Contents lists available at ScienceDirect

## **Research Policy**

journal homepage: www.elsevier.com/locate/respol

# Understanding productivity dynamics: A task taxonomy approach

Tiago Fonseca<sup>a,b</sup>, Francisco Lima<sup>b,\*</sup>, Sonia C. Pereira<sup>c</sup>

<sup>a</sup> World Maritime University, Sweden

<sup>b</sup> CEG-IST, Instituto Superior Técnico, Universidade de Lisboa, Portugal

<sup>c</sup> Barnard College, Columbia University, and Columbia School of Social Work, United States

### ARTICLE INFO

JEL classification: D24 L23 O33 Keywords: Taxonomy Productivity Routinization Technological change Polarization

## 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 reveals 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.

#### 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 et al., 2003).<sup>1</sup>

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 et al., 2016). 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?

In order to answer these two questions, we propose a taxonomy based on the task-approach followed by the routinization literature.<sup>2</sup> We classify firms according to the tasks performed by their workforce

https://doi.org/10.1016/j.respol.2017.11.004

Received 19 December 2016; Received in revised form 10 November 2017; Accepted 12 November 2017 Available online 22 November 2017 0048-7333/ © 2017 Elsevier B.V. All rights reserved.





<sup>\*</sup> Corresponding author.

E-mail address: francisco.lima@tecnico.ulisboa.pt (F. Lima).

<sup>&</sup>lt;sup>1</sup> 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 et al., 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.

<sup>&</sup>lt;sup>2</sup> 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 et al., 2016; Castex and Kogan Dechter, 2014; Hunt and Nunn, 2017; Mishel et al., 2013). Yet, most evidence still corroborates the routinization hypothesis.

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 et al. (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 2004 and 2009.<sup>3</sup> 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 et al., 1998; Bresnahan, 1999; Krueger, 1993; Krusell et al., 2000).<sup>4</sup> 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 adopted it in the workplace, thus leveraging productivity of the high-skilled workers due to their complementarity effect (Acemoglu, 1998; Autor et al., 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 et al., 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 et al., 1998). Moreover, the investment in computers and R&D lead to an increase in the pace of skill upgrading (Autor et al., 1998; Machin and 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 et al., 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 et al., 2006; Goos and Manning, 2007). Portugal was no exception, and both Centeno and Novo (2014) and Fonseca et al. (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 et al. (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 et al. (2003) and extended by Autor et al. (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 et al. (2015) are able to identify the employment effects of

<sup>&</sup>lt;sup>3</sup> 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.

<sup>&</sup>lt;sup>4</sup> 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.

Download English Version:

# https://daneshyari.com/en/article/7384617

Download Persian Version:

https://daneshyari.com/article/7384617

Daneshyari.com