is similar to the Polarized: more than one-third assigned to two tasks and less than one-sixth assigned to the third task.

[11] Managers face uncertainty about the profitability of an innovative technology (Jensen, 1982), need to gather information to estimate profitability (McCardle, 1985) and form expectations about future technology improvements (Weiss, 1994). Thus, the adoption is not immediate once the new technology proves to be technically feasible, as managers engage in a complex decision process towards the adoption of innovations and its timing (Jensen, 1988).

Uniform firms are firms that do not focus on neither of the three tasks – they have similar shares of employees in abstract, manual and routine tasks. In practice, the distance between the shares of employees in each task does not exceed one-sixth and each share can vary between a minimum of 22.2% (when the two other tasks equal 38.9% each) and a maximum of 44.4% (when the two other tasks equal 27.8% each). In both cases, the distance between tasks does not surpass 16.7% (or 1/6). In section 4 we apply this taxonomy to Portuguese firms and show the visual mapping of these eight categories in the space of manual and abstract shares making it clear that these criteria define an area at the center of the space defined by the three tasks. The final category – Other – includes firms with combinations of tasks difficult to categorize: they are neither focused on one or two tasks, neither they are uniform. Instead, they are at the frontier between Uniform and the remaining categories, and they ensure that small variations in the share of workers in one task does not lead to a reallocation from Uniform to another category.

In sum, we have three types of categories (apart from the category Other): (i) the firm is task-focused, i.e., focuses in one task – Abstract, Routine or Manual; (ii) the firm is intensive in two tasks (Polarized, Abstract-Routine or Routine-Manual) – at the boundary of the focused categories; (iii) the firm balances the three tasks (Uniform) – the center of the task-space. We further discuss our category definitions in section 4, where we map the density of firms in each category for the Portuguese case. We also present results for robustness checks concerning our taxonomy boundaries in section 5.3.

2.3 Productivity

Given that the labor market is polarizing, the workforce is either polarizing within the firm – firms are increasing their share of abstract and manual workers; or across firms – firms are increasingly specializing in manual or abstract tasks, or a combination of the two. In any case, we should expect that firms reorganize their production in response to technological changes. Productivity is the efficiency with which a firm converts its inputs into outputs, and its estimation is usually done by resorting to a production function.[12]

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

Several authors have augmented the simple production functions to accommodate other inputs besides capital and labor. An example is ICT input which has been positively associated with firms productivity (Bloom, Sadun and Reenen, 2012; Bresnahan, Brynjolfsson and Hitt, 2002; Brynjolfsson and Hitt, 2003; Greenana and Mairesse, 2000). R&D measures have also been added to the production function to capture its effect on the firms' output (e.g., Czarnitzki and Thorwarth, 2012; Kancs and Siliverstovs, 2016).

Total factor productivity (TFP) is a measure of productivity that has the advantage of being invariant to the factor inputs observed by the econometrician, usually capital and labor, 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 Brynjolfsson, 2012). TFP can be obtained by estimating the production function elasticities and then computing the residual that is idiosyncratic to the firm.

The computation of firms' TFP enables productivity comparisons, in particular to grasp the differences between the aggregate productivity of groups of firms classified according to a given taxonomy.[13] Considering the complementarity between abstract tasks and technology, as firms adopt new technologies and employ more abstract workers relative to routine workers, productivity should increase. Conversely, firms which lag in adopting newer technologies and thus employ a large pool of routine workers, should experience lower productivity levels and a slower growth rate.

2.3.1 Methodology to estimate productivity

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

[13] Aggregate productivity is computed by the weighted sum of firms' productivity using market share as weights, which can be measured by value added.

and selection biases. 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 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. Ackerberg, Caves and Frazer (2015) (ACF hereafter) build on Olley and Pakes (1996) and Levinsohn and Petrin (2003) to propose an alternative model where they address collinearity problems. In particular, they argue that the LP method can result in the non identification of the labor coefficient. Both OP and LP methods hinge on the inversion of the investment or intermediate inputs demand functions. The method proposed by ACF employs a similar procedure, yet the function inverted is conditional on labor inputs. The use of ACF method also obtains consistent estimates even when unobserved labor shocks are present (e.g., firm-specific shocks to price of labor).

The literature still provides several other models and estimation methods. Wooldridge (2009) suggests a more efficient method to estimate Olley and Pakes (1996) by using generalized method of moments. However, none of those are exempt from strong 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 depends on what assumptions the researcher is comfortable with.

We approach the estimation problem using ACF methodology, but for comparability we also estimate the production functions using the LP and OP methodology. Following ACF, 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, firm i's 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 and is given by the residual ϵ_{it}.

Both ACF, LP and OP consider that the residual can be decomposed into two parts: a 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 ACF, LP and OP diverge. While OP uses investment as an instrumental variable for endogeneity, LP uses the intermediate inputs and ACF allows both specifications. 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. Adding on LP, ACF estimation method entails the inversion of the intermediate inputs demand function conditional on Ω_{it} and k_{it} as LP, but also includes l_{it}. This strategy solves the problem of collinearity that can arrive when using LP method.

We use all three estimation methods to obtain productivity estimates for each firm in the sample in order to compare and asses the robustness of our estimates. ACF estimation is performed using the method proposed by Manjón and Mañez (2016). LP and OP methods are estimated as proposed by Petrin, Poi and Levinsohn (2004) and Yasar, Raciborski and Poi (2008) respectively. However, as we have underlined before, we focus on TFP estimated by ACF method in subsequent analysis.

2.4 Productivity Dynamics

Changes in the productivity of incumbent firms can take place through two channels: a general shift in the productivity distribution and market share reallocations (Olley and Pakes, 1996). The first channel occurs when, for example, a productivity augmenting technology leads to a general shift in productivity across firms; whereas market reallocation occurs when that technology is only adopted by a restricted group of firms that then increases their market share and pulls aggregate productivity growth. In addition to productivity changes among incumbents, market entry and exit may play an important role in aggregate productivity. It may be the case that young firms with a large share of abstract workers adopt new technologies and are able compete with established firms (Hobijn and Jovanovic, 2001), or that 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, the Melitz and Polanec (2015) dynamic version of Olley and Pakes (1996) productivity decomposition takes into account both incumbents, entrants and exiting firms. Several other authors have used similar decomposition methods (e.g., Bartelsman, Haltiwanger and Scarpetta, 2013; Eslava et al., 2010) or provide extensions to account for firm dynamics (e.g., Hyytinen, Ilmakunnas and Maliranta, 2016; Maliranta and Määttänen, 2015).

By construction, firms can move between categories of the taxonomy over time. To account for that, we build on the augmented version of the Olley and Pakes (1996) decomposition proposed by Melitz and Polanec (2015). The authors include additional terms for market exitors and entrants, which we extend further by adding task transitions as well. Transitions occur when firms move from one taxonomy category to the other. The idea is that firms can readjust their task inputs due, for example, to falling price of computer capital and new technology adoption, transitioning from one category to another. Thus, not including a transition term will potentially miss an important source productivity growth. We include two additional terms: entrance through transition and exit through transition between firm categories. A firm is considered to enter through transition when it is observed in both periods but transited from one firm category to another. The same reasoning applies to exit through transition.

Following Melitz and Polanec (2015), we consider that aggregate productivity Φ_t is the sum of survivors and exitors (period 1) or entrants (period 2) productivity weighted by their market shares (s). The index S represent the survivors, X the exitors and E the entrants. The aggregate productivity of a group G in time t is computed by the weighted average of firms' productivity (ϕ) using market share (s) as weights, that is $\Phi_{Gt} = \sum_{i \in G}(s_{it}/s_{Gt})\phi_{it}$. We extend Melitz and Polanec (2015) by including the transitions terms denoted by X_{tr} for exit through transition and E_{tr} for entrance through transition as stated in Equation 3.[14]

$$\Delta\Phi = \Delta\bar{\phi}_S + \Delta cov_S + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}) + s_{E_{tr}2}(\Phi_{E_{tr}2} - \Phi_{S2}) + s_{X_{tr}1}(\Phi_{S1} - \Phi_{X_{tr}1}) \quad (3)$$

Where the first two components are the same as in Olley and Pakes (1996) decomposition: $\Delta\bar{\phi}_S$, the change in the unweighted average productivity component, measures the change in survivors' productivity distribution, and Δcov_S, the reallocation component, captures the productivity change due to market share reallocations of surviving firms.[15] 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 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 firms that exit through change in task focus with the surviving firms group that do not change their task focus.

[14] For further details on the decomposition equations see Appendix A1.

[15] Market share reallocation are measured similarly to a covariance, but excluding the number of observations term: $cov_S = \sum_i (s_{it} - \bar{s}_t)(\phi_{it} - \bar{\phi}_t)$

3 Data

We use the Portuguese linked employer-employee dataset *Quadros de Pessoal* (QP) created by the Portuguese Ministry of Labor in the 1980s. It contains yearly information of all Portuguese firms with at least one employee, excluding agriculture, military, public administration and self-employed workers. The dataset provides access to longitudinal information from 1986 to 2012 (except for 1990 and 2001 that were not released at worker-level) containing several firm-level and worker-level characteristics as industry, firm size, workers' occupations or schooling. We match QP with the firm dataset named *Sistema de Contas Integradas das Empresas* (SCIE) from Statistics Portugal that contains information on firms' balance sheets 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, personnel records, and firms' characteristics.

We restrict our analysis to full-time workers (minimum of 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).[16] After merging the two datasets we obtain more than 118 thousand firms in 2004 and 143 thousand in 2009 in manufacturing and services, as shown in Table 2. 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 and 80% in 2009). Small firms (less than 50 employees) predominate, representing around 96% of all firms.

We focus our analysis on the years covered by the firms' data set SCIE (2004-2009) as we need accounting information to estimate firms' productivity. However, for the application of the taxonomy, which relies on personnel information, we can observe the evolution of employment and number of firms in each firm category of the taxonomy for 1995-2012.

[16] 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 2: Firms across industries and size (2004-2009)

	2004	2005	2006	2007	2008	2009	Total
Manufacturing							
High-Tech	0.4	0.4	0.4	0.2	0.2	0.1	0.3
Medium-High-Tech	2.5	2.4	2.2	1.8	1.7	1.7	2.0
Medium-Low-Tech	10.1	9.8	8.4	6.6	6.2	6.1	7.8
Low-Tech	12.6	12.4	11.0	12.9	12.1	11.7	12.1
Services							
Knowl.-Intens.	11.9	12.3	21.8	17.3	18.3	19.0	17.1
Less Knowl.-Int.	62.4	62.6	56.2	61.2	61.5	61.3	60.8
Firm size							
[1,10[	75.1	75.5	76.6	76.1	76.7	77.1	76.2
[10,50[	21.0	20.8	19.6	20.2	19.6	19.4	20.0
[50,100[	2.3	2.2	2.1	2.1	2.1	2.0	2.1
[100,250[	1.1	1.1	1.1	1.1	1.1	1.1	1.1
>=250	0.5	0.5	0.5	0.5	0.5	0.5	0.5
No. observations	118,223	122,481	142,933	141,240	146,858	143,689	815,424

Note: All values are expressed as a share in percentage, unless otherwise stated. Standard Industries aggregated according to technology and knowledge intensity, following the classification by OECD and Eurostat (Hatzichronoglou, 1997). Firm size measured by the number of employees.

4 Application of the taxonomy

We apply our new taxonomy to Portuguese firms in order to capture the effects of recent labor changes in the workplace on firm's task input and productivity. 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). The figure provides a visual description of how the taxonomy categories are allocated in the labor mix space as each point in the graph is a firm in 2009. By consequence, a more dense area reflects a higher number of firms in that particular area. Depending on the task organization of the firm, firms are allocated differently in the triangle. Focused firms are closer to the vertices, while more balanced firms are located towards the middle, with Uniform firms in the center. In a robustness checks section to our estimations, we test a modification to the boundaries in Figure 1 where we reassign firms in the boundary areas (Abstract-Routine and Routine-Manual) to their adjacent categories: Abstract, Routine and Manual.

Table 3 shows the percentage of firms in each category for a larger range of years than the merged data and the theoretical uniform distribution that would result if firms were distributed equally across the space of the eight categories as defined by the three tasks.

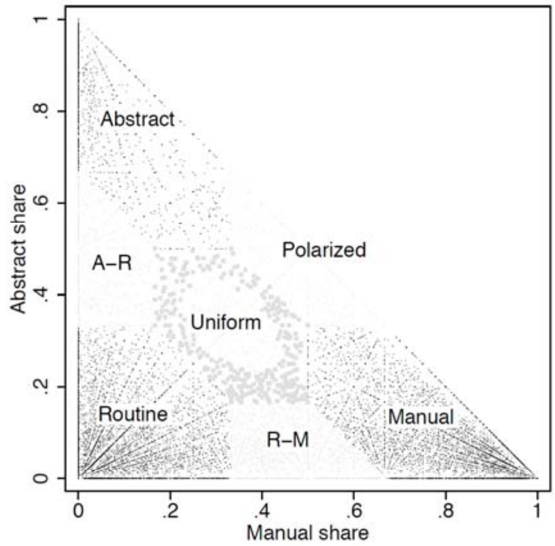

Figure 1: Taxonomy applied to 2009 Portuguese firms

Notes: Data from Quadros de Pessoal. Firms' density in 2009. Unlabeled grey squares around the Uniform category correspond to category Other. The region A-R stands for Abstract-Routine and R-M for Routine-Manual.

The Routine and Manual categories represent around 76% of all firms and surpass what would be expected if one assumed a uniform distribution (19%+19%). As a consequence, the boundary region Routine-Manual is also more dense than if firms were distributed equally in the taxonomy space, though it becomes less dense in 2012. Approximately 14% of the total number of firms fall within the Abstract-Routine and Routine-Manual categories (the boundary categories). However, this guarantees that firms do not change category with small changes in their task content and also ensures that there are substantial differences between each focused category of firms. The other boundary region – the Polarized category – between the Abstract and Manual categories accounts for a small fraction of firms, though increasing from 1% in 1995 to almost 3% in 2012 (1.6% on average). The Uniform category is marginal, accounting for less than 0.7% of all firms and, at least for the Portuguese reality, could be ignored. The same happens with the category Other. The robustness of our taxonomy comes at the small cost of creating regions or gaps where firms do not fall within any of the remaining categories. This category, which we denominate Other, represents less than 1% of all firms on any given year (the grey squares in the graph around Uniform firms from Figure 1).

Time trends of the share of firms in each category allow for a dynamic view of firms

Table 3: Observed and theoretical uniform share of firms by firm category

	Share of firms (%)					
Firm category	1995-2012	1995	2004	2009	2012	Uniform distribution
Abstract	6.44	3.25	4.32	7.99	13.54	19.44
Manual	34.74	35.17	35.61	33.89	31.55	19.44
Routine	41.98	45.48	42.20	40.39	37.37	19.44
Polarized	1.61	1.15	1.25	1.86	2.67	8.33
Abstract-Routine	3.99	3.13	2.81	4.05	6.29	8.33
Routine-Manual	10.08	10.74	12.81	10.66	6.97	8.33
Uniform	0.48	0.42	0.38	0.48	0.67	5.56
Other	0.69	0.66	0.62	0.69	0.95	11.11

Note: The theoretical uniform distribution arises from assuming firms equally distributed across the space defined by the three tasks. The years 2004-2009 correspond to the two datasets merged.

based on their labor input. Because workers with high intensive routine tasks' occupations are being substituted by computers or computer driven-machines, we can expect Routine focused firms, that is firms employing mostly routine intensive labor, to decrease in importance. Figure 2 plots the trends in the share of firms in each task category for the period 1995 to 2012. During this period, Routine focused firms decrease their share both in terms of employment (from 51% to 40%) and in number of firms (from 45% to 38%). In contrast, Abstract focused firms – the firm category that benefits the most from complementarities between abstract workers and technology – show an increase in their employment share (from 2% to 10%) and number of firms (from 3% to 13%). Manual firms increase slightly their employment share (27% to 30%) accompanied by a modest decrease in the number of firms (35% to 32%).

Polarized firms show a modest rise in importance, but their share in both employment and number is much smaller (less than 2.8% in both dimensions at any given year) than firms focused in one task. For that reason, in subsequent analyses we just consider the focused group: Abstract, Routine and Manual. We have also omitted Uniform firms from the rest of the paper as their share is very small throughout (less than 1%). Boundary regions (Abstract-Routine and Routine-Manual) are also omitted from the remainder of our analysis, for simplicity. Since their combined share is constant throughout the period (around 14%), we do not expect this simplification to bias our results. Though there is a slight increase in the share of Abstract-Routine firms, this is offset by a decrease in the share of Routine-Manual, which mirrors the increasing trend in Abstract and decline in Routine and Manual firms. As a robustness check, in section 5.3 we provide results from productivity estimations when different boundaries are used which re-allocate Abstract-Routine and Routine-Manual firms to one of the task focused categories.

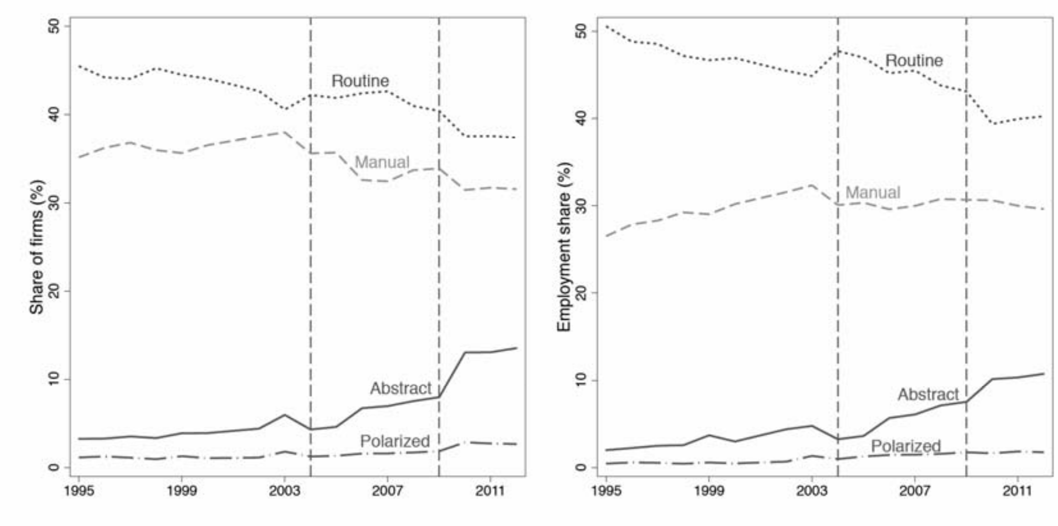

Figure 2: Share of firms and employment by firm category
Notes: Vertical lines represent the time window (2004-2009) when the two datasets are merged.

Table 4 presents summary statistics by firm category. Abstract firms are slightly smaller, followed by Manual and Routine that are the largest. However, interestingly, Abstract firms experience the largest growth in size over the period from an average of 10.5 to 13 workers. In any case, the Portuguese entrepreneurial landscape is dominated by SMEs, with more than 70% of firms having less than 10 employees for any firm type in any given year. The three categories of firms are clearly distinct in terms of their employees' education. Abstract firms' share of college educated employees is 28.2% in 2004 and rises to 43.5% in 2009, while this share does not exceed 9.7% for Routine and 4% for Manual in 2009. Abstract firms are mostly concentrated in knowledge-intensive services, whereas Routine and Manual are mostly in less knowledge-intensive services. In manufacturing and by 2009, Abstract firms are spread across medium high-tech to low-tech, while Routine firms tend to be low-tech and Manual firms medium low-tech. Abstract firms are more capital intensive, followed by Routine and Manual. Value added and R&D investments follow the same pattern. It is impressive that in 2009 R&D investment of Abstract firms is almost four times higher than Routine firms and ten times than Manual firms. Abstract firms are apparently more productive and make more intensive use of technology and knowledge and they tend to be more concentrated in service industries than others. The percentage of Portuguese firms in high tech manufacturing is less than 0.4% in any firm type. It is also worth of note that Abstract firms are also younger.

The industry-level representation of the various categories of firms shows the advantage of our taxonomy classification over a simpler industry classification, as firms of different categories can belong to the same industry. Using 2009 Portuguese data we observe that Abstract firms have a large share in hospital activities, computer programming, consultancy, education and engineering industries, while Manual firms are concentrated in construction, restaurants, cleaning and transportation of goods. Routine firms are mostly concentrated in retail sale of cloths, monetary intermediation, wholesales of household goods and footwear manufacturing. There are also industries that cluster in more than one task. For example, accounting, bookkeeping and auditing activities is a top 15 employing industry in both Abstract and Routine categories. This suggests that some accounting and auditing firms are specialized in routine tasks, while others are focused on abstract activities. Table A4.2 (in the Appendix) shows how employment by firm category is distributed for the top 15 employing industries. Our taxonomy captures more variation than a standard NACE 3-digits industry codification can. For several industries, the share of Abstract, Manual and Routine firms is very similar, suggesting that the taxonomy reveals nuances among industries that were not addressed so far in the literature.

5 Estimation Results

5.1 Productivity

The estimation of the production functions considers the usual inputs (labor and capital) used in OP, LP and ACF methods. We use value added as the output variable. Some debate exists around the use of value added, revenues or, when viable, quantities as output measures. When a firm innovates on an existing product or service, the quantity

Table 4: Summary statistics by firm category for 2004 and 2009

	2004				2009			
	All	**Abstract**	**Routine**	**Manual**	**All**	**Abstract**	**Routine**	**Manual**
Firm size								
[1,10[	75.66	80.4	72.3	79.0	77.46	79.5	76.0	78.7
[10,50[	20.52	16.4	22.7	18.4	18.99	17.2	19.8	18.4
[50,100[	2.22	1.9	2.8	1.5	2.03	1.9	2.3	1.7
[100,250[	1.12	0.9	1.5	0.7	1.04	0.9	1.3	0.8
>=250	0.49	0.3	0.6	0.4	0.48	0.6	0.5	0.4
Mean (no. employees)	13.72	10.5	15.7	11.7	13.61	13.0	14.7	12.5
	(97.86)	(45.81)	(117)	(74.84)	(124.58)	(92.89)	(150.62)	(92.76)
Mean firm age	15.92	10.96	15.98	16.45	14.89	12.19	15.28	15.06
	(13.09)	(10.26)	(13.52)	(12.83)	(13.18)	(9.8)	(13.6)	(13.28)
Manufacturing								
High-Tech	0.4	2.9	0.3	0.2	0.1	0.3	0.2	0.1
Medium-High-Tech	2.4	2.0	1.4	3.6	1.6	2.0	1.1	2.1
Medium-Low-Tech	10.7	1.3	10.7	11.9	6.1	1.4	2.9	11.0
Low-Tech	12.7	3.4	19.6	5.7	12.2	1.1	20.6	4.9
Services								
Knowl.-Intens.	10.7	60.3	8.5	7.4	17.3	69.8	15.4	7.1
Less Knowl.-Int.	63.1	30.1	59.6	71.2	62.7	25.5	59.9	74.9
College	5.29	28.2	5.2	3.0	10.14	43.5	9.7	4.0
	(0.17)	(0.36)	(0.16)	(0.12)	(0.24)	(0.39)	(0.22)	(0.14)
Capital per employee	44.77	59.83	48.22	38.85	58.49	77.82	61.08	50.86
	(292.4)	(211.1)	(390.4)	(105.4)	(317.5)	(211.1)	(347.3)	(181.2)
VA per employee	19.09	31.22	21.05	15.28	20.82	32.50	22.61	15.94
	(51.00)	(76.2)	(64.3)	(18.8)	(60.5)	(76.2)	(61.2)	(20.1)
R&D expend. p.emp.*	40.82	114.81	41.97	20.02	40.73	144.42	38.51	15.36
	(1012.41)	(1951.90)	(1045.94)	(587.94)	(1155.61)	(1982.00)	(1187.75)	(467.46)
No. Observations	118,223	5,108	49,894	42,099	143,689	11,478	58,037	48,690

Notes: All values are expressed as a share in percentage, unless otherwise stated. Standard deviation for non-percentage values between parenthesis. Firm size categories are measured by the number of employees. College refers to the share of college graduates in the firms' workforce. VA is the value added. VA and capital are in thousands of 2009 euros (GDP deflator). *R&D expenditures per employee are in 2009 euros (GDP deflator) and are only available from 2006 onwards, hence the statistics presented in the 2004 column correspond to 2006 values.

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. In addition, value added can be a better option to measure output 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 Jr., 2012), and value added may suffer temporary decline. Thus, choosing value added or revenue has both advantages and downsides.

We include in Appendix Table A4.3 the descriptive statistics for output and inputs of the production function by industry. The full estimable sample consists of more than 800 thousand firms for the 2004-2009 period, mostly from services (78%), followed by low-tech and medium-low-tech manufacturing (20% combined). To obtained our productivity measure, we estimate a production function applying the ACF method. We present the results in Appendix Table A4.4, together with the estimated coefficients by the LP or OP methods using the same sample used in ACF estimation. The estimated coefficients decrease with the ACF method, which we would expect, especially for labor, given that the method deals with the possible labor endogeneity.

We retrieve the (log) TFP as the productivity measure from the residual of the production function estimation. Figure 3 plots the aggregate log productivity (aggregated using the value added shares as weights) for the ACF method by firm category for 2005-2009 (the lag used in the ACF method implies that the estimation starts in 2005).[17] Abstract are the most productive firms, followed by Routine, with Manual firms being the least productive. The distance between Abstract, Routine and Manual productivity estimates is relatively high (between Manual and Abstract the distance grow from 0.88 log points in 2005 to 1.07 log points in 2009). The results show that aggregate productivity has stagnated between 2005 and 2009 in line with the slow GDP growth during the decade (less than 1% yearly) and the 2008 financial crisis. Overall, the stagnation in the aggregate productivity is present across all firm categories, except Abstract that exhibits growth.

[17]The results from LP and OP methods can be found in Appendix Figures A3.1 and A3.2.

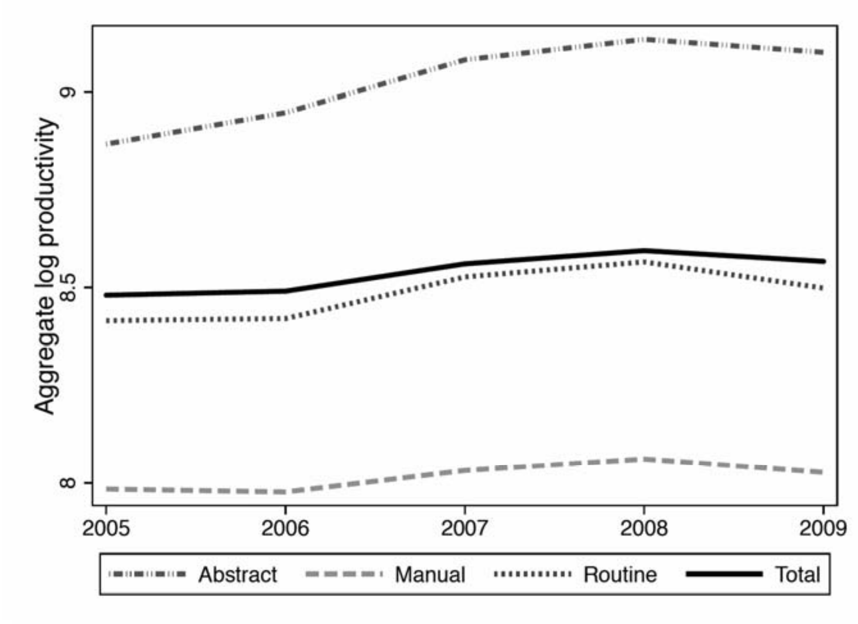

Figure 3: Total factor productivity by firm category

Notes: Total factor productivity 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 Ackerberg, Caves and Frazer (2015) (ACF) method. Estimation results from Table A4.4.

5.2 Productivity dynamics

Although we are able to characterize productivity change by firm category, the sources of its dynamics are unknown. Productivity growth can be due to a general shift in the productivity distribution that affects all firms equally or at least each firm category equally. Alternatively, it can be due to changes due to incumbents (or survivors) market reallocation, firm entry and exit, or firms transitioning from one category to another. To analyze the productivity dynamics, we apply our extended version of Olley and Pakes (1996) and Melitz and Polanec (2015) dynamics decomposition method as developed in section 2.4. Similar methodologies have been applied to productivity analysis (e.g., Hyytinen and Maliranta, 2013), yet none enables capturing the productivity dynamics that are inherent to our specific taxonomy.

Table 5 presents the results from application of the decomposition using the productivity results from ACF estimation.[18] We test the significance of the changes from the base year (2005) using the methodology proposed by Hyytinen, Ilmakunnas and Maliranta

[18] For operational reasons, we have to exclude from the decompositions firms less than two years old and firms with gaps in the dataset.

(2016). A complete description of the method used can be found in Appendix A2. Entry and exit due to transitions between categories can only be computed by firm category, and therefore are not included in this table. The firm market shares s are computed based on value added. We present the results setting 2005 as the base year (period 1) and then varying the end year (period 2) from 2005 to 2009. The total productivity change is almost nil for the whole period (-0.001 log points). The main source of productivity growth is market reallocations (0.08 log points in 2009 – changes in market shares of incumbent firms, the reallocation component), though this driver of growth is hampered by a sharp decrease in the productivity distribution of incumbent firms (-0.113 log points in 2009 – the average productivity component). The relative contribution of the various components does not change much over time, with the incumbents' contribution (the average productivity component) becoming progressively more negative, along with the increasing relative contributions from the reallocation and exitors components.[19] The entrants' contribution remained constant until 2008, increasing only modestly between 2008 and 2009, when the negative contribution of incumbent firms on productivity growth became larger.

Table 5: Productivity growth decomposition

	Total	**Survivors**		**Entrants**	**Exitors**
	Change	**Avg prod**	**Reallocation**		
2006	0.006	-0.035***	0.042***	-0.002**	0.001**
2007	0.011***	-0.044***	0.059**	-0.002**	-0.001**
2008	0.001***	-0.082***	0.07***	-0.002**	0.016**
2009	-0.001***	-0.113***	0.08***	0.002**	0.03

Notes: Decomposition performed using TFP results for all firms (estimation results from Table A4.4 (ACF)). The base year is 2005. Average productivity (Avg prod) component refers to $\Delta\bar{\phi}_S$ (change in the unweighted average productivity) and the reallocation component is Δcov_S, where $cov_S = \sum_i (s_{it} - \bar{s}_t)(\phi_{it} - \bar{\phi}_t)$ (market share reallocations). Entry is computed by $s_{E2}(\Phi_{E2} - \Phi_{S2})$ and exit by $s_{X1}(\Phi_{S1} - \Phi_{X1})$. * 10% significant, ** 5% significant and *** 1% significant. For details on the significance tests see Appendix A2.

Table 6 breaks down the productivity decomposition for the three main firm categories (Abstract, Manual and Routine), including transitions between tasks.[20] Together, focused firms represent more than 82% of the pooled sample. Total productivity growth from 2005 to 2009 is positive and large for Abstract firms (0.221 log points), while for Routine and Manual productivity is decreasing (-0.006 and -0.015 respectively).

[19] 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.

[20] For simplicity we present the decomposition for focused firms, though the numbers are computed using the full sample firms.

The market share reallocations effect is the larger main driver of productivity growth between 2005 and 2009 for all firm categories, along with firm exit from the Abstract category, both through transition to another category and through market exit. However, this growth is dampened by a negative average productivity component, i.e., the average productivity of surviving firms (especially Routine firms) contributes negatively to the aggregate productivity growth. In the case of Routine and Manual firms, the average productivity component is almost sufficiently large to cancel out all the remaining components. The productivity differences for entry and exit from Routine and Manual are generally not significant or of small magnitude, though the signs of these terms show a tendency of entrants and exitors to be associated with lower productivity, which we would expect: new firms are still catching up to the incumbents and exiting firms are underperformers. For Abstract firms, the negative change in the average productivity component does not dominate the overall effect, and growth is first propelled by market reallocation and second, by less productive firms either leaving the Abstract category or the market (positive variations mean that firms leaving the category are less productive than those remaining).

In sum, the aggregate productivity growth in the Portuguese economy has two main drivers: market reallocations for all firm categories, that is, the most productive Abstract, Routine and Manual firms expanding more than the least productive, with the effect being strongest for the Abstract group; and the least productive firms exiting the market (especially from the Abstract category). Our decomposition also shows that firms transitioning out of the Abstract category, i.e. firms that somehow do not sustain their large share of abstract tasks contribute positively to the productivity growth of this category – their productivity is lower than stayers, while firms transitioning into Routine also contribute negatively to the Routine category productivity growth – their productivity is lower than incumbents. It could be that low performing abstract firms that slip into the routine category, either because they reduce abstract tasks or because they expand routine tasks are behind these effects, a phenomenon that deserves further research. On the overall, however, productivity growth from the above mentioned growth drivers is canceled out by a sharp decrease in incumbents' productivity over time for the Routine and Manual categories, but not for the Abstract, which drive productivity growth.

Table 6: Productivity growth decomposition by firm category

	Total	Survivors				Transitions	
	Change	Avg prod	Reallocation	Entrants	Exitors	Entrants	Exitors
Abstract							
2006	0.036***	-0.04***	0.009**	-0.005	0.003***	0.03	0.039**
2007	0.183***	-0.033***	0.013***	-0.007	0.019***	0.139	0.052***
2008	0.244***	-0.047***	0.112**	-0.013	0.034***	0.103	0.055***
2009	0.221***	-0.056***	0.161***	0.013	0.053***	-0.025	0.075***
Routine							
2006	0.005	-0.036***	0.053***	-0.003***	-0.002***	-0.01***	0.003**
2007	0.025***	-0.05***	0.097***	-0.006***	-0.008***	-0.01***	0.003***
2008	0.003***	-0.101***	0.101**	-0.005**	0.008***	-0.003***	0.004***
2009	-0.006***	-0.129***	0.112***	-0.014***	0.031***	-0.007***	0.001***
Manual							
2006	-0.013	-0.032***	0.038***	-0.005***	-0.006***	-0.009	0.001
2007	0.014***	-0.035***	0.065***	-0.004***	-0.013***	-0.001	0.002
2008	0.018***	-0.07***	0.098***	-0.008***	-0.004***	0.001	0.001
2009	-0.015***	-0.098***	0.09***	-0.011***	0.006***	-0.004	0.001*

Notes: Decomposition performed using TFP results by firm category (estimation results from Table A4.4 (ACF)). The base year is 2005. Average productivity (Avg prod) component refers to $\Delta\bar{\phi}_S$ (change in the unweighted average productivity) and reallocation component is Δcov_S, where $cov_S = \sum_i (s_{it} - \bar{s}_t)(\phi_{it} - \bar{\phi}_t)$ (market share reallocations). 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 $s_{X_{tr}1}(\Phi_{S1} - \Phi_{X_{tr}1})$. * 10% significant, ** 5% significant and *** 1% significant. For details on the significance tests see Appendix A2.

5.3 Robustness checks

In this section we present a sensitivity analysis where we change the boundaries of our taxonomy to check the robustness of our productivity results to the definition of firm categories. In particular, we reduced the boundary areas by assigning Abstract-Routine and Routine-Manual firms to adjacent categories. Abstract-Routine firms are assigned to Abstract if their abstract share is greater or equal to 50% and to Routine otherwise. Similarly, Routine-Manual are assigned to Manual if their manual share is at least 50% and to Routine otherwise.

The boundary areas Abstract-Routine and Routine-Manual were created to provide a clear separation between main categories, so that small changes in the firm task organization would not translate into large shifts in the classification of firms, minimizing discontinuities in our data. By doing so, approximately 14% of the firms are not classified as task focused and are therefore not the focus of our analysis. In this section we examine what changes in our results when those firms are included and allocated to the three main categories (Abstract, Manual, and Routine). This new partition of space re-allocates approximately 14% of firms to a different category and reduces the categories out of the analysis to less than 2.8%.

When we use the modified taxonomy, the results for the aggregate productivity estimates do not change much (see Appendix Figure A3.3). In particular, the productivity ranking remains: Abstract firms are the most productive, followed by Routine and Manual. As a consequence of the different partition of space and firms not being uniformly distributed over task-focused categories, Routine firms' productivity is now slightly above total aggregate productivity. Regarding productivity growth trends, they mimic the previous results, suggesting that our results are not substantially affected by changing the taxonomy's boundaries, even when a larger number of firms is included in the analysis of the focused categories.

Next, we repeat the productivity decomposition analysis using the modified taxonomy. The results are summarized in Appendix Table A4.5. The results are very similar with the ones from our original taxonomy, with one exception. While before exitors acted as a positive driver for growth in productivity in the Abstract category, they are now a source of decline in the aggregate productivity growth of Abstract firms. This implies that firms that are more productive than the average Abstract firms are the ones leaving the market. Since we showed before that productivity growth through exit was much more pronounced for Abstract firms than for the remaining categories, it is not surprising that when the Abstract category is broadened to encompass firms with a lower percentage of abstract workers, this productivity driver becomes diluted or even reversed. Also, the magnitude of this coefficient is relatively small when compared with the main driver of productivity growth, market reallocations. Of the 18 drivers of productivity growth presented, only one showed a significant change with a modified taxonomy which includes 14% more firms. This gives support to the robustness of our taxonomy definitions to small changes. It also confirms that the removal of firms in the boundaries around task focused firms is warranted, since using sharper distinctions between categories produces sharper results.

In sum, our taxonomy is able to capture different trends that are not greatly affected by changes in its defining boundaries. We therefore conclude that this tool is robust for studding different firm types that exhibit significant differences in terms of productivity and productivity growth conceptualized in the light of the routinization model.

6 Discussion and policy implications

Our study has found that the main driver of productivity growth has been the market share expansion of the most productive firms, followed by the exiting of the least productive.[21] Moreover, we have established a link between productivity growth and the organization of activities inside firms. The results from our productivity decomposition show that firms focusing in Abstract tasks are driving productivity growth. The reallocation of market shares to the most productive firms and the exiting of the least productive

[21] This result is in line with previous productivity decompositions. For example, Baily, Hulten and Campbell (1992) found that for US data that increasing output shares among high-productivity plants and decreasing output shares among low-productivity plants are a major drive in industry productivity growth. They also found that the relative role of entry and exit depends on the business cycle with the role of exit of the least productive firms becoming more important for productivity growth during recessions. We do not have a period long enough to test this second finding, which is an interesting subject for further research.

has a stronger impact on productivity growth among Abstract firms, pointing to a stronger process of creative destruction among this group. In addition, the trends in employment and number of firms provide descriptive evidence that polarization in the Portuguese labor market is mostly being driven by firms following different specialization paths as opposed to an increasing polarization of activities within each firm.[22]

How relevant are our results for other economies, namely European ones? Portugal is a country with similar R&D investment (as a percentage of GDP in 2014) to Spain, Italy and Luxemburg (1%-1.5%), though smaller than Finland, Sweden and Denmark (>3%), the European countries with the highest investment. The European Union (28 countries, EU-28 thereafter) average is 2% which is similar to China (2% in 2013), but lower than the U.S. (2.8% in 2012) and Japan (3.5% in 2013) (Eurostat, 2016). In addition, 21% of those aged between 15 and 34 years old in Portugal have completed tertiary education (EU-28: 24.5%), an increase from 12% in 2007, to values similar to Finland (22.4%), Greece (24.3%) and higher than Italy (14.9%) and Germany (16.9%), though smaller than Spain (29.7%) and Ireland (33.5%). Also, employment in high-technology manufacturing is close to the levels found in the Netherlands, Spain or Sweden (in the 0.5-0.6% range), but employment in knowledge intensive services (1.6%) is lower than in Ireland (4.2%) or Sweden (4.3%), for example (Eurostat, 2013). While Portugal shows some impressive figures, it still falls short in some economic indicators and experiences low labor productivity (78% of the EU-28, average 2005-2015), placing it clearly below the technological frontier.

The economic characteristics of Portugal are shared with other European regions, making it an interesting case to draw evidence from. Portuguese regions are typically grouped together with regions located in Southern and Eastern European countries, but depending on the methodology applied, also with some regions from France, Ireland, UK and Northern European countries. Several classifications identify patterns of innovation at the regional level using mainly innovation and knowledge indicators (such as R&D and patents). For example, Moreno and Miguélez (2012) classifies all seven Portuguese regions (NUTS2) as *Noninteractive Regions*, with short access to external knowledge along with other regions of southern Europe (Greece, parts of Spain and Italy) and eastern European

[22]The assessment that polarization is observed across firms and not within firms does not preclude the rise of wage inequality within firms (e.g., see Barth et al. (2016).

countries but also some regions in France, UK, Ireland and northern Europe representing 113 out of 287 regions. Capello and Lenzi (2012) include most Portuguese regions as having the (potential to be) a *smart and creative diversification area* again along with regions mostly from southern and eastern European countries but also some from Finland and the U.K., for example. These areas are characterized by low innovation and knowledge variables, but high in capabilities and innovation potential.[23] Navarro et al. (2009) place most Portuguese regions in the group of *peripheral agricultural regions with a strong economic and technological lag*.[24]

The creation of regional innovation policies that combine innovation with other policies, namely those directed at education, training and the creation of networks to enlarge knowledge and innovation capabilities of the region is prevalent in the (regional) innovation policy literature (e.g., Asheim, Boschma and Cooke, 2011; Camagni and Capello, 2013; Laranja, Uyarra and Flanagan, 2008; Magro and Wilson, 2013). Tödtling and Trippl (2005) in particular argue that innovation policy should be defined at the regional level to respond to differences in activities performed in each region. The authors make two claims: innovation is not exclusive of the best performing and innovative regions; and competitiveness is not achieved with the same innovation activities across all regions. Therefore, when it comes to innovation, a one size fits all policy will not fit the diverse needs of different regions. Moreover, innovation policies directed only at investment in R&D and technology do not guarantee that all innovation barriers will be overcome. The authors identify three main regional innovation systems characterized by low innovation and knowledge capabilities: *old industrial regions*, locked in the specialization of traditional and mature industries; *fragmented metropolitan regions* lacking the capacity to benefit from knowledge externalities and agglomeration economies and characterized by low levels of interaction between universities and firms and firms among themselves; and *peripheral regions* characterized by low absorptive capacity, predominance of small and medium enterprises (SMEs), lacking dynamic clusters and focusing on incremental and process

[23] Northern Portugal is included in a *smart technological application area* and Lisbon in an *applied science area* along with other regions from central and northern Europe.

[24] Lisbon is the exception belonging to the cluster of *central regions with an intermediate economic and technological capacity*. See also Marsan and Maguire (2011) for categorization of regions at the OECD level.

innovation. Portuguese regions share many characteristics of Tödtling and Trippl (2005)'s *peripheral regions*, as suggested by their categorization according to the classifications mentioned earlier as well as by the prevalence of SMEs (SMEs prevail even among Abstract firms, as seen in our data).

Given its regional characteristics, innovation policy for Portugal should aim at lowering start up costs to attract new firms, mainly Abstract (whose investments in R&D are higher), improve the innovation capabilities of SMEs, foster the creation of clusters of interconnected enterprises, and provide opportunities for market share expansion, perhaps by facilitating expansion into foreign markets. Concerning knowledge capabilities, education and training policies are needed to provide medium and high level skills. Lisbon and the north of Portugal also share some characteristics of the Tödtling and Trippl (2005)'s fragmented metropolitan regions, where knowledge providers such as high quality universities and research organizations should be expanded, investing in specialized but flexible skills and creating stronger ties with local industries.

Education and training policies are particularly important for Portuguese regions. Portugal is an example of an economy with a severe skill mismatch, revealed by the high incidence of long-term unemployment: averaging more than 40% of total unemployment since 2000, reaching 55.4% in 2016.[25] The supply of skills is determinant for technology deployment, an issue frequently neglected in the routinization literature as we have mentioned in section 2.1. Acemoglu (1997) showed that the adoption of new technologies by firms is contingent on the skills available in the labor market. Our results support this, as high skills seem to have a major role in the expansion and growth of Abstract firms which employ increasingly larger shares of college graduates than any other firm type (from 28.25 to 43.5% in a five years span). Consequently, policies that foster education and training are essential for innovation and productivity growth, an issue also emphasized by McCann and Ortega-Argilés (2015).

While the process innovation behind the creation and growth of Abstract firms may increase the demand for high-skill workers resulting from the complementarity between

[25] Only four of the EU-28 countries have higher incidence in 2016: Greece (72%), Slovakia (60.3%), Bulgaria (59.1%), and Italy (57%.4%). Nonetheless, almost half of the EU-28 unemployed search for a job for 12 months or more (46.4%).

abstract activities and computer capital, the overall employment may decrease, leading to technological unemployment (see Vivarelli (2014) for a review). Low skilled workers may look for jobs in Routine or Manual firms mostly concentrated in less technology and knowledge intensive sectors. However, our results show that Routine firms have seen their share decline over time, together with a slight decline in their average number of employees. Low skilled workers may therefore experience higher hazards of job termination (Castro Silva and Lima, 2017), receive lower wages (Clark and Kanellopoulos, 2013), may be caught in a low-pay no-pay cycle (Stewart, 2007) or fall into long-term unemployment (Baumol and Wolff, 1998). If policies aiming at increasing knowledge capabilities are an important part of an innovation policy system, it is also true that education and training policies are needed to ameliorate the possible undesired consequences of the Abstract firms rise on the country's skill mismatch.

7 Conclusion

In this paper we use Portuguese matched employer-employee data to seek answers to two main questions. First, is job market polarization and the disappearing of routine jobs which have been documented in many developed economies taking place mainly within firms or across firms? And second, how does the make up of tasks performed by firms contribute to aggregate productivity growth? In order to answer these questions, we propose a new firm taxonomy based on the shares of three types of tasks performed by the firm's workforce. According to this taxonomy, firms can be Abstract, Routine or Manual focused, or they can focus on a combination of two or three tasks. This taxonomy aims to capture the recent trends in technological change, which are visibly substituting certain tasks performed by human labor for computer capital – the so-called routinization hypothesis.

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, mainly knowledge intensive services and, to a lesser extent, high and medium-tech manufacturing. They tend to be SMEs, though increasing in dimension, and they absorb most of the growth in college educated workers. The rise of Abstract, decline of Routine and the stable share of Manual firms, suggests that labor market polarization is not due to job polarization within firms (polarized firms are less than 2%), but rather to the increased predominance of firms specializing in abstract tasks and the decline of firms specializing in routine tasks.

Furthermore, we conclude that productivity growth is mostly driven by two main factors: first, increased market shares of the most productive incumbents; and second, exiting of the least productive firms, especially Abstract firms. However, the overall decline in productivity of incumbent firms (especially Routine) has resulted in stagnation of the Portuguese aggregate productivity between 2004 and 2009, a phenomenon not unique to Portugal, but common to other regions of southern Europe, rendering our conclusions relevant to a wider set of economies.

Our taxonomy enables us to understand that focused Abstract firms lead the productivity growth, though because of their yet small share, this did not translate into overall 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 also require high-skilled workers. Also, promoting enterprises to re-organize their labor inputs so they can focus on Abstract tasks can lead to increases in aggregate productivity.

It is not surprising that Portugal is associated with low productivity, as its levels of physical and human capital are still well below the European average, comparable to similarly lagging European regions. Innovation policies directed at these regions require the development of innovation and knowledge capabilities to promote the growth and creation of competitive firms, and in turn productivity growth. To accomplish that, policy-makers need to consider innovation policies together with education and training policies as well as policies supporting SMEs. Moreover, the high prevalence of long-term unemployment and the existence of large segments of the labor market where short duration and low-wage jobs prevail will probably persist or be aggravated with the deepening of the routinization process. The reverse is also true: the lack of the supply of skills will hamper the innovation capabilities of firms and regions. These structural imbalances reinforce the need do design policies that can form a coherent regional policy system to promote productivity growth and cohesion.

The increased complexity of processes and specialization in innovation activities are leading firms to re-organize their internal structure towards more abstract tasks in order to cope with new technologies and leverage their innovative performance. The firm events identified in our productivity decomposition – surviving, entry, exit or transitioning between taxonomy categories – should also reflect differences in firms' characteristics and capabilities. Investments in human capital or changes in the firm size can reflect task re-configurations and adaptation due to technological change, as it is the case of the mean share of college graduates in Abstract firms increasing a staggering 15 percentage points in our five years of analysis. Further research within and across firm categories is needed to understand what additional firm characteristics and firm events can drive productivity growth, such as capital use, R&D intensity and exporting and innovation strategies, along with the optimal combination of abstract, manual and routine workers.

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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

$$\Delta\Phi = \Delta\bar{\phi}_S + \Delta cov_S + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}) + s_{E_{tr}2}(\Phi_{E_{tr}2} - \Phi_{S2}) + s_{X_{tr}1}(\Phi_{S1} - \Phi_{X_{tr}1}) \quad \text{(A.7)}$$

A2 Statistical tests for the decomposition

We follow Hyytinen, Ilmakunnas and Maliranta (2016) to tests for the differences presented in Tables 5, 6 and A4.5.

Consider two periods, $t = 1, 2$, where the first period corresponds to 2005 (the first year of the ACF estimation) and the second period varies from 2006 to 2009. Borrowing the notation from Hyytinen, Ilmakunnas and Maliranta (2016), we define θ as the unweighted mean of productivity and γ the covariance between the shares and productivity (the market share reallocation component). The decomposition as proposed in Equation 3 defines five groups of firms: survivors (S), market entrants (E), transition entrant (E_{tr}), market exitors (X), and transition exitors (X_{tr}). As described in Appendix A1, in period 1, we observe three mutually excludable groups: survivors and exitors (market and transition); in period 2: survivors and entrants.

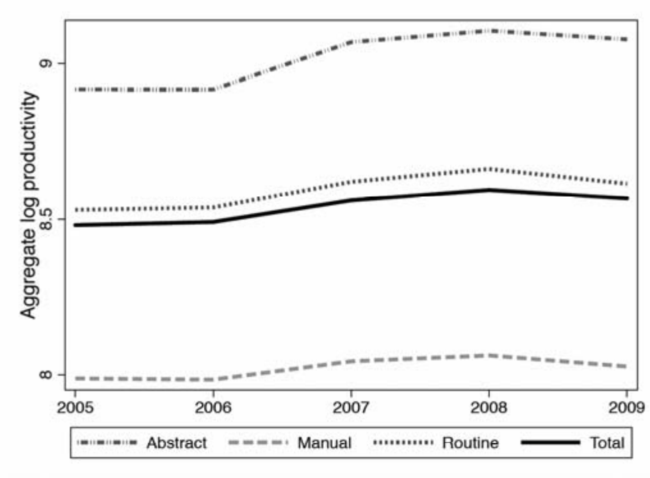

Figure A3.3: Total factor productivity – modified taxonomy definition

Notes: Total factor productivity 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 Ackerberg, Caves and Frazer (2015) (ACF) method. Estimation results from Table A4.4. Taxonomy boundaries changed so that firms in boundary regions are reassign as focused Abstract, Routine, and Manual.

Table A4.5: Productivity growth decomposition – modified taxonomy

	Total	Survivors				Transitions	
	Change	Avg prod	Reallocation	Entrants	Exitors	Entrants	Exitors
Abstract							
2006	-0.038	-0.041***	-0.007	0.01	0.004***	-0.034***	0.029**
2007	0.102***	-0.031***	0.003**	0.01	-0.034***	0.125	0.03***
2008	0.157***	-0.054***	0.096**	-0.001	-0.017**	0.095	0.038***
2009	0.129***	-0.063***	0.155***	0.021*	-0.041***	0.009	0.049***
Routine							
2006	0.018***	-0.037***	0.055**	-0.003**	0.004***	-0.012**	0.01*
2007	0.036***	-0.05***	0.09*	-0.008**	0.004***	-0.014***	0.014**
2008	0.023***	-0.097***	0.106***	-0.009**	0.023***	-0.014**	0.013**
2009	0.006***	-0.128***	0.11**	-0.021*	0.049***	-0.017**	0.013**
Manual							
2006	-0.008	-0.032***	0.04***	-0.005***	-0.003***	-0.004	-0.003
2007	0.019***	-0.036***	0.069***	-0.004***	-0.009***	0.002	-0.003
2008	0.016***	-0.072***	0.092***	-0.006***	0.001***	0.006	-0.004
2009	-0.019***	-0.102***	0.084***	-0.008***	0.009***	0.005	-0.006*

Notes: Decomposition performed using TFP results by firm category (estimation results from Table A4.4 (ACF)). The base year is 2005. Average productivity (Avg prod) component refers to $\Delta\bar{\phi}_S$ (change in the unweighted average productivity) and reallocation component is Δcov_S, where $cov_S = \sum_i (s_{it} - \bar{s}_t)(\phi_{it} - \bar{\phi}_t)$ (market share reallocations). 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 $s_{X_{tr}1}(\Phi_{S1} - \Phi_{X_{tr}1})$. * 10% significant, ** 5% significant and *** 1% significant. For details on the significance tests see Appendix A2.