Understanding productivity dynamics: a task taxonomy approach

Tiago Fonseca[*,†] Francisco Lima[†] Sonia C. Pereira[‡]

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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.

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

JEL codes: D24, L23, O33

[*]World Maritime University

[†]CEG-IST, Instituto Superior Teécnico, Universidade de Lisboa

[‡]Barnard College, Columbia University, and Columbia School of Social Work

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 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. 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; Kerr, Maczuskij and Maliranta, 2016; Maliranta, 2013). However these studies have not looked at firm total factor 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. 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?

[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.

In order to answer these two questions, we propose a taxonomy based on the task-approach followed by the routinization literature.[2] We classify firms according to the tasks 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 tasks. 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. Our 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

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

2004 and 2009.[3] Our results raise the question of how policy-makers should design policies to foster productivity and reduce the skill mismatch occurring in labor markets undergoing similar changes. If innovation policies should promote Abstract firms, education and training policies within a regional innovation system 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 foundations on which our work is based. Section 3 describes de data used. Section 4 develops the new taxonomy. Section 5 presents the estimation results in three parts: total factor productivity estimates (Section 5.1), productivity dynamics analysis (Section 5.2) and robustness checks (Section 5.3). Section 6 discusses the policy implications of our results and section 7 concludes.

2 Background: technology, skills, and productivity

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).[4] New technologies can be difficult to master and thus require more skills. Usually, more educated workers are 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

[3]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.

[4]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.

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 searching 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.

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. The model classifies tasks performed by workers into abstract, routine and manual. Routine tasks are those that can be done by following a set of well-determined rules and can therefore be programmed into a machine (e.g. bookkeeping, clerical work, repetitive assembly, and monitoring jobs). Abstract tasks are related with solving problems, managing, dealing with complex communications, designing and programming and other creative tasks that require cognitive skills (e.g. 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. Finally, manual tasks generally require few cognitive skills, but require more flexibility than computers can offer and cannot be automated (e.g. cleaners, gardeners and plumbers).

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.[5] 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

[5]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.

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.[6]

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 firms to reorganize their production in response to technological change. These organizational shifts in turn, are likely to affect firm productivity and productivity growth. In particular, 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.

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.[7] 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). The estimation of firms' TFP enables productivity comparisons, in particular to grasp the differences between the

[6]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).

[7]See for example Bertschek and Kaiser (2004), Bloom and Van Reenen (2007), Chun, Kim and Lee (2015), Haskel, Pereira and Slaughter (2007), Venturini (2015). Augmented production functions with ICT inputs (Bloom, Sadun and Reenen, 2012; Bresnahan, Brynjolfsson and Hitt, 2002; Brynjolfsson and Hitt, 2003; Greenana and Mairesse, 2000) or R&D (Czarnitzki and Thorwarth, 2012; Kancs and Siliverstovs, 2016) have also been used in the literature.

aggregate productivity of groups of firms classified according to a given taxonomy.

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 upward. 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, we resort to Melitz and Polanec (2015) dynamic version of Olley and Pakes (1996) productivity decomposition which 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); provided extensions to account for firm dynamics (e.g., Hyytinen, Ilmakunnas and Maliranta, 2016; Maliranta and Määttänen, 2015); or developed a firm lifecycle decomposition approach (Hyytinen and Maliranta, 2013).

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 this 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 the routinization hypothesis and link two previously independent literatures: job market polarization and firm productivity.

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).[8] After merging the two datasets we obtain more than 118 thousand firms in 2004 and 143 thousand in 2009 in manufacturing and services (Table A4.3 in the Appendix). 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' dataset 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.

4 A firm taxonomy based on tasks

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;

[8] 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.

[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).

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 dynamics.

Our taxonomy assumes that the production of goods and services in the firm is accomplished by executing one or multiple tasks following Autor, Katz and Kearney (2006). 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. We have conducted several robustness checks to our taxonomy by employing different taxonomy boundaries, which we discuss in Section 5.3.

[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.

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 a 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.

Table 1: Taxonomy categories and boundaries

Firm Task Category	**Share of employees**		
	Abstract (A_s)	**Manual (M_s)**	**Routine (R_s)**
Abstract (A)	≥1/2	<1/3	<1/3
Manual (M)	<1/3	≥1/2	<1/3
Routine (R)	<1/3	<1/3	≥1/2
Polarized	≥1/3	≥1/3	≤1/6
Abstract-Routine	≥1/3	≤1/6	≥1/3
Routine-Manual	≤1/6	≥1/3	≥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		

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 that managers 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 and subject to uncertainty and error.[11] Furthermore, the decision

[11]Managers face uncertainty about the profitability of an innovative technology (Jensen, 1982), need to

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). We consider two additional categories focusing 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.

Uniform firms are firms that do not focus on neither of the three tasks – they have

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).

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). 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.

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. 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, surrounded by firms in the category Other.

Table 2 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. 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

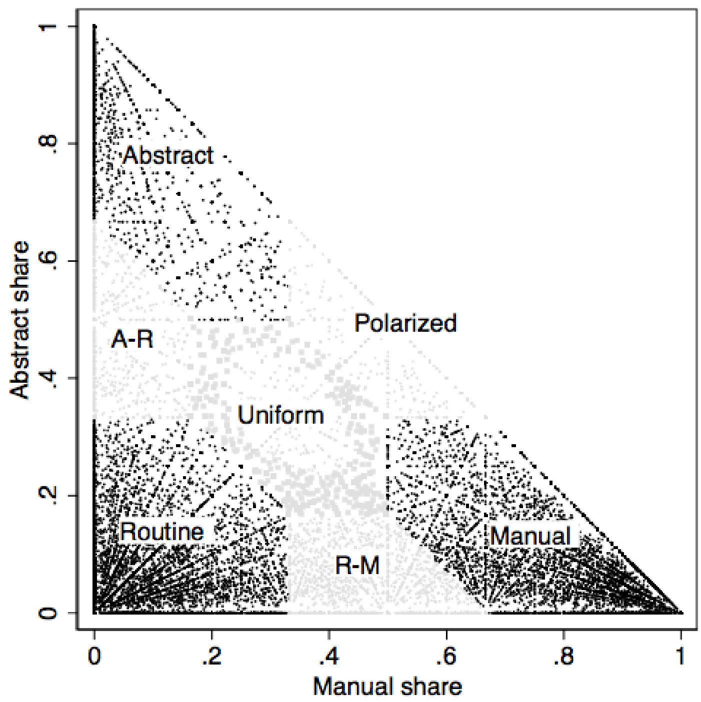

Figure 1: Taxonomy applied to 2009 Portuguese firms

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.

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, can 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 based on their labor input. Figure 2 plots the trends for the share of firms in each task category for the period 1995 to 2012. During this period, Routine focused firms decrease

Table 2: 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.

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.

Table 3 presents summary statistics by firm category. Abstract firms are slightly

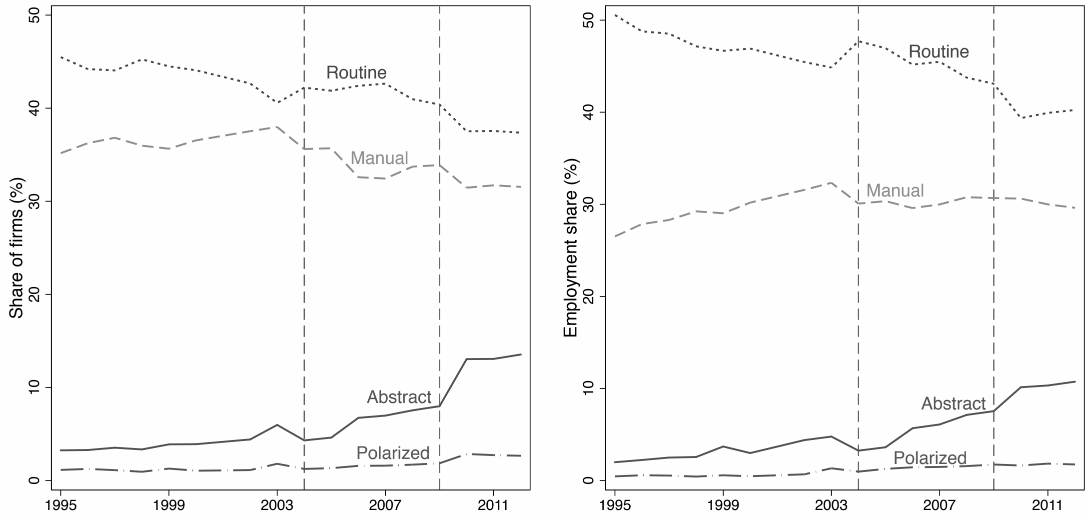

Figure 2: Share of firms and employment by firm category
Notes: Vertical lines represent the time window (2004-2009) when the two datasets are merged.

smaller, followed by Manual and Routine that are the largest. However, 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 small and medium enterprises (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 firms in 2009. Abstract firms are mostly concentrated in knowledge-intensive services, whereas Routine and Manual are mostly prevalent 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 in Abstract firms is almost four times higher than in Routine and ten times higher than in 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. It is also worth of note that Abstract firms are younger than Routine and Manual.

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

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 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. We apply the estimation method proposed by Ackerberg, Caves and Frazer (2015) (ACF hereafter). This method builds on Olley and Pakes (1996) (hereafter OP) and Levinsohn and Petrin (2003) (here-

Table 3: 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.

after LP) to obtain consistent estimates even when unobserved labor shocks are present (e.g., firm-specific shocks to price of labor).[12]

Following ACF, we consider a production function with Cobb-Douglas technology with capital and labor as inputs and value added as the output variable, estimated as proposed by Manjón and Mañez (2016) (see Section 5.3 for results with the LP and OP methods). TFP is what cannot be explained by the observable inputs and is given by the residual of the production function. 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). Appendix Table A4.4 presents the descriptive statistics for output and inputs of the production function by industry and Appendix Table A4.5 shows the estimation results.

Figure 3 plots the aggregate log productivity (log TFP aggregated using 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). Abstract firms are the most productive, 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 grows 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 observed during the decade (less than 1% yearly) and the 2008 financial crisis. Overall, the stagnation in aggregate productivity is present across all firm categories, except Abstract which exhibits growth.

5.2 Productivity dynamics

Although we are able to characterize productivity change by firm category, the sources of these 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 productivity dynamics, we develop an extended version of Olley and Pakes (1996)

[12] See Ackerberg, Caves and Frazer (2015) and Manjón and Mañez (2016) for a discussion.

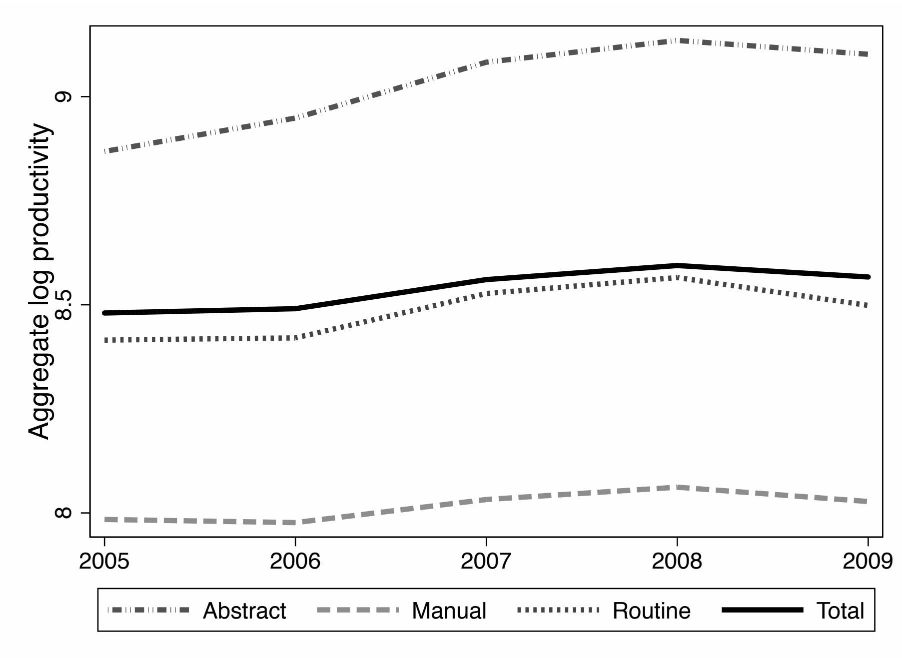

Figure 3: Total factor productivity by firm category

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 A4.5.

and Melitz and Polanec (2015) dynamics decomposition method.

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 1.[13]

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

Where the first two components are the same as in Olley and Pakes (1996) decomposi-

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

tion: $\Delta\bar{\phi}_S$, 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.[14] 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.

Table 4 presents the results from applying this decomposition to the productivity results from the ACF estimation.[15] We test the significance of the changes from the base year (2005) using the methodology proposed by Hyytinen, Ilmakunnas and Maliranta (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.[16] The

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

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

[16] 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.

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 4: 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 A4.5 (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 5 breaks down the productivity decomposition for the three main firm categories (Abstract, Manual and Routine), including transitions between tasks.[17] 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), and negative for Routine and Manual (-0.006 and -0.015 log points respectively).

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 for 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

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

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 drive 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 both Routine and Manual categories, but not for the Abstract, which drive productivity growth.

Table 5: 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 A4.5 (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

As explained in section 5.1, the ACF method builds on OP and LP methods. For comparability, we also estimate the production function using LP and OP methods as proposed by Petrin, Poi and Levinsohn (2004) and Yasar, Raciborski and Poi (2008) respectively (appendix Table A4.5 presents the results). The estimated coefficients increase in comparison with the ACF method, which we would expect, especially for labor, given that the ACF method deals with the possible labor endogeneity. The ranking across the firms categories and evolution of the aggregate log productivity of both alternative methods is similar to that of ACF (results in Appendix Figures A3.1 and A3.2.)

We also perform 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. 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. Furthermore, we ran 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 solely on clusters would generate a purely geometric division of the space, failing to provide a connection with the theory.

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. We next examine what changes in our results when those firms are allocated to the three main categories (Abstract, Manual, and Routine). We reduce 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, to the Routine-Manual firms. This new partition of space 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. Regarding productivity growth trends, they mimic the previous results. The results for the productivity decomposition are very similar with the ones from our original taxonomy (Appendix Table A4.6), 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. 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.

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.[18] 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 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.[19]

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%)

[18]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.

[19]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).

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 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.[20] Navarro et al. (2009) place most Portuguese regions in the group of *peripheral agricultural regions with a strong economic and technological lag.*[21]

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;

[20] 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.

[21] 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.

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 SMEs, lacking dynamic clusters and focusing on incremental and process 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.[22] The supply of skills is determinant for technology deployment, an issue frequently neglected in the routinization literature as we have mentioned in section 2. 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 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.

[22]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%).

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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Appendix

A1 Decomposition equations

Olley and Pakes (1996) decompose aggregate productivity in a given year Φ_t into two components:

$$\Phi_t = \bar{\phi}_t + \sum_i (s_{it} - \bar{s}_t)(\phi_{it} - \bar{\phi}_t) \tag{A.1}$$

The first component, $\bar{\phi}_t$, corresponds to the unweighted average productivity. The second term is the sum of the products between market share s_{it} and firm's productivity ϕ_{it} (both demeaned), which is similar to a covariance – it measures the relationship between the output (market shares) and productivity. The larger the coefficient of the sum is, the higher the share of output is reallocated to more productive firms. The literature often refers to this coefficient as the reallocation component. 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 value added and aggregate productivity Φ_t is computed as the weighted sum on market share of the log TFP (obtained from the production functions' estimation).

We add on Melitz and Polanec (2015) dynamic composition by including the transitions terms denoted by X_{tr} for exit through transition and E_{tr} for entrance through transition.

Thus, the decomposition for periods 1 and 2 can be written as:

$$\Phi_1 = s_{S1}\Phi_{S1} + s_{X1}\Phi_{X1} = \Phi_{S1} + s_{X1}(\Phi_{X1} - \Phi_{S1}) + s_{X_{tr}1}(\Phi_{X_{tr}1} - \Phi_{S1}) \tag{A.2}$$

$$\Phi_2 = s_{S2}\Phi_{S2} + s_{E2}\Phi_{E2} = \Phi_{S2} + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{E_{tr}2}(\Phi_{E_{tr}2} - \Phi_{S2}) \tag{A.3}$$

where the index S represent the survivors, X the exitors and E the entrants; Φ_t is the aggregate productivity and s the market share. Transitions terms 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

$$\Delta\Phi = \Delta\bar{\phi}_S + \Delta cov_S + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}) + \\ s_{E_{tr}2}(\Phi_{E_{tr}2} - \Phi_{S2}) + s_{X_{tr}1}(\Phi_{S1} - \Phi_{X_{tr}1}) \quad (A.4)$$

A2 Statistical tests for the decomposition

We follow Hyytinen, Ilmakunnas and Maliranta (2016) to tests for the differences presented in Tables 4, 5 and A4.6.

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 1 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.

To test the differences, the equation to be estimated for productivity (Φ) is:

$$\begin{aligned}
\Phi = {} & \theta_{S1} \times d_{S1} + \gamma_{S1} \times s^*_{S1} \\
& + \theta_{X1} \times d_{X1} + \gamma_{X1} \times s^*_{X1} \\
& + \theta_{Xtr1} \times d_{Xtr1} + \gamma_{Xtr1} \times s^*_{Xtr1} \\
& + \theta_{S2} \times d_{S2} + \gamma_{S2} \times s^*_{S2} \\
& + \theta_{E2} \times d_{E2} + \gamma_{E2} \times s^*_{E2} \\
& + \theta_{Etr2} \times d_{Etr2} + \gamma_{Etr2} \times s^*_{Etr2}
\end{aligned} \tag{A.5}$$

where d are the dummies for each group-time; s^* is the rescaled share computed as $(s - \bar{s})/(var_s N)$ for each relevant group in each period; $\bar{s}$, var_s and N are respectively the mean share, variance and the number of observations in the group. The shares are defined as in Appendix A1. For our application, another subscript is needed for the firm category – Abstract, Routine, Manual – that results in three times the coefficients presented in Equation A.5.

The equation is estimated with no constant. The standard errors are obtain through bootstrapping (200 replicates) as Φ is the estimated total factor productivity.[23] In order to test the the productivity growth decomposition of Tables 5 and A4.6 (and Table 4 without the firm categories), we statistically test the diferences as follows:

- The unweighted average productivity: $\theta_{S2} - \theta_{S1} = 0$
- Market share reallocation (the covariance term): $\gamma_{S2} - \gamma_{S1} = 0$
- Market Entrants: $(\theta_{E2} + \gamma_{E2}) - (\theta_{S2} + \gamma_{S2}) = 0$
- Market Exitors: $(\theta_{S1} + \gamma_{S1}) - (\theta_{X1} + \gamma_{X1}) = 0$
- Transition Entrants: $(\theta_{Etr2} + \gamma_{Etr2}) - (\theta_{S2} + \gamma_{S2}) = 0$
- Transition Exitors: $(\theta_{S1} + \gamma_{S1}) - (\theta_{Xtr1} + \gamma_{Xtr1}) = 0$

[23] To test the difference in the total factor productivity (Φ in Equation A.5), the total change presented in the first column of the total growth decomposition, we simply run the regression $\Phi_t = cte + d_2 \quad (t = 1, 2)$, and test for $d_2 = 0$.

A3 Figures

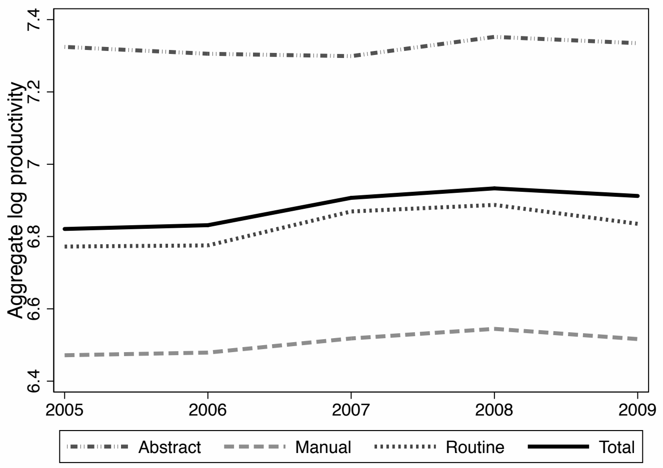

Figure A3.1: Total factor productivity by firm category using OP method

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 Olley and Pakes (1996) (OP) method. Estimation results from Table A4.5.

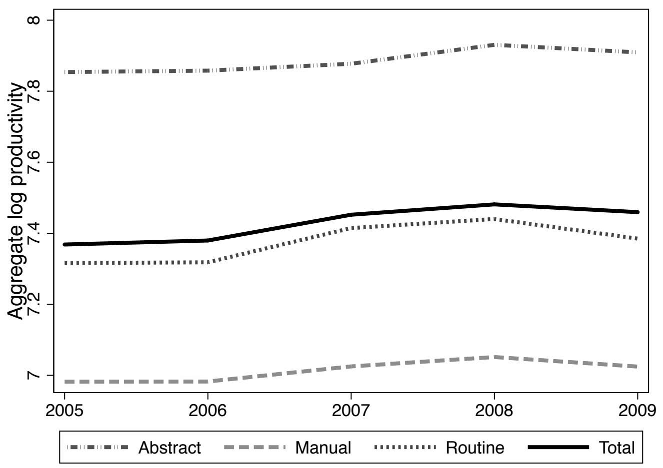

Figure A3.2: Total factor productivity by firm category using LP method

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 Levinsohn and Petrin (2003) (LP) method. Estimation results from Table A4.5.

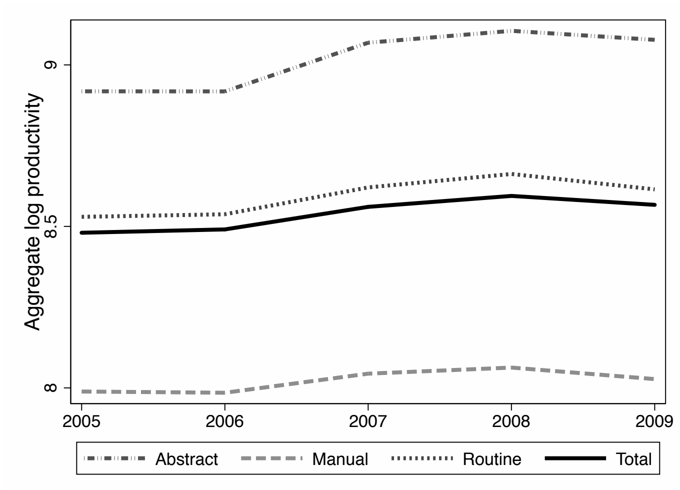

Figure A3.3: Total factor productivity – modified taxonomy definition

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 A4.5. Taxonomy boundaries changed so that firms in boundary regions are reassign as focused Abstract, Routine, and Manual.

A4 Tables

Table A4.1: 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 US employment data and a detailed cross-walk. Task allocation is based on the most intensive task in a given occupation.

Table A4.2: Top 15 employing industries: firm task distribution

NACE	**Designation**	**% Share of employment**				
		Overall	**Abstract**	**Manual**	**Routine**	**Polarized**
41.2	Construction of residential and non-residential buildings	5.9	0.62	89.75	1.07	4.01
47.1	Retail sale in non-specialised stores	3.6	0.08	2.66	95.47	0.02
56.1	Restaurants and mobile food service activities	3.3	0.01	95.80	2.46	0.10
47.7	Retail sale of other goods in specialised stores	3.2	11.17	10.90	63.02	5.13
78.2	Temporary employment agency activities	2.9	0.08	25.93	20.93	0.27
14.1	Manufacture of wearing apparel, except fur apparel	2.7	0.02	0.26	97.90	0.00
81.2	Cleaning activities	2.2	0.16	98.47	0.36	0.10
64.1	Monetary intermediation	2.0	0.02	0.00	96.06	0.00
43.2	Electrical, plumbing and other construction installation activities	1.9	6.37	78.45	3.66	3.84
49.4	Freight transport by road and removal services	1.8	0.04	87.44	5.67	0.12
87.3	Residential care activities for the elderly and disabled	1.6	2.07	94.34	0.09	3.12
46.3	Wholesale of food, beverages and tobacco	1.6	0.11	18.98	50.61	0.14
55.1	Hotels and similar accommodation	1.6	0.02	80.20	1.57	0.06
47.5	Retail sale of other household equipment in specialised stores	1.6	0.62	12.48	69.73	0.29
88.9	Other social work activities without accommodation	1.5	10.41	64.55	0.92	22.99

Notes: Data from SCIE 2009. Industries are NACE 3-digits codification. The share of employment by type of firm is calculated for each industry. Overall employment is the share of total employment in the particular industry.The results omit Uniform, Routine-Abstract and Routine-Manual firms' share of employment.

Table A4.3: 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.

Table A4.4: Production function descriptive statistics by year

	2004	2005	2006	2007	2008	2009	2004-2009
log VA	11.26	11.38	11.38	11.41	11.40	11.34	11.24
	(1.46)	(1.42)	(1.42)	(1.43)	(1.45)	(1.45)	(1.48)
log capital	11.76	11.94	11.96	11.96	11.98	11.94	11.78
	(1.71)	(1.66)	(1.66)	(1.65)	(1.66)	(1.68)	(1.72)
log labor	1.72	1.79	1.78	1.75	1.75	1.71	1.67
	(1.04)	(1.05)	(1.05)	(1.07)	(1.07)	(1.06)	(1.06)
log intermediate	11.56	11.69	11.74	11.17	11.12	10.97	11.10
	(2.1)	(2.05)	(1.99)	(2.5)	(2.52)	(2.48)	(2.43)
log investment	8.39	8.79	8.88	8.94	8.85	8.62	8.78
	(2.52)	(2.78)	(2.43)	(2.4)	(2.42)	(2.45)	(2.48)
Observations	118,223	122,481	142,933	141,240	146,858	143,689	815,424

Notes: Working data for 2004-2009 used for ACF estimation. Intermediate inputs are the sum of materials and energy. All values, except labor, are in 2009 euros (GDP deflator). Labor refers to the number of employees. Standard deviation between parenthesis.

Table A4.5: Production function estimates

	ACF	LP	OP
log k	0.239***	0.278***	0.315***
	0.025	0.004	0.013
log l	0.653*	0.750***	0.743***
	0.045	0.002	0.002
Obs.	575400	575400	485648

Notes: Data for 2004-2009. The dependent variable is the log value added. Estimation performed ACF, LP and OP methods. The sum of materials and energy are used as the intermediate inputs proxy when estimating the production function by ACF and LP methods. * 10% significant, ** 5% significant and *** 1% significant.

Table A4.6: Productivity growth decomposition – modified taxonomy

	Total Change	**Survivors** Avg prod	Reallocation	**Entrants**	**Exitors**	**Transitions** 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 A4.5 (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.