U.PORTO

FEP FACULDADE DE ECONOMIA
UNIVERSIDADE DO PORTO

How the changes in the demand and supply of graduates and postgraduates have been shaping their labor market performance?

Pedro Tomás Neto Paiva

Dissertation

Master in Economics

Supervised by

Professor Anabela de Jesus Moreira Carneiro

Professor Hugo Casal Figueiredo

2021

Acknowledgments

The conclusion of this work is a moment of gratitude to all who helped me along this path.

A very special thank you to Professor Anabela Carneiro for all her truly tireless follow-up and brilliant guidance throughout this challenge and for the multiple suggestions, clarifications, and incentives she gave. I thank Professor Hugo Figueiredo for his encouragement and his availability.

I am also grateful to the Statistical Department of the Ministry of Labor, Solidarity, and Social Security (GEP-MTSSS) and "Instituto Nacional de Estatística" (INE) for granting access to the "Quadros de Pessoal" data set.

Finally, a big thank you to all those who have always been there: my family and friends. They know who they are. They made it so much easier.

This research has been financed by Portuguese public funds through FCT - Fundação para a Ciência e a Tecnologia, I.P., in the framework of the project with reference PTDC/CED-EDG/29726/2017.

Abstract

The massification of access to higher education in Portugal has increased the supply of graduates and postgraduates in the labor market. On the demand side, technological progress has affected recruitment patterns, favoring highly qualified workers, due to their complementarity with capital. This new framework values occupations that require a high level of social interaction and, in this way, social skills become fundamental.

Using a rich administrative matched employer-employee data set – Quadros de Pessoal – over the period 2010-2018 and the O*NET classification of occupations, this study seeks to assess how these structural changes in demand and supply are shaping employment and wages. graduates and postgraduates in Portugal.

The data reveal that it is in routine cognitive occupations that graduates are increasingly represented, as opposed to non-routine occupations (abstract or interpersonal), where masters are more represented. However, the proportion of master workers in routine cognitive occupations has increased in the last decade.

Despite the decline in the wage premium to higher education in Portugal in recent years, we observe a slight increase in the wage premium for masters relative to graduates – 4.7% in 2018 against 3.7% in 2010, reaching about 8% in 2018 in the 20-34 years old cohort.

The decomposition of the sources of the raw wage gap between masters and bachelors showed that differences in experience and seniority, as well as employment in top hierarchical positions and in industries that pay higher wages, offers masters a wage advantage over bachelors.

Finally, the econometric results also show that workers employed in non-routine abstract and routine cognitive occupations benefit from a wage bonus, relative to workers employed in non-routine interactive occupations, that varies, respectively, between 9.4% and 12.7% if a high level of social skills is required.

JEL codes: I26, J31, O33

Keywords: Job polarization; Higher Education; Social Skills; Wage returns; Matched employer-employee data

Resumo

A massificação do acesso ao ensino superior em Portugal veio aumentar a oferta de licenciados e pós-graduados no mercado de trabalho. Do lado da procura, o progresso tecnológico afetou os padrões de recrutamento, privilegiando trabalhadores altamente qualificados, pela complementaridade com o capital. Este novo quadro valoriza ocupações que requerem alto nível de interação social, tornando as competências sociais fundamentais.

Utilizando uma base de microdados de empresas e trabalhadores – *Quadros de Pessoal* – ao longo do período 2010-2018 e a classificação O*NET de ocupações, este estudo procura avaliar como estas mudanças estruturais na procura e na oferta estão a moldar o emprego e salários dos licenciados e pós-graduados em Portugal.

Os dados revelam que é nas ocupações rotineiras cognitivas que os licenciados estão cada vez mais representados, por oposição às ocupações não-rotineiras (abstratas ou interpessoais), onde os mestres estão mais representados. Contudo, a proporção de trabalhadores mestres em ocupações rotineiras cognitivas aumentou na última década.

Apesar da diminuição do prémio salarial ao ensino superior em Portugal nos últimos anos, observa-se um ligeiro aumento do prémio salarial dos mestres face aos licenciados - 3,7% em 2010 contra 4,7% em 2018, atingindo quase 8% em 2018 nos indivíduos com 20-34 anos.

A decomposição das fontes da diferença salarial bruta entre mestres e licenciados mostrou que as diferenças de experiência e antiguidade, bem como o emprego em cargos hierárquicos superiores e em indústrias que pagam salários mais elevados, oferecem aos mestres uma vantagem salarial sobre os licenciados.

Finalmente, os resultados econométricos mostram que os trabalhadores empregados em ocupações abstratas e rotineiras cognitivas beneficiam de um bónus salarial que varia entre 9,4% e 12,7%, respetivamente, comparativamente aos empregados em ocupações não-rotineiras interpessoais, se exigido um nível elevado de competências sociais.

Códigos-JEL: I26, J31, O33

Palavras-chave: Polarização do emprego; Ensino superior; Competências transversais; Retornos salariais; Dados empregador-empregado

Index

Figures Index

Tables Index

1. Introduction

Since the mid-twentieth century, the labor market has undergone an unprecedented transformation, both on the demand side and on the supply side. This transformation is widespread in many countries, although it occurs at very different paces.

Portugal has registered a progressive and systematic improvement in the qualification levels of workers, reconfiguring the characteristics of the supply in the labor market, mainly since the 1980s. This achievement is particularly the result of successive extensions of mandatory schooling and the massification of access to higher education, which led to remarkable growth in the number of graduate and postgraduate workers (Figueiredo et al., 2017). [1]

On the demand side, technological progress has disrupted labor relations and recruitment processes. The development of computing, robotics, and artificial intelligence, in recent years, led to a demand increase in favor of highly skilled workers and to a demand decrease of workers who performed routine tasks that can be easily replaced by automation.

The routinization hypothesis (Autor, Levy, & Murnane, 2003) points in this direction, indicating the decrease in employment in routine occupations because of the introduction of technology in production processes, which allowed for the growth of productivity (World Bank, 2016). However, technological progress seems to have more repercussions on the labor market than those already mentioned, as the use of capital allows to increase the productivity of highly qualified workers, due to its complementarity with technology. In this way, the use of technology in companies not only leads to a reduction in routine work, now performed by computers or robots, but also stimulates the employment of workers better prepared to keep up with technological development, capable of, in a smaller number, perform, with a substantially higher degree of efficiency, the tasks previously performed by mid-level skilled workers (Johnson, 1997).

Although this bias increases employment and wages in occupations that require higher skill levels, the same applies to occupations where workers with a low level of education are employed (Autor, Katz, & Kearney, 2006; Goos & Manning, 2007; Spitz-Oener, 2006). This occurs particularly in manual tasks, where technological equipment is not yet able to provide an effective response. This led to a phenomenon of polarization of the labor market, with a

[1] The Bologna reform was very important in this process.

drop in employment in routine tasks and a growth in employment in manual tasks and abstract tasks (those that require knowledge and abstraction). Consequently, the polarization of employment led to a wage polarization, with the highest wage variations observed at the top and bottom of the wage distribution.

The conclusions presented by some recent studies for the US context, pointing to a drop in the wage premium of the most skilled workers since the end of the twentieth century and the beginning of the new century, raised alarms (Valletta, 2019). They raised the debate on whether the theoretical hypotheses that supported the polarization trend would remain intact, or whether we were facing a new context in the labor market, especially in terms of wage distribution. Some more recent literature has concluded what seminal studies already safeguarded – as the supply of skilled workers increases, their wage premium will fall, in a period of maturity of the technology (Beaudry, Green, & Sand, 2016). However, this drop was the target of a strong discussion among specialists and, therefore, must be analyzed with great caution.

Recent studies show that there is a strong wage gap between graduate and postgraduate workers (Lindley & Machin, 2016), so that the drop in the wage premium for higher education does not seem to be the same at all levels. Additionally, there is evidence that, despite the rapid automation process and advances in artificial intelligence, the ability of technology to simulate and monitor human action is, in our days, still very limited, in other words, the main advantages of social skills, which are embodied in teamwork, collaboration, negotiation, learning processes, are not yet effectively carried out by machines and computers, but are, however, increasingly valued by employers (Deming, 2017; Deming & Kahn, 2018).

In this framework, it is of utmost importance to assess how employers are remunerating graduates and to what extent they differentiate bachelors from masters. This analysis will take into account the type of occupation where the graduates are employed, which are determined based on the tasks performed by workers (Fonseca, Lima, & Pereira, 2018b) and social skills needed to perform those tasks (Deming, 2017). In fact, nowadays it is particularly important regarding non-routine cognitive work, not only higher levels of education and job training but also, a set of transversal skills, which do not only measure technical issues but above all aspects of interpersonal relationships between workers and customers, commonly referred to as social skills.

The largest source of information on the labor market in Portugal is compiled in microdata from *Quadros de Pessoal*, a longitudinal employer-employee database that contains information on Portuguese workers and companies in the private sector. We use this very precious information for the most recent years, from 2010 to 2018, which we complement with two O*NET additional databases that allow the measurement of the characteristics of each occupation (4-digits) regarding the intensity of the tasks performed, and the measurement of the level of social skills.

Based on worker-level data on a sample of 4 156 461 employees with higher education, this dissertation aims to assess how the above-mentioned structural changes in the demand and supply side are shaping employment and wages of graduates and postgraduates in Portugal.

The contribution of this study to the current literature is twofold: (i) to evaluate how the employment composition in terms of occupations (measured by the intensity of tasks and social skills) evolved in the last decade for graduates and postgraduates; (ii) to evaluate the wage returns to graduates and postgraduates to assess the sources that explain the raw wage gap between graduates and postgraduates.

The dissertation is organized as follows. Section 2 presents the literature review. Section 3 presents the databases used in the empirical study and describes the methodology used to measure the contents of occupations. Section 4 describes some recent trends in the Portuguese labor market, in the 2010-2018 period regarding employment composition. Section 5 present the estimates of wage premiums for graduates and postgraduates and Section 6 the decomposition of the sources of the raw wage gap between graduates and postgraduates. Section 7 concludes.

2. Literature review

2.1 Employment trends

The evidence of a complementary relationship between the use of technologies in the productive processes and qualified work (Griliches, 1957), which dates back to the beginning of the 20th century, supports the hypothesis of the existence of a technological bias in favor of highly skilled workers (SBTC hypothesis). This complementarity is indicated as one of the causes for the polarization of employment, with empirical support (Autor, Katz, & Krueger, 1998), corroborating previous studies that concluded that the intensification of the demand for workers with these characteristics was positively related to strong investments in technological equipment and research and development mechanisms (Berman, Bound, & Griliches, 1994).

In practice, technological progress allows a much smaller group of workers with higher levels of qualification to be able to perform an equal or higher volume of tasks compared to what was previously performed by many workers with lower levels of qualification (Johnson, 1997). Therefore, technology is expected to enhance the growth in the productivity of skilled labor, which translates into a shift in the labor demand curve for workers with these characteristics (Berman et al., 1994; Katz & Murphy, 1992). This phenomenon was already visible, from an empirical point of view, from the second half of the twentieth century, with the changes in the wage pattern and in the employment profile in countries where technological changes were already applied and consolidated in the production processes (Juhn, Murphy, & Pierce, 1993; Levy & Murnane, 1992). In this way, the complementarity between technology and qualified work allows generating wage gains in workers endowed with these skills, empirically corroborating the SBTC theoretical hypothesis.

However, after some empirical work that focused on the dynamics registered in the American and British labor markets, developed by Autor et al. (2006) and Goos and Manning (2007), respectively, it was quickly understood that the SBTC hypothesis, alone, would be insufficient to explain the changes observed in these labor markets.

Autor et al. (2003) and Autor et al. (2006), in their studies, identified, since the 1990s, the existence of a new phenomenon that, together with the SBTC hypothesis, could validly contribute to a sustained trend of employment polarization. In this alternative view, not incompatible with the SBTC hypothesis, the authors sought to identify the effects of the increasing use of technology in production processes, capable of modifying the tasks performed by workers in their workplace, which, consequently, changed the requirements that firms demand from their workers. Although the idea that between technology and qualified work there is a complementary relationship remains valid, the idea that technological capital can replace workers who perform routine tasks is added. In the latter, the tasks are now carried out through programmed equipment: the so-called "Routine-Biased technical change hypothesis". This hypothesis (RBTC) affects a particular group of workers whose tasks can be performed by machines and programmable equipment, since they are characterized by the pursuit of a set of indications or well-defined rules. These workers are, in general, characterized by intermediate qualification levels, being, for the most part, in the middle of the distribution of wages (Goos & Manning, 2007).

The approach to routinization becomes clearer with the specification of the model proposed by Autor et al. (2003), later extended in Autor et al. (2006). In this model of routinization, the premises presented above are assumed: technology is, on the one hand, complementary to highly qualified work, while, on the other hand, it is a substitute for work with average qualification levels, that is, routine. Here, based on a vision of task-based work, a taxonomy of occupations, defined at three major levels, is proposed: abstract tasks, routine tasks, and manual tasks. The first, the abstract tasks, are performed by workers with high levels of qualification, linked to challenges in terms of management, programming, and creativity, where the ability to solve problems, leadership, and critical thinking are fundamental. Workers with intermediate skill levels are associated with routine tasks, such as administrative or assembly work. Note, however, that these can still be distinguished into two sub-levels: routine cognitive tasks, with occupations associated with accounting, text or data correction, and quality checking; and routine manual tasks, related to equipment operationalization and control activities. Finally, the authors identify a last level of tasks that workers can perform - manual tasks, which do not require high levels of qualification, but where automation is difficult to apply, considering the flexible character, and difficult to normalize (see the case of DIY and gardening or repair work, for example).

The expected results of this taxonomy are quite clarifying regarding the impact of the polarization of the labor market. Due to its complementarity with technological capital, as technology becomes more intensive in the means of production, employment in abstract tasks grows, as a result of greater demand, driving the rise in wages, due to the productivity increases it provides. Associated with the preference for qualified workers, a decrease in demand for workers with intermediate-level qualifications, who perform routine tasks, which can be replaced by machines capable of carrying out these tasks is expected (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2018). Therefore, it is expected that the intensification of technology in the production processes will increase the number of these workers who are transferred to jobs of a predominantly manual nature, since they tend to have a comparative advantage in the jobs that perform manual tasks, when compared with the abstract tasks, feeding the trend of polarization of employment and, consequently, of wages (Fonseca, Lima, & Pereira, 2018a).

The routinization dynamics are sustained by a vast empirical literature that, in general, supports the hypothesis already mentioned: the fall in employment in routine tasks is verified in the United States (Autor & Dorn, 2013; Autor et al., 2006; Autor, Katz, & Kearney, 2008) and on the European continent (Goos, Manning, & Salomons, 2014), highlighting the studies carried out for the United Kingdom (Goos & Manning, 2007), for Germany (Dustmann, Ludsteck, & Schönberg, 2009) and for Portugal (Centeno & Novo, 2014; Fonseca et al., 2018a).

The trend of polarization in the labor market cannot, however, be fully explained by the hypotheses previously explored. Like any economic phenomenon, there are many causes that can contribute to these changes in the labor market. The globalization of the goods and services and labor market, with the growth of international trade flows, can also contribute to the polarization of employment. Focusing on the analysis of offshoring operations, that is, of displacement of production, some authors conclude that these may contribute to the polarization dynamics already mentioned, because of opening economies to the outside (Blinder & Krueger, 2013; Goos et al., 2014). The displacement of production takes the form of moving parts of the production chain from one industry to other territories.

If in the past, industrial reallocation was almost limited to manufacturing productions, which were transferred to other countries to reduce production costs, today the reallocation extends to the remaining sectors of activity, with the growth in the number of workers in emerging and developing economies (Blinder, 2006). As the occupations that are the target of reallocation are now transversal to the taxonomy of Autor et al. (2003), this is an issue that deserves particular attention, as these operations provide, in developed countries, downward pressure on jobs and wages, mainly those of a routine nature (Ebenstein, Harrison, McMillan, & Phillips, 2014).

2.2 Wage trends

2.2.1 The stagnation of the wage premium for workers with higher education

As discussed in the previous sections, the phenomenon of polarization of employment and, consequently, of wages, motivated by the routinization of tasks and the intensification of the demand for qualified work, increased the wage premium for the most skilled workers, who perform abstract tasks, pushing middle educated workers to lower-wage occupations.

However, with the beginning of the new century in the 2000s, the strong wage premium that can be observed in graduated workers seems to have been leveled (Beaudry et al., 2016; Valletta, 2019). According to these authors, the new century puts an end to the period of polarization envisaged by the vast literature indicated in the previous subsection, which pointed to the growth in demand for workers who perform high-paid cognitive tasks, either endogenously (Katz & Murphy, 1992) or exogenously (Acemoglu, 2002; Beaudry & Green, 2005), and to drop in the demand for work in routine occupations in the middle of the wage distribution, transferred to jobs in low-paid manual occupations.

The polarization of employment has driven considerable growth in wage returns to highly qualified work, rewarding the comparative advantage of these workers in performing cognitive tasks. Despite this evolution, since 2000, in the US, there has been a decline in the demand for cognitive tasks, performed on a large scale by skilled workers. This is because these more qualified workers started to perform tasks previously performed by less qualified workers. This cascading phenomenon, which occurs from highly skilled workers to the least, pushes skilled workers with lower levels of qualifications successively further down and, ultimately, into unemployment. The revolution generated by the new information and communication technologies, due to the impact on the organization of companies, is crucial to understand this growth and subsequent decline in the search for cognitive tasks. If ICT takes the form of a trivial investment of capital, we understand that during a first (initial) stage, after the investment, the demand for work for cognitive tasks is high and growing. In a second phase (maturity), with established capital stock, demand is fueled by the need to maintain this new capital. However, it is here that the demand, although higher than the stage before the investment, is lower than that recorded in the investment stage. In the US, this maturity phase has been reached since 2000 - the great reversal in the demand for cognitive skills and tasks (Beaudry et al., 2016).

The resulting slowdown in the wage premium for qualification, particularly for higher education, found by Beaudry et al. (2016) and Valletta (2019) is, however, not at all surprising. The results pointed out by these authors may coexist with a situation in which the number of educated workers in the labor market increases and the demand for these workers increases. Thus, they can be the cause of a drop in the wage premium of skilled labor, as expected (Autor, 2017).

In the group of more qualified workers, those with a bachelor', master' or doctoral degree, the trend towards inequality seems to be accentuated in recent years. The positive evolution of this group of workers in the labor market has led to an increase in the internal wage gap. This analysis becomes more enlightening if we consider the two groups advanced by the most recent literature - graduates (bachelors or equivalent) and postgraduates (masters and doctorates). This is because, bearing in mind the stagnation and deceleration of the wage premium described above, this phenomenon is mainly visible in the first group. In the opposite direction, postgraduates see their wage premium evolve favorably. But, after all, can the additional qualification of postgraduates explain these differences compared to graduates? To some extent yes, as selection into occupations is not random. Postgraduates tend to be more concentrated in a more restricted set of occupations, and mostly in non-routine occupations. And even if that were not the case, the wage premium for postgraduates in routine tasks is higher than that earned by graduates (Lindley & Machin, 2016).

The automation of production processes is the clearest sign of the success of innovation and technology in recent decades, and they are now gaining more importance in the discussion of the future of the labor market. If at the end of the 20th century, scholars' concerns were focused on polarization trends and their challenges, the new century accelerated this entire process of transformation, raising new doubts and challenges. The achievements in the areas of new technologies not only became able to perform physical tasks, through robotics but also, through artificial intelligence, they became able to perform intellectual tasks, cognitive computing, which were performed by graduate workers (Brynjolfsson & McAfee, 2014; Levy & Murnane, 2012), expanding the concept of "routine work" (Autor, 2015a).

The accelerated developments in information technology and robotics in recent decades, combined with recent achievements in the field of artificial intelligence, have opened new horizons in terms of the working mechanisms of production processes, now evidently marked by a concern with innovation and a greater demand for permanent updating of workers to new digital realities (Autor & Dorn, 2013). The greater complementarity of occupations exercised by postgraduate workers with technology is, therefore, an ally for this wage differential between graduates and postgraduates, raising the wage premium of the former and replacing workers in the second group (Lindley & Machin, 2016).

2.2.2 The role of social skills

Frey and Osborne (2017), in an analysis for the US, alert to the enormous potential for automation of productive activities, exemplified in the 702 occupations identified as subject to computerization. If verified, this will accentuate the polarization phenomena in the labor market (Autor, 2015b), triggering serious consequences on the supply and demand of skills and economic and social implications (Brynjolfsson & McAfee, 2014).

However, there are tasks where automation seems unable to replace human labor. Occupations related to social interaction are a clear example – automation does not seem to be the answer, but technology is a key complement. Tacit knowledge, which guides the ability to understand and react to our interlocutors, is today a very sensitive area for technology (Autor, 2015b), especially in cases where it becomes necessary to “put in the interlocutor's place” (Camerer, Loewenstein, & Prelec, 2005). This technology and automation gap allows for the growth of task-intensive occupations where social skills are highly relevant, coexisting with the decline of employment in routine occupations and the stagnation of employment in non-routine cognitive tasks. This appreciation by employers of social skills such as collaborative work, teamwork (negotiation tasks), coordination and oral communication skills (Deming, 2017), leadership and decision-making skills (Deming, 2021) has increased since the 2000s.

The scant literature aimed to find empirical evidence for wage returns on social skills has come to positive conclusions. The wage premium for social skills is positive and these skills are complementary to cognitive skills (Deming, 2017; Weinberger, 2014). Workers with a higher level of social skills tend to be more likely employed in occupations where these skills are more intensive and, in that case, achieve an even higher wage premium (Deming, 2017). Simultaneously, employment in these tasks is growing, with clear evidence that better-paid jobs require increasingly higher levels of these two skills: social and cognitive, particularly in the most productive companies (Deming & Kahn, 2018).

In recent years, increased demand by companies for cognitive and social skills may, in part, have accentuated wage inequality (Deming & Kahn, 2018). However, the ability of companies to better absorb new technologies, complementing them with qualified and quality work, is the main driver of this inequality (Song, Price, Guvenen, Bloom, & von Wachter, 2018).

3. Data

3.1 Quadros de Pessoal – Portuguese database

The data presented in this study come from "Quadros de Pessoal" database (QP herein), which aggregates the employer-employee data collected annually through a survey by the Portuguese Ministry of Labor, Solidarity and Social Security. The survey is mandatory for all companies in the private sector that have at least one wage earner. Civil servants, self-employed workers, and domestic workers are not covered by QP.

This database provides information on firms, workers, and establishments. From this database, it is possible to obtain information about the characteristics of the firms, such as: starting date, the industry code (4 digits), its location (NUTS II), the number of workers it employs, its legal structure, the capital stock, ownership, the volume of annual sales. In the same way, it is possible to obtain information about workers, such as gender, age, nationality, education, seniority in the company, skill, and occupation level (3 digits), working hours (regular and extra), wages (base salary, regular and irregular bonuses, and overtime pay), professional status (employer, employee or other) and type of contract (permanent or fixed-term).

This study covers the period from 2010 to 2018. The choice for the analysis of the 2010-2018 period results from the uniformity of classification of some variables after 2009 namely the amendment of the Portuguese Classification of Business Activities (CAE-Rev3) carried out in 2007, and of the Portuguese Classification of Occupations (CPP2010), based on the most recent revision of the International Standard Classification of Occupations (ISCO-08) – a crucial variable for this analysis.

Our sample comprises 22 702 720 wage earners aged between 18 and 66 years (working age workers) in mainland Portugal and in the Autonomous Regions of Madeira and the Azores, in the 2010-2018 period. Observations that do not contain an indication of the employee's number, date of admission to the firm, profession, or schooling were dropped from the analysis.

For the purposes of statistical and econometric analysis, two sub-samples were also defined: The first sample includes workers with at least a secondary degree. This sample includes 9 949 907 observations over the 2010-2018 period. Table 1 presents the number of observations by educational level by year. According to Table 1, the number of workers with higher education[2] increase by 44.41% between 2010 and 2018, while the number of workers with secondary education[3] increase by 42.02%.

Table 1 - Evolution of the number of workers with higher education (bachelors or equivalent and masters) and the number of workers who completed only secondary education (comparison group), Portugal, 2010-2018

	Workers with higher education	**Workers with secondary education**
2010	392 716	569 938
2011	408 779	585 545
2012	412 088	552 828
2013	424 103	571 610
2014	448 315	609 209
2015	473 728	648 786
2016	499 318	696 103
2017	530 278	749 973
2018	567 136	809 454
Total	4 156 461	5 793 446

The second sample only considers workers with a bachelor or equivalent degree and workers with a master's degree. This sample includes 4 156 461 observations over the 2010-2018 period. Table 2 presents the number of observations by educational level and by year. Table 2 shows that the number of workers with a master's degree more than tripled between 2010 and 2018, which is largely explained by the Bologna process that facilitates access to higher education and, in particular, to a master's degree[4].

[2] Since Portugal still has a low volume of workers with a doctoral degree in the private sector, with an evolution with high variability, it was decided not to include workers with a doctoral degree in the analysis of sections 5 and 6.

[3] The inclusion of workers with secondary education in our analysis is justified by the need to establish a group comparable with the group of workers with higher education.

[4] Note that the number of workers with bachelor or equivalent degree increased by 34.25% in 2010-2018 period, in Portugal, while the number of workers with master degree increased by 249.33%.

Table 2 - Evolution of the number of bachelor and master workers, Portugal, 2010-2018

	Bachelor	**Master**
2010	374 155	18 561
2011	386 503	22 276
2012	387 314	24 774
2013	394 824	29 279
2014	413 779	34 536
2015	433 148	40 580
2016	451 728	47 590
2017	475 068	55 210
2018	502 296	64 840
Total	3 818 815	337 646

3.2 Occupations task content measurement

Contrary to studies that chose to catalog workers and companies according to industry or region (Asheim & Coenen, 2006; Cooke, Urange, & Etxebarria, 1997; Malerba, 2002), the analysis that is intended to be carried out here, using the QP employer-employee microdata, implies the adoption of a taxonomy capable of incorporating information about the character of the tasks performed by workers. In addition, it is necessary to have a taxonomy that can measure at least some relevant aspects of social skills.

The O*NET online database is the highly comprehensive reporting tool, aggregating classifications of various variables for nearly a thousand occupations. Among the six major dimensions of available information, there are interactions relating to workers' characteristics, workers' requirements, experience requirements, occupational requirements, workforce characteristics, and specific information on occupations[5]. The pioneering study by Acemoglu and Autor (2011), which presented the taxonomy in five tasks – non-routine analytic/abstract and non-routine interactive, routine cognitive and routine manual, and non-routine manual, used variables from this database, such as Goos et al. (2014). The fact that the O*NET database provides so many variables, makes it possible to be able, approximately, by different paths, to reach these five categories. Frey and Osborne (2017) by using O*NET,

[5] Based on National Center for O*NET Development.

demonstrate this, adopting a forward-looking perspective of the impacts of automation on the labor market and occupations, extending this phenomenon to all tasks.

The measures that we will use here to classify the tasks are the result of a work conducted by Mihaylov and Tijdens (2019), who aimed to elaborate a new measure for the content of occupation tasks, based on ISCO-08. The benefit of using this database is based not only on the fact that it is a more recent measure, but also on the fact that it is already adjusted to ISCO-08, and, therefore, to the microdata made available in the QP. This measure, at the four digits occupations, also allows for a more detailed analysis of the content of occupation tasks. Mihaylov and Tijdens (2019), following the methodology adopted by Spitz-Oener (2006), grouped a set of 3 264 tasks into the five categories defined by Acemoglu and Autor (2011). In the first stage, they attempted to find out if each task had automation potential or not, categorizing it as routine or non-routine. In the second stage, they aimed to know to what extent the execution of this task required cognitive or manual skills, which allows cataloging between routine and non-routine cognitive tasks, and between routine and non-routine manual tasks. In the last step, they intended to distinguish non-routine cognitive tasks between non-routine analytic/abstract and non-routine interactive tasks.

Following closely the approach proposed in Fonseca et al. (2018b), which assumes that the production of goods and services takes place through the execution of tasks, based on the measurement of the content of the tasks of an occupation, given by the Portuguese Classification of Occupations (CPP2010 4-digits) adjusted to ISCO-08, it is possible to classify the occupation that a worker has as one of the five categories mentioned above, considering the type of task that he performs with more intensity.

For this purpose, for each task category, a ranking was created that sought to order the occupations (given by CPP/ISCO-08) by degree of intensity. Once the ranking of the five categories of tasks has been established, it is possible to know the position that each occupation has in each of the five categories of tasks. The classification of the intensity of each of the occupations (by ISCO-08) is given by the superior position that this occupation registers compared to the others in the set of five categories.

Thus, as we can see in Table 3, out of a total of 416 occupations[6], 89 are intensive in non-routine abstract/analytic tasks, 76 are classified as non-routine interactive tasks, 87 belong to the group of non-routine manual tasks, 86 as routine cognitive tasks and the remaining 78 as routine manual tasks.

Table 3 - Classification of workers' occupations, by technological intensity, Portugal, 2010-2018

Occupations	Number of occupations
Non-routine abstract/analytic	89
Non-routine interactive	76
Non-routine manual	87
Routine cognitive	86
Routine manual	78

3.3 Social skills content measurement

The O*NET database has invaluable information about the characteristics of the occupations, in terms of the worker's requirements, especially with regard to social skills, which is the field of interest for our study. There you will find a vast array of variables that cover all types of workers' skills.

Deming (2017) defines the intensity of an occupation in social skills as the average of four variables indicated in the subsection referring to social skills in the O*NET database, that is, the average of the items “Social Perceptiveness”, “Coordination”, “Persuasion” and “Negotiation”. In our case, we follow this methodology closely, extending it to other

[6] Occupations such as Services Managers Not Elsewhere Classified (1439), Process Control Technicians Not Elsewhere Classified (3139), Other Artistic and Cultural Associate Professionals (3435), Sales Workers Not Elsewhere Classified (5249), Handicraft Workers Not Elsewhere Classified (7319) and Stationary Plant and Machine Operators Not Elsewhere Classified (8189) who classified as residual occupations, are also not considered in the analysis.
Occupations such as Legislators (1111), Creative and performing artists not elsewhere classified (2659), Religious associate professionals (3413), Pawnbrokers and money-lenders (4213), Astrologers, fortune-tellers, and related workers (5161), Building structure cleaners (7133), Fur and leather preparing machine operators(8155), Textile, fur, and leather products machine operators not elsewhere classified (8159), Drivers of animal-drawn vehicles and machinery (9332), Street and related services workers (9510), and Sweepers and related labourers (9613), as they do not have information for the variables that embody the social skills intensity indicator, are also not considered in the analysis.

dimensions, such as “Instructing” and “Service Orientation”, which may be particularly relevant to the Portuguese context.

Having obtained the average intensity value of each occupation in social skills[7], it was decided to group the occupations into three groups according to their intensity: a first group, "higher", which aggregates one-third of the most intensive occupations in social skills; a second group, “lower”, that gathers the one-third of the less intensive occupations in these skills; and a third group, “medium”, which includes the remaining one-third of occupations with intermediate level intensity. In this way, we obtain three homogeneous groups in terms of the number of occupations that compose it, since the "higher" and "medium" groups both have 139 occupations, and the "lower" group has the remaining 138.

Table 4 - Classification of workers' occupations by social skills level, Portugal, 2010-2018

Social skills level	**Number of occupations**
High	139
Medium	139
Low	138

[7] The average value of the intensity of each occupation in social skills is given by the average of the scores of the six dimensions considered, for each occupation: Social Perceptiveness, Coordination, Persuasion, Negotiation, Instructing and Service Orientation.

4. Employment composition

The period under analysis here, which covers the interval between 2010 and 2018, is characterized by a drop in the total number of workers until 2013, and by recovery from there until the end of the period, in 2018. This evolution results from the job destruction process caused by the economic and financial crisis that Portugal experienced between 2011 and 2014. The recovery of employment is observed from 2014 onwards. Since then and until the end of the period, there is a clear trend towards recovery and job creation (Figure 1).

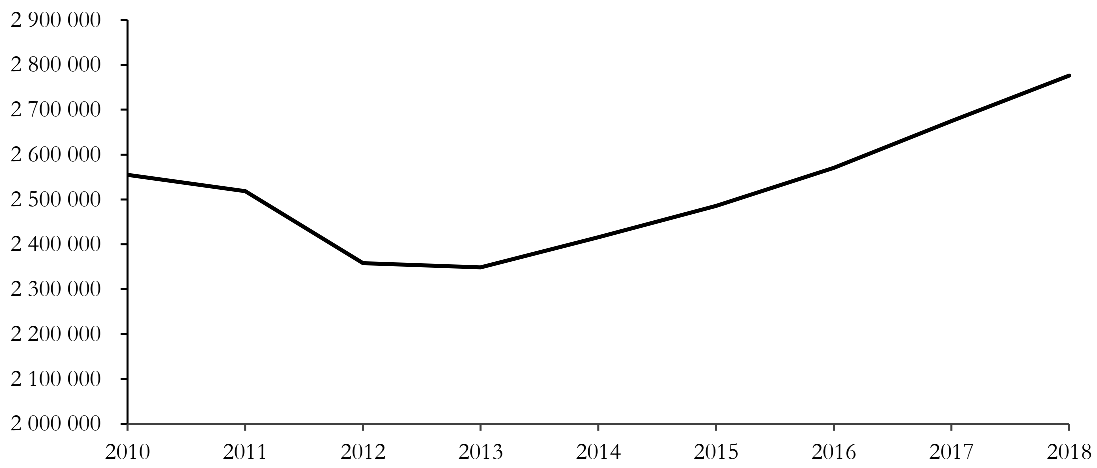

Figure 1 - Total number of workers, Portugal, 2010-2018

4.1 Worker's Age

Figure 2 presents the distribution of workers by age groups. Between 2010 and 2014, we found a greater difference in the composition of the workforce in Portugal, evident in the drop in the weight of younger workers (20-34 years old) and the growth in the weight of older workers (55-66 years old). This dynamic is consolidated in the final period, albeit at a slower pace.

The evolution described here may result from the job destruction process and the younger emigration wave during the period of adjustment of the Portuguese economy, associated with the structural demographic dynamics of population aging, including the legal increase in the retirement age, since 2014.

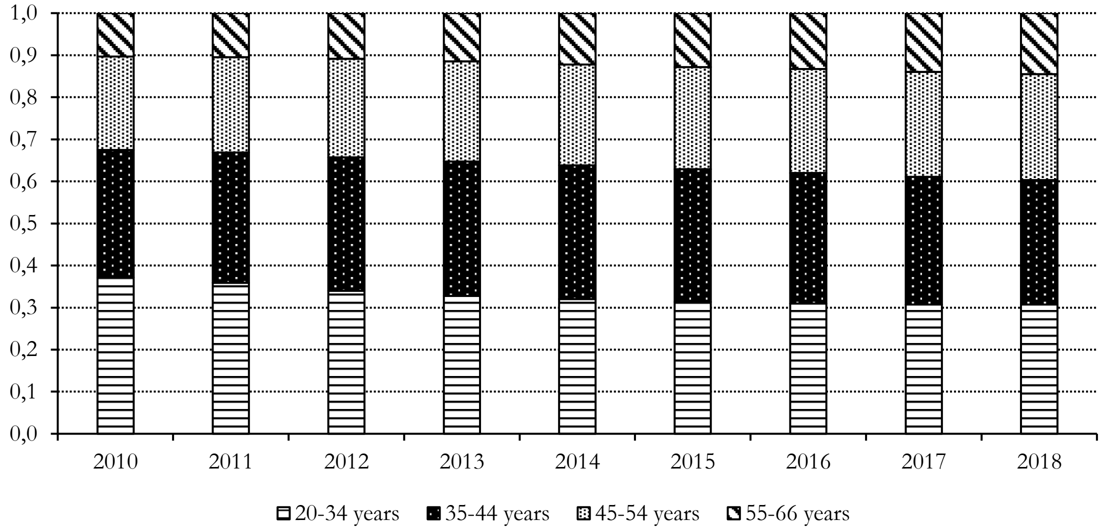

Figure 2 - Evolution of the distribution of workers by age, Portugal, 2010-2018

Figure 3 presents the distribution of workers with higher education by age group. In contrast to what we observed in Figure 2, in our sample of interest, more than three-quarters of workers belong to the younger age groups in 2018, compared to more than 83 percent in 2010. Here, the dynamics of demographic aging are also evident, with a drop in the contribution of the cohort of individuals aged between 20 and 35 years and an increase in the contribution of the remaining cohorts[8].

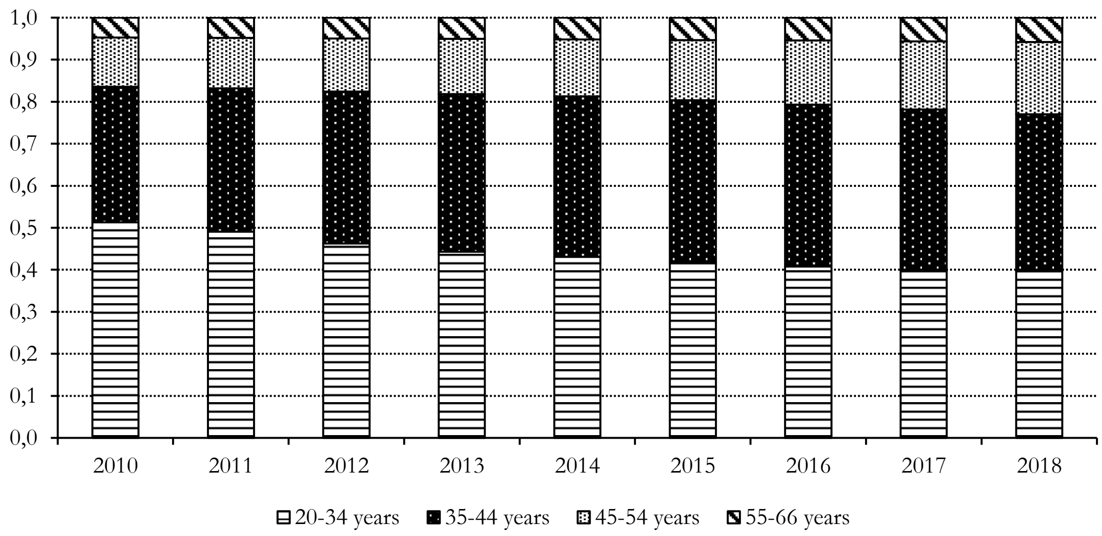

Figure 3 - Evolution of the distribution of workers with high education by age, Portugal, 2010-2018

[8]The growth in the contribution of the cohorts of individuals aged between 35 and 44 years old (5.20 pp) and between 45 and 54 (5.40 pp) is highlighted.

4.2 Worker's Education

The 2010-2018 period is also characterized by the positive evolution in the educational levels of Portuguese workers. According to Figure 4, 2018 is the first year in which workers with at least secondary education account for more than 50 percent of total workers. At the beginning of the period, this same percentage was less than 40 percent. In 2018, almost 30 percent of Portuguese workers had secondary education as their completed level of education, and more than 20 percent had completed some higher education course.[9] In 2010, workers with higher education were only about 16 percent of the total, and those who completed secondary education represented just over 22 percent.

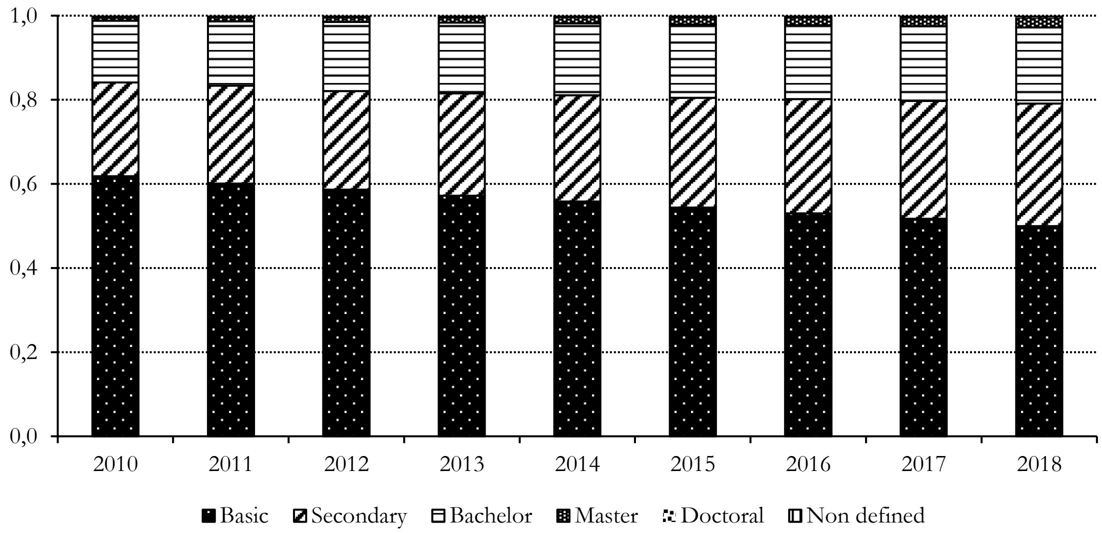

Figure 4 - Distribution of Portuguese workers by schooling level, Portugal, 2010-2018

Figure 5 presents the growth rate of the number of Portuguese workers with higher education. Noteworthy is the growth in the number of workers with a master' degree, always above two digits. Except for 2012, the growth rate of these workers is always above 16 percent per year.

The number of doctorates, in the post-crisis period, follows this positive trend, also growing at two digits, with a slowdown in recent years[10]. Surprisingly is the fact that the growth of

[9] Considering workers who completed a bachelor's degree or equivalent, master' and PhD.

[10] The high variability in the evolution of the number of doctoral workers, together with the still low number of doctorates in company staff, justify the exclusion of these workers from the group of workers with higher education that we will use in the analysis carried out in this chapter and in subsequent ones.

graduates is lower than that of all levels of education, except basic education. The existence of integrated master' degrees under the Bologna Reform may explain this evolution.

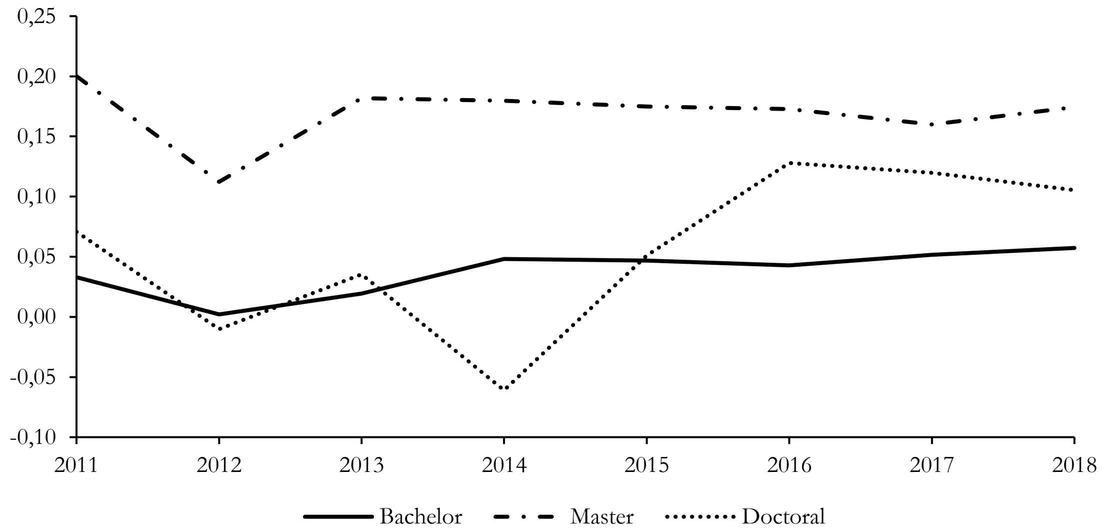

Figure 5 - Variation in the number of workers with higher education, by schooling level, Portugal, 2010-2018

4.3 Industry characteristics

Figure 6 presents the distribution of workers according to the taxonomy defined by Eurostat (2016, 2018), according to NACE Rev 2 (3 digits-codes). The organization distinguishes industries by level of technology and services by their intensity of knowledge.

The distribution of workers does not change much. However, there are sectors that register a consistent growth dynamic, such as knowledge-intensive services. This sector, which groups four knowledge-intensive subsectors (High-tech services, market services (excluding financial intermediation and high-tech services), financial services, and other services), observed, except in financial services, a consolidating and increasing contribution to total employment.

If, on the one hand, the contribution of employment in knowledge-intensive services grows, and in "Other sectors" decreases, on the other hand, the contribution of the low-tech manufacturing sectors and less knowledge-intensive services remains unchanged. This maintenance of the contribution of the two sectors is because they group essential economic activities in the Portuguese economy: the low-tech manufacturing sector includes important sectors for employment in Portugal, such as the textile and clothing, agri-food, or furniture industry, among others; less knowledge-intensive services cover activities associated with tourism, a key sector in Portugal.

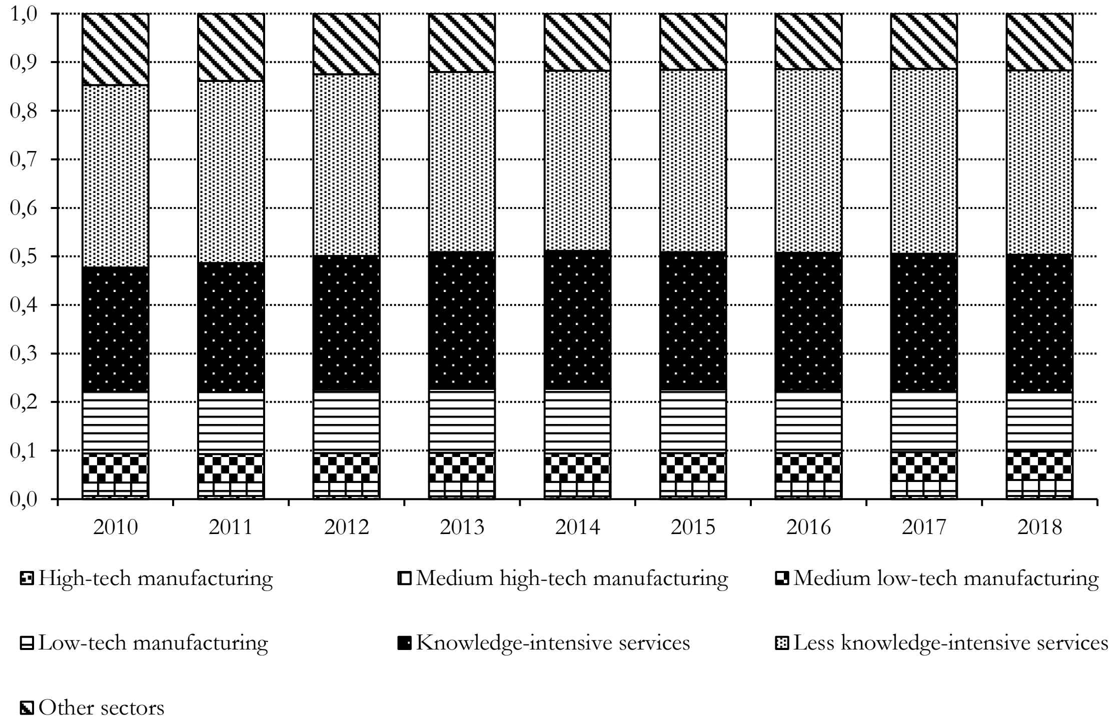

Figure 6 - Distribution of workers by sectors of technological intensity, Portugal, 2010-2018

As mentioned in subsection 3.1, the interest group in our analysis is composed of workers with higher education, including graduates (bachelors or equivalent) and postgraduates (masters) [11]. As we have seen, in 2018, more than a quarter of workers in Portugal completed higher education, such as a bachelor' or master' degrees.

Figure 7 shows the distribution of workers by industry type technological intensive (manufacturing) knowledge-intensive (services). The employment of workers with higher education is mainly in the service sector, totaling more than 80 percent. The strong contribution of employment in knowledge-intensive services should be highlighted, which represents more than 55 percent of total employment.

[11] For more information, see Table 1 and Table 2, in subsection 3.1. For comparison purposes, we will also use the group of workers with secondary education.

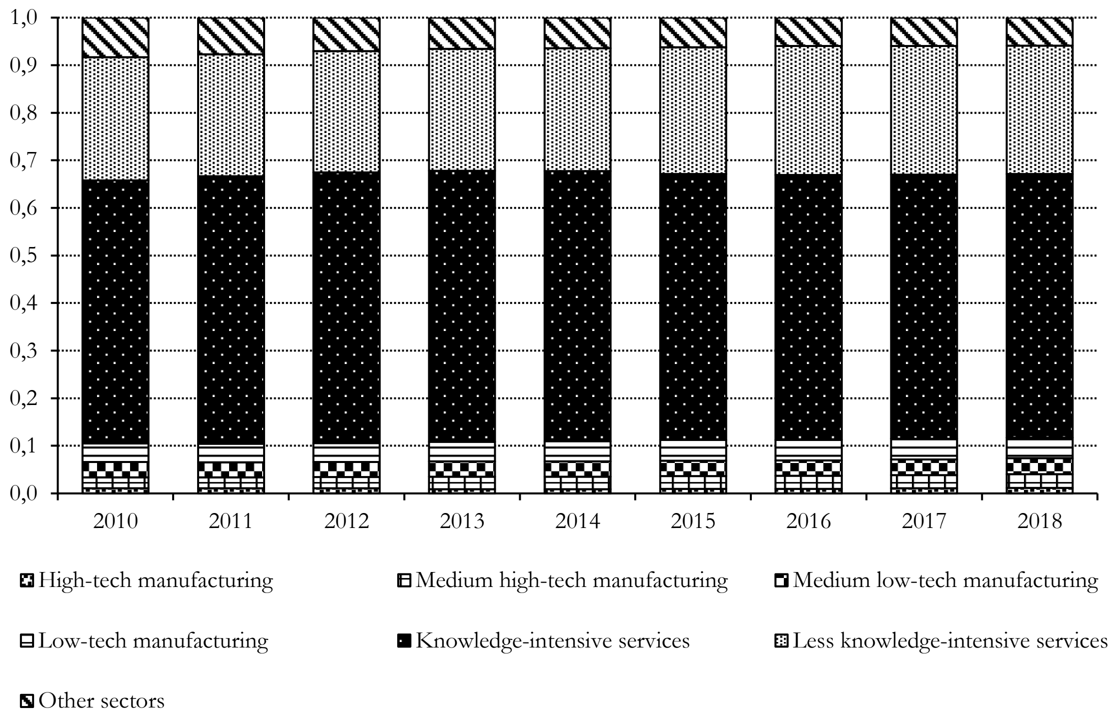

Figure 7 - Distribution of workers with high education by sectors of technological intensity, Portugal, 2010-2018

4.4 Occupation

4.4.1 Intensity of routine and non-routine tasks

Figure 8 presents the distribution of workers according to the five-occupation task intensity as defined in subsection 3.2.

This distribution does not undergo major changes in the period from 2010 to 2018. Almost 29 percent of the nearly 23 million workers considered in the period 2010-2018 are in a non-routine manual occupation, the occupation that employs the most workers in Portugal. The remaining workers are distributed among the remaining four occupations: non-routine interactive (about 13%), non-routine analytical/abstract (about 15%), routine cognitive (about 25%), and routine manual occupations (about 18%).

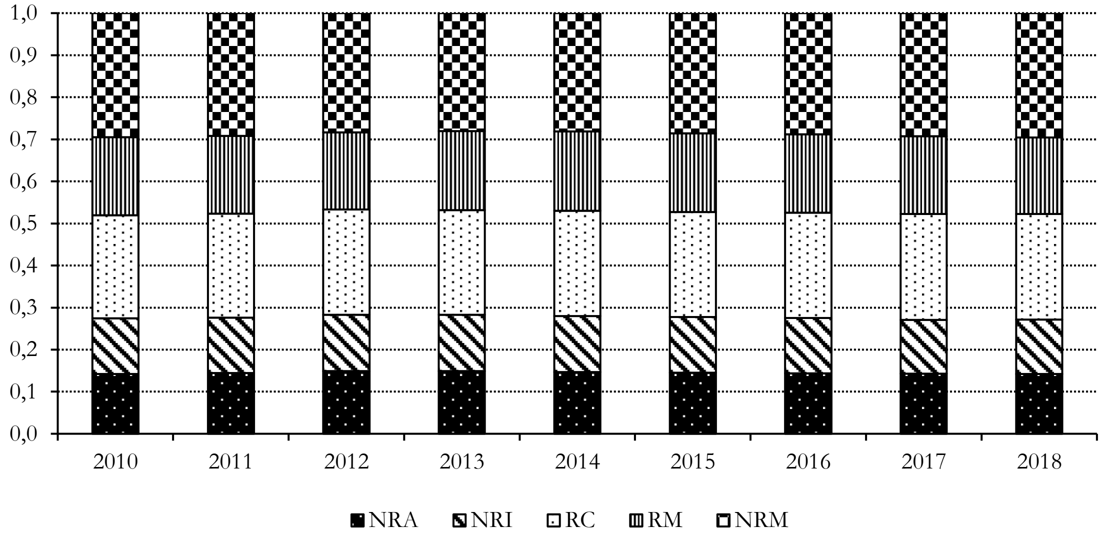

Figure 8 - Evolution of the distribution of workers by occupation (tasks), Portugal, 2010-2018

Figure 9 presents the employment of master' degrees by occupations according to tasks intensity. We observe an increasing trend in employment in routine cognitive occupations for workers with a master's degree. The contribution of this occupation to the total employment of master workers grew by almost 5% over the 2010-2018 period.[12]

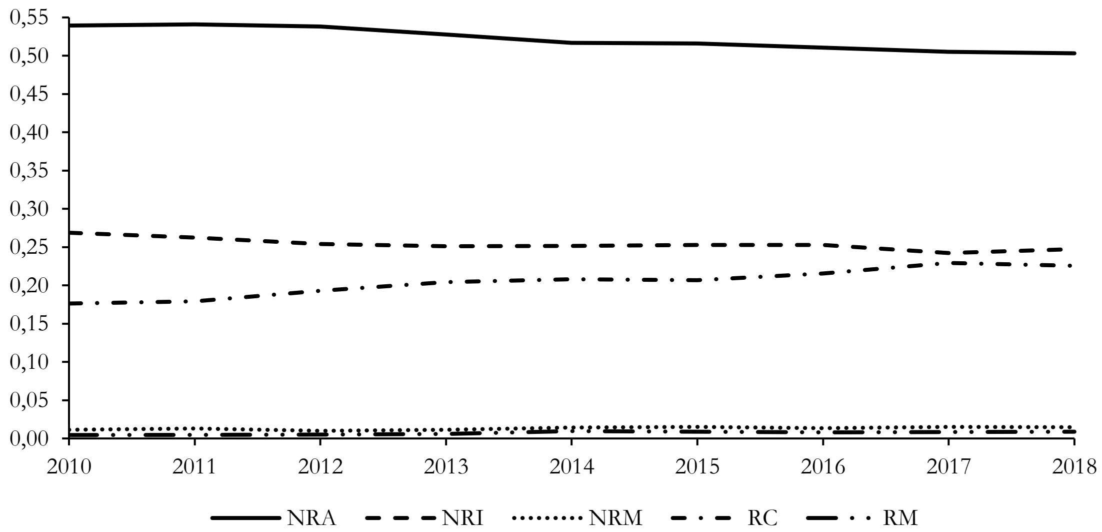

Figure 9 - Evolution of the distribution of workers with master's degree by occupation (tasks intensity), Portugal, 2010-2018

[12] All the aspects mentioned in this analysis of the distribution of master workers among the five occupation groups cannot lose sight of the high growth in the number of these workers in Portugal, because of the implementation of the Bologna Reform.

Conversely, employment in non-routine cognitive occupations (analytic/abstract and interactive) shows a slight downward trend. If, in 2010, non-routine analytic/abstract occupations represented almost 54 percent of the "master's" jobs, in 2018, this representation barely exceeded 50 percent. Interesting for the analysis is the evolution of the non-routine interactive occupations. These follow the downward trend in non-routine analytics occupations, but at a slower pace.

Table 5, which presents the evolution of the distribution of graduated workers by the five occupations, by task intensity, shows a drop in the importance of non-routine abstract occupations in the total employment of these workers. The contribution of non-routine interactive occupations to the total employment of graduate workers has also been decreasing, though at a slower pace than the evolution of non-routine abstract occupations.

Table 5 - Evolution of the distribution of graduated workers (bachelor or equivalent) by occupation (tasks intensity), Portugal, 2010-2018

	2010	2011	2012	2013	2014	2015	2016	2017	2018
NRA	47.46%	47.22%	46.73%	46.24%	45.26%	44.73%	43.96%	43.40%	42.65%
NRI	25.91%	25.18%	24.89%	24.75%	24.63%	24.36%	24.25%	23.83%	24.05%
NRM	2.56%	2.53%	2.86%	2.90%	3.14%	3.56%	3.76%	4.19%	4.62%
RC	23.16%	24.12%	24.56%	25.00%	25.73%	25.97%	26.60%	27.03%	26.99%
RM	0.90%	0.96%	0.96%	1.11%	1.24%	1.37%	1.43%	1.55%	1,69%

An opposite trajectory is observed for the routine cognitive occupations and manual occupations (routine and non-routine). The contribution of cognitive routine occupations to the employment of these workers grows by 3.85 pp between 2010 and 2018. Non-routine and routine manual occupations registered a more modest growth, of 2.06 pp and 0.74 pp, respectively. This evolution corroborates what the literature indicates, which points to the transfer of employment in non-routine analytical/abstract and interactive occupations to workers with even higher levels of education (with master' and doctorate degrees). Consequently, for graduated workers, the contribution of employment in routine and manual occupations grows.

To understand the extent to which more schooling translates into the performance of certain tasks and, consequently, occupations, we will also analyze the group of workers with secondary education, essential to compare with the group of graduates and postgraduates (Figure 10).

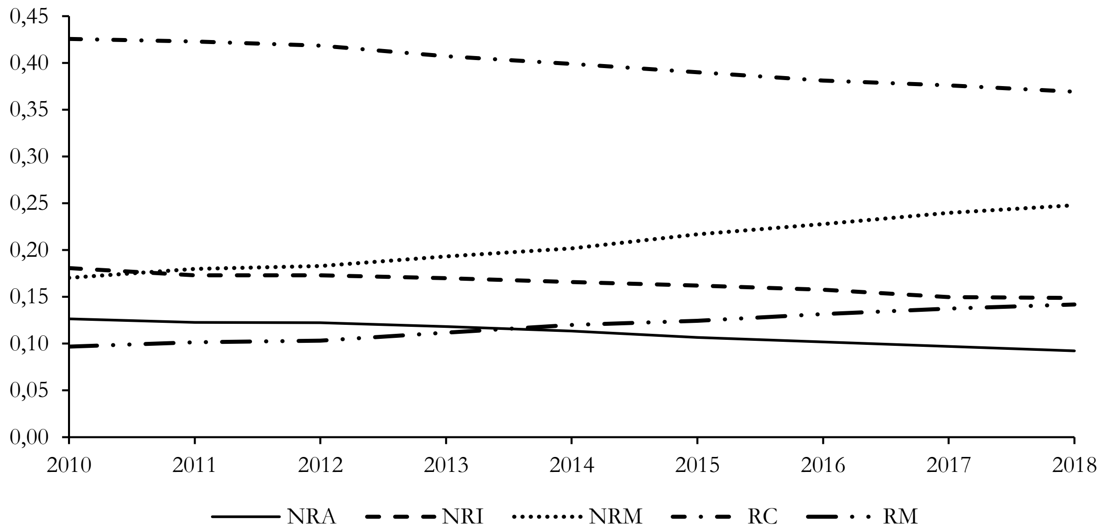

Figure 10 - Evolution of the distribution of workers with secondary education by occupation (tasks intensity), Portugal, 2010-2018

Based on the analysis of the group of workers with secondary education, in Figure 11, it is evident the fall in the contribution of these workers in employment in routine cognitive occupations and the growth of manual occupations (routine and non-routine). In 2010, almost 43 percent of workers with secondary education were employed in routine cognitive occupations, while in 2018, they were already less than 37 percent. On the other hand, workers with secondary education in non-routine manual occupations represent solely 17 percent in 2010, while in 2018 they represented almost 25 percent of workers with secondary education.

4.4.2 Intensity of social skills

Figure 11 shows the distribution of workers according to the level of social skills of the 4-digits occupation – low, medium, and high – as defined in subsection 3.3.

As with the distribution of workers by occupations, also here, in the period between 2010 and 2018, there are no structural changes in the distribution of workers in the three levels of social skills. One-fourth of workers are employed in occupations that require a high-level of social skills, 30 percent a medium level, and the remaining 45 percent a low-level.

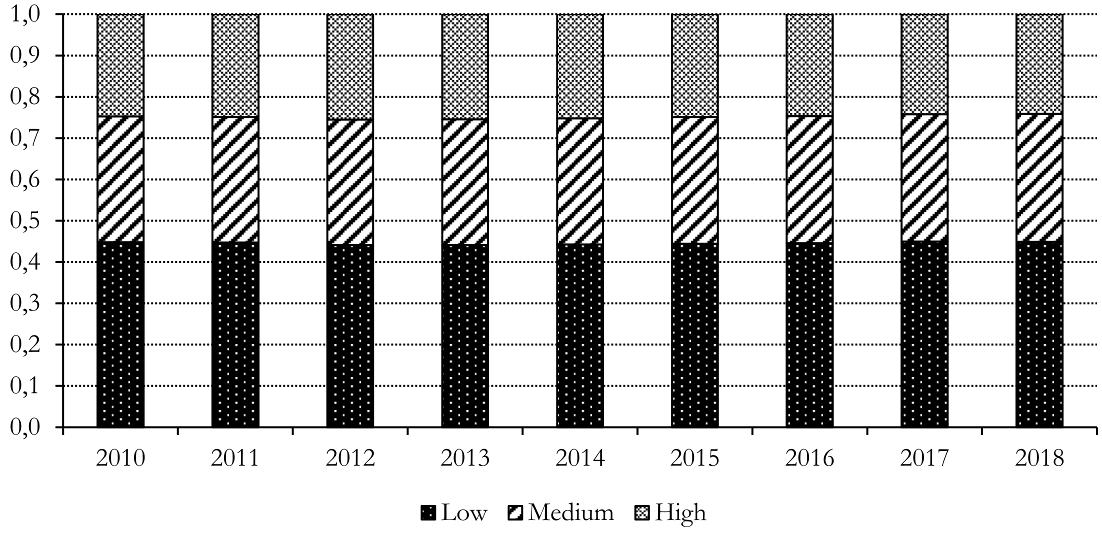

Figure 11 - Evolution of the distribution of workers by social skills level, Portugal, 2010-2018

Now, we cross the two dimensions of occupations features in tasks intensity and social skills. Figures 12, 13, and 14 show the results of this cross, showing, respectively, the distribution of graduates, postgraduates, and workers with only secondary education, by the three levels of social skills, according to their occupation[13].

According to Figure 12, more than three-quarters of graduate workers who are in non-routine abstract occupations belong to the group of high social skills. In non-routine interactive occupations, this presence in the group of high social skills exceeds 87 percent in the entire period 2010-2018. In manual occupations, whether routine or non-routine, the majority of graduated workers belong to the low social skills group, with a contribution of around 80 and 60 percent, respectively. In routine cognitive occupations, about 60 percent of graduate workers are in the middle social skills intensity group.

[13] The group of workers who are in non-routine interactive occupations with low intensity in social skills, as well as workers who are in routine manual occupations with high intensity in social skills, do not present any observations.

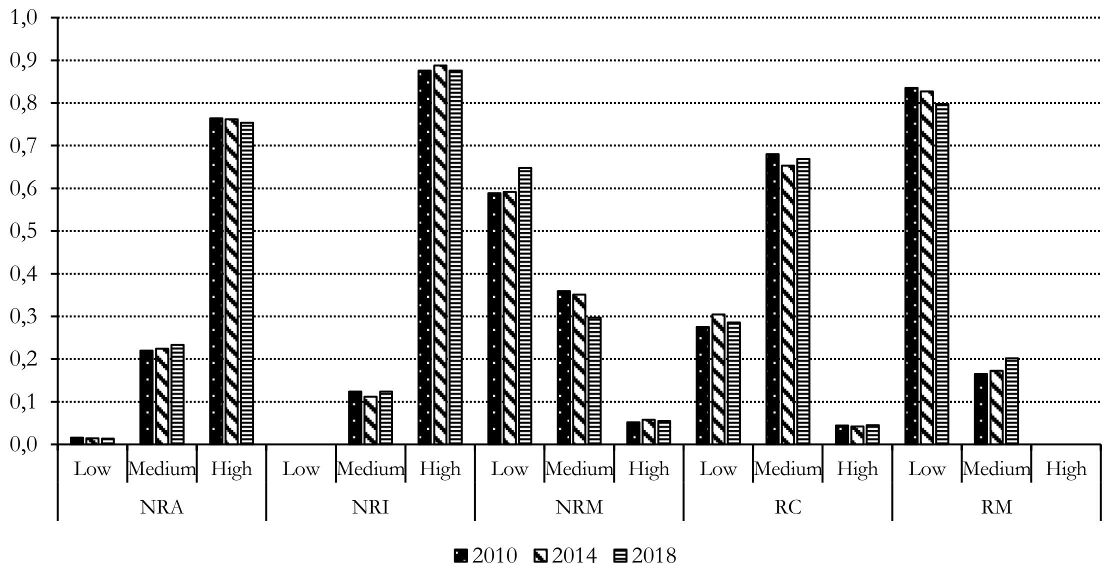

Figure 12 - Evolution of the distribution of bachelors by social skill level, Portugal, 2010-2018

Comparing the distribution of graduated workers (Figure 12) with the distribution of postgraduate workers (Figure 13), overall, there is no major change regarding the distribution of postgraduates by social skills intensity groups, according to their occupation.

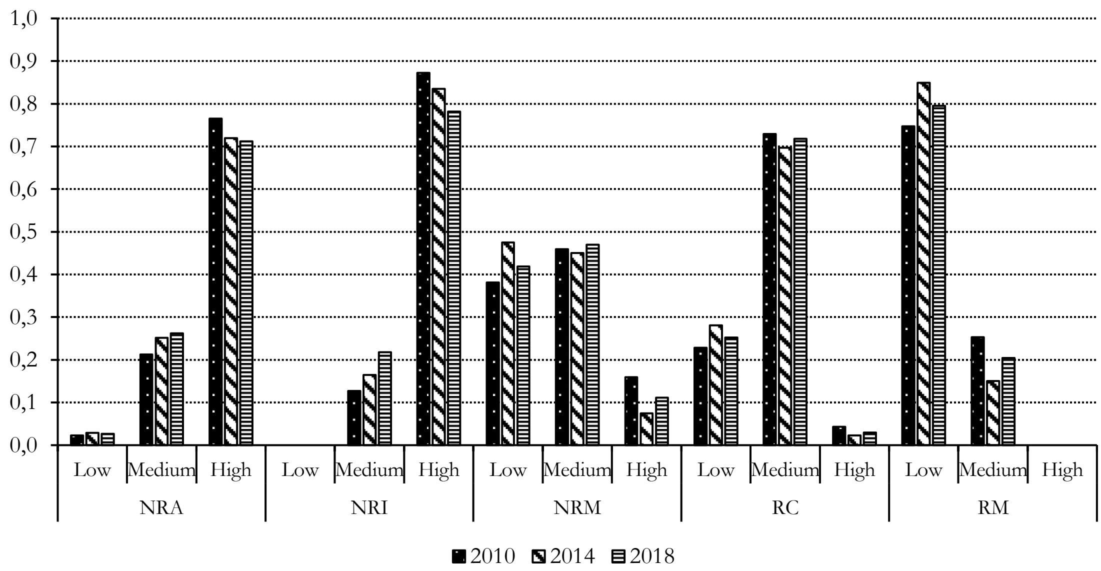

Figure 13 - Evolution of the distribution of masters by social skill level, Portugal, 2010-2018

The difference between this distribution of graduates and postgraduates lies essentially in the allocation of workers to non-routine manual occupations. If for graduated workers, a large majority were in the lower-intensity group of social skills, in postgraduate workers, there is greater balance, with the medium intensity group standing out in more recent years.

Finally, for comparative purposes, Figure 14 shows the distribution of workers with secondary education by levels of social skills, according to their occupation. Here, and compared to the analysis carried out for graduate and postgraduate workers, some notable differences are evident. First, and though at a low value (about 4 percent), we find workers with secondary education who are employed in routine manual occupations and who are part of the high social skills group[14]. Second, compared to graduates and postgraduates, there is a greater concentration of workers with secondary education who are in non-routine interactive occupations in the group of high social skills (about 90 percent). The same cannot be said for non-routine abstract occupations, where the distribution between the high and medium group (of social skills) is less uneven as in manual occupations (routine and non-routine), between the low and medium group (of social skills).

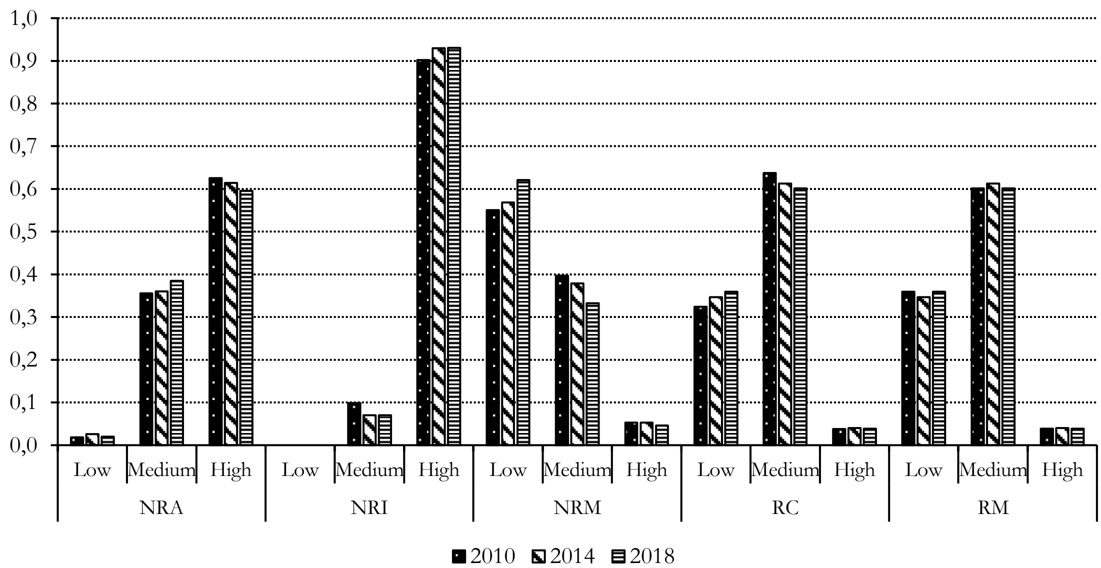

Figure 14 - Evolution of the distribution of workers with secondary education by social skill level, Portugal, 2010-2018

[14] The group of workers who are in non-routine interactive occupations with low intensity in social skills do not presents any observations.

5. Econometric analysis

To study the evolution of the wage premium of graduate and postgraduate workers, we now turn to econometric estimation. The objective is to find empirical evidence for the existence of a wage differential between graduates and postgraduates and to assess the explanatory reasons for this fact. Thus, we estimate a Mincerian wage equation (Mincer, 1974) that allows us to measure the wage premium for master workers, compared to graduates and for masters and graduates, compared to workers with secondary education.

5.1 Evolution of the wage premium to higher education

As shown in section 5, although the number of master workers is growing, it is still very low. Thus, it is also important to capture the wage premium for higher education, that is, the premium that workers with postgraduates and graduates receive, compared to that earned by workers with only secondary education. To achieve this objective, we estimated regression (1) for the group of workers with secondary education, graduates, and masters. We then have two variables of particular interest: “bachelor", which captures the wage premium of graduated workers, compared to workers with only secondary education; "master", which captures the wage premium of the masters compared to workers with secondary education.

Thus, the regression to be estimated is given by:

$$\begin{aligned} ln\, wage_{i,t} = {} & \alpha_1\, bachelor_i + \alpha_2\, master_i + \beta_1\, nrm_{i,t} + \beta_2\, rc_{i,t} + \beta_3\, rm_{i,t} \\ & + \beta_4\, nra_{i,t} + \gamma_1\, rc_{i,t} * ss_{high_{i,t}} + \gamma_2\, rm_{i,t} * ss_{high_{i,t}} + \gamma_3\, nra_{i,t} \\ & * ss_{high_{i,t}} + \delta\, \boldsymbol{year}_t + \theta\, \boldsymbol{X}_{i,t} + u_{i,t} \end{aligned}$$

$$i = 1, \dots, N; t = 1, \dots, T \,, \qquad \textbf{(5.1)}$$

where $wage_{i,t}$ is the real hourly wage of worker i in year t (hourly wage is defined as the ratio of base wage plus regular benefits over normal hours of work); $bachelor_i$ is a dummy variable that equals one if a worker completed a bachelor’s degree or equivalent, and zero otherwise and $master_i$ is a dummy variable that equals one if a worker completed a master's degree, and zero otherwise; nrm_i, rc_i, rm_i, nra_i are dummy variables that equal one if a worker is in non-routine manual, routine cognitive, routine manual, and non-routine abstract occupations, respectively, and zero otherwise (omitted category: non-interactive routine); to evaluate to what extent wages are determined by the level of social skills is a given occupation a set of interaction terms - $rc_i * ss_{high_i}, rm_i * ss_{high_i}, nra_i * ss_{high_i}$ – were included, where ss_{high_i} is a dummy variable that takes 1 if the worker is part of the high-level social skills group, and 0 otherwise; the parameters γ capture the worker's additional wage premium generated by being in one of the occupations with high social skill intensity; $\mathbf{year}_{i,t}$ is a vector of time dummy variables; $\mathbf{X}_i$ is a vector that includes control variables for the worker's characteristics (female, age, seniority, and qualification) and for firms characteristics (size, location, and industry); $u_{i,t}$ is a random error.[15]

5.2 The wage premium to a master's degree

To verify the existence of a wage differential between graduate and postgraduate workers, we restricted our sample to workers with higher education - bachelors or equivalent and masters.

Now, the model applied here writes as[16]:

$$ln\, wage_{i,t} = \alpha_1\, master_i + \beta_1\, nrm_{i,t} + \beta_2\, rc_{i,t} + \beta_3\, rm_{i,t} + \beta_4\, nra_{i,t} + \gamma_1\, rc_{i,t} * ss_{high_{i,t}} + \gamma_2\, rm_{i,t} * ss_{high_{i,t}} + \gamma_3\, nra_{i,t} * ss_{high_{i,t}} + \delta\, \boldsymbol{year}_t + \theta\, \boldsymbol{X}_{i,t} + u_{i,t}$$

$$i = 1, \dots, N; t = 1, \dots, T, \qquad \textbf{(5.2)}$$

where $master_i$ is a dummy variable that equals one if a worker completed a master's degree, and zero otherwise (bachelor or equivalent degree) and captures the wage premium of a master's degree compared to a bachelor's degree[17].

[15] For a detailed description of the variables included in the model, see Annex 1.
[16] Regression (2) is applied to the sub-sample composed of bachelor or equivalent workers and master workers.
[17] The remaining variables included in the model (2) are identical to those included in model (1).

5.3 Regression results

Figure 15 shows the results of the regression estimation (1) for the nine years of the 2010-2018 period, that is, the wage differential between workers with higher education (both for bachelors and masters), compared to workers with only secondary education. [18] [19]

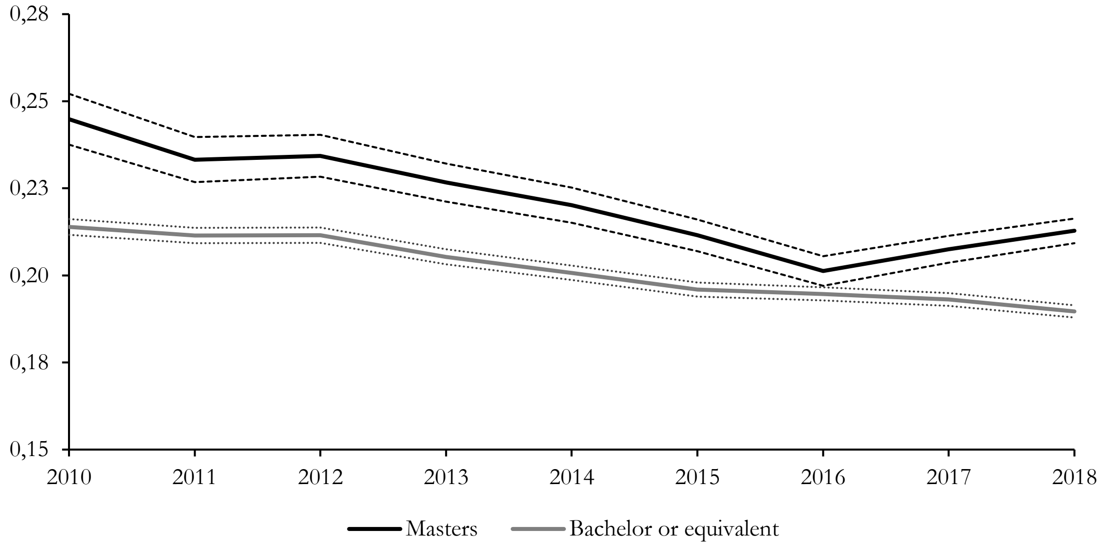

Figure 15 – Evolution of the wage premium to master's and bachelor's or equivalent versus workers with secondary education, Portugal, 2010-2018

The results are clear in two fundamental aspects. The first is that the wage differential between workers with higher education and those with only secondary education is in the order of 20 percent. The second is that this differential has been falling over the period, both for the masters and for the bachelors, although in the last years of the period, the masters seem to be recovering.

Figure 16 shows the estimates obtained for the coefficient α – the master wage premium relative to a bachelor's degree – when estimating regression (5.2) for the period under review (2010-2018). [20]

[18] Estimation results have a 95% confidence level.

[19] The period over which our analysis focuses is marked by a very positive evolution of the schooling level in Portugal, as the percentage of workers who completed secondary education and completed higher education increased.

[20] Estimation results have a 95% confidence level.

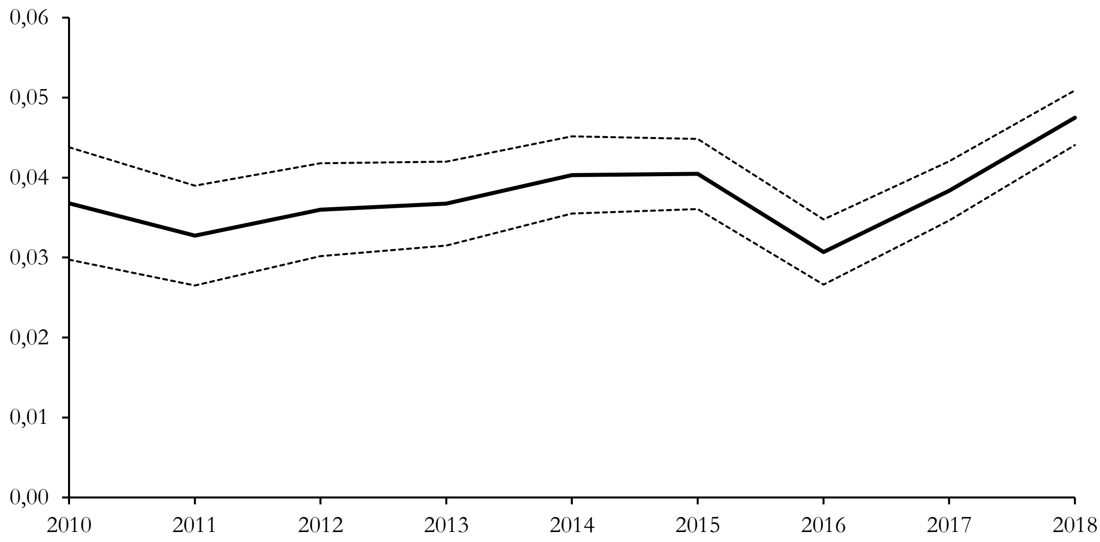

Figure 16 – Evolution of the wage premium of master versus bachelor's degree, Portugal, 2010-2018

Throughout the period, the wage differential between a master's and a bachelor's degree is in the order of 3.5 percent, until 2013, reaching more than 4 percent in 2014 and 2015. 2016 marks the interruption of the sustained growth pace that had been coming since 2011. Since 2016, an acceleration of the pace of growth in the wage premium for masters is evident, approaching, in 2018, 4,8 percent.

Bearing in mind that the number of graduates and postgraduates in the total of workers grows in the period 2010-2018, being particularly relevant in the younger age groups, regressions 1 and 2 were estimated for the following cohorts: workers aged between 20 and 34 years, 35 and 44 years, 45 and 54 years and, finally, 55 and 66 years. Comparing the wage premium of masters and bachelor workers by age group, thus allows to dispel some doubts and distinguish between the aggregate trend and the trends of evolution of each group, particularly as to the circumstances that influence the evolution of each cohort.

Figure 17 shows the estimates obtained for the wage differential between bachelors and workers with secondary education for the four defined cohorts. We conclude that the decline in the bachelor's wage premium is mainly driven by the decline for the 20-34 cohort of more than 6 pp. The remaining cohorts follow the same trend, although the evolution is more tenuous, except for the 55-66 cohort, which rises slightly.

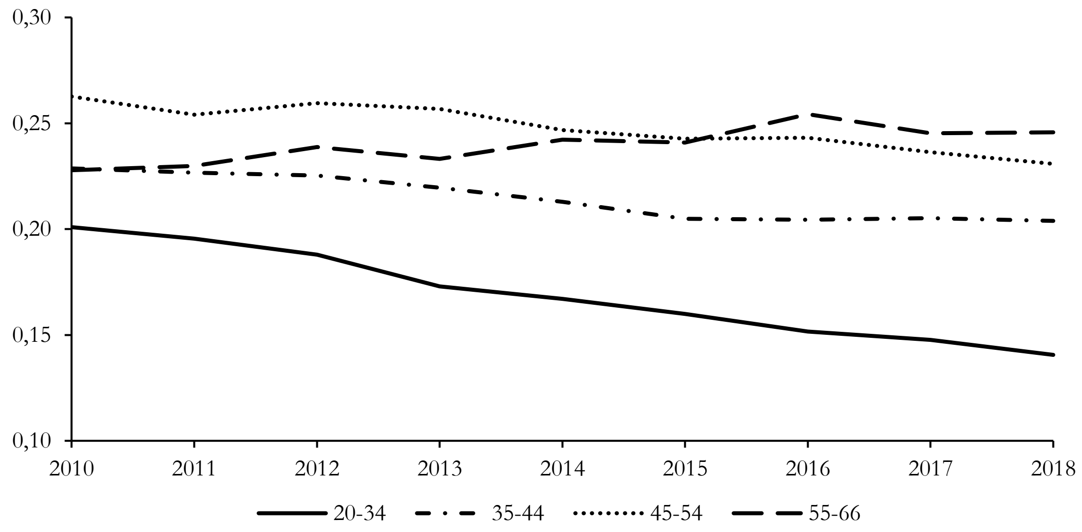

Figure 17 – Evolution of wage premium to bachelor's versus workers with only secondary education, by age groups, Portugal, 2010-2018

Similarly, Figure 18 shows the wage differential between master workers and workers with secondary education for the 4 sub-groups already indicated. The declining trend in the wage premium of the 35-44 and 20-34 cohorts is clear, although for the latter the evolution is characterized by great instability and a negligible drop. This may explain the smaller drop in the wage premium for masters when compared to bachelors.

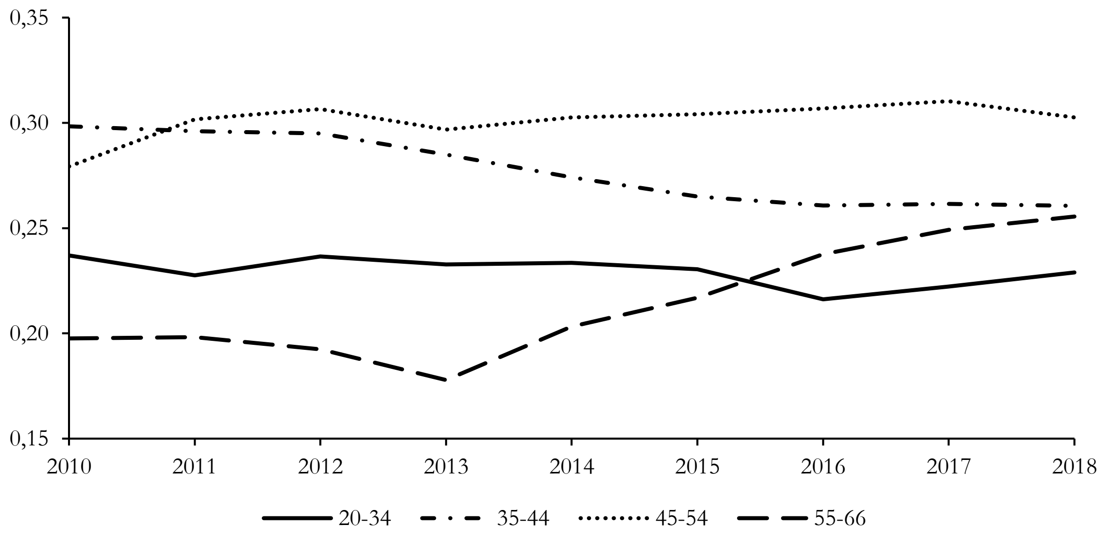

Figure 18 – Evolution of wage premium to master's versus workers with only secondary education, by age groups, Portugal, 2010-2018

Finally, Figure 19 presents the evolution of the master's versus bachelor's wage premium for four cohorts. As might be expected, it is in younger age groups that the wage premium is higher (as opposed to older groups, where professional experience is more relevant). Until 2013, it was in the second-youngest group that the wage premium was highest. Only from 2013 onwards, master workers aged between 20 and 34 years will have the highest wage premium.

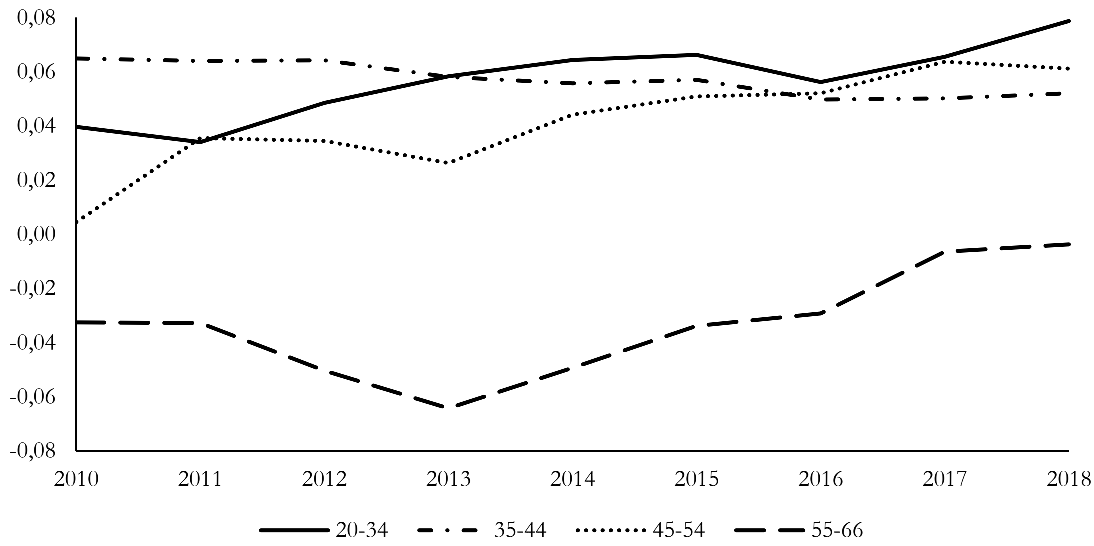

Figure 19 – Evolution of wage premium of master versus bachelor' degree by age groups, 2010-2018

The increase in the wage premium for master workers aged 45 to 54 years is remarkable. These workers start from 2010 with an almost zero premium and reach in 2017 a premium of more than 6 percent, exceeding the wage premium for master workers aged 35-44, which has been falling since 2010.

6. Decomposition of the sources of the raw wage gap between bachelors and masters

6.1 Gelbach's decomposition

Gelbach (2016) presents a decomposition method that assumes that the logarithm of wages, given by **Y**, is explained by two types of sets of variables: the base variables, $\mathbf{X_1}$, and the additional variables, $\mathbf{X_2}$. In this way, it becomes possible to decompose the bias that results from the omission of relevant explanatory variables in the specification of an econometric model.

Thus, the linear relationship between **Y** and **X**[21] is given by:

$$\boldsymbol{Y} = \boldsymbol{X_1\beta_1} + \boldsymbol{X_2\beta_2} + \boldsymbol{\varepsilon}\,. \tag{6.1}$$

When we proceed with the estimation of the regression (5.2) by the ordinary least squares (OLS) method, we obtain an OLS estimator for the vector $\boldsymbol{\beta}$ given, as usual, by:

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X'X})^{-1}\boldsymbol{X'Y}. \tag{6.2}$$

If we estimate the full model (model that includes $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$), we will obtain an unbiased OLS estimator for the vector of coefficients $\boldsymbol{\beta}$.

On the other hand, in the estimation of the base model, we did not include the vector $\boldsymbol{X_2}$, so the OLS estimator for the coefficients is given by:

$$\widehat{\boldsymbol{\beta}}_{\boldsymbol{1}} = (\boldsymbol{X_1}'\boldsymbol{X_1})^{-1}\boldsymbol{X_1}'\boldsymbol{Y}. \tag{6.3}$$

Such that:

$$\widehat{\boldsymbol{\beta}}_{\boldsymbol{1}}^{\boldsymbol{base}} = \widehat{\boldsymbol{\beta}}_{\boldsymbol{1}} + \boldsymbol{\Gamma}\widehat{\boldsymbol{\beta}}_{\boldsymbol{2}} = \boldsymbol{\beta_1} + \boldsymbol{\delta}, \tag{6.4}$$

where $\boldsymbol{\Gamma}$ is the matrix of coefficients that result from the projection of the columns of the matrix $\boldsymbol{X_2}$ onto the columns of the matrix $\boldsymbol{X_1}$.

From this, it is deduced that:

$$\boldsymbol{X_2} = \boldsymbol{X_1\Gamma} + \boldsymbol{W}, \tag{6.5}$$

[21] Matrix **X** is given by: $\boldsymbol{X} = [X_1 \quad X_2]$

where $\mathbf{W}$ is the adaptive matrix of the projected residuals.

From (6.4), we can infer that $\boldsymbol{\delta}$ is the measure of the bias that results from the fact that the OLS estimator of coefficients matrix $\boldsymbol{\beta_1}$ does not include $\boldsymbol{X_2}$, that is, $\boldsymbol{\beta_1}^{\boldsymbol{base}}$ differs from $\boldsymbol{\beta_1}$ in $\boldsymbol{\delta}$.

Knowing that $\widehat{\boldsymbol{\beta}}_{\boldsymbol{1}}^{\boldsymbol{base}} = \boldsymbol{\beta_1} + \boldsymbol{\delta}$, (assuming the OLS estimator of $\widehat{\boldsymbol{\beta}}_{\boldsymbol{1}}^{\boldsymbol{full}}$ is consistent for $\boldsymbol{\beta_1}$), the estimator of $\boldsymbol{\delta}$ is given by:

$$\widehat{\boldsymbol{\delta}} = \widehat{\boldsymbol{\beta}}_{\boldsymbol{1}}^{\boldsymbol{base}} - \widehat{\boldsymbol{\beta}}_{\boldsymbol{1}}^{\boldsymbol{full}}. \tag{6.6}$$

We apply the Gelbach decomposition to evaluate the source of the wage differential between bachelor's and masters' workers[22]. For this, in the base model, in matrix $\boldsymbol{X_1}$ we will consider only the "master" variable and time dummies, that is, the $\boldsymbol{\beta_1}^{\boldsymbol{base}}$ coefficient estimate of the master dummy variable will correspond to the gross wage differential of the masters in relation to the bachelors. In the full model, we will include the additional variables to avoid the omitted variable bias. The full model corresponds to the model defined in equation (5.2).

6.2 Results of Gelbach decomposition

Before proceeding with the decomposition indicated above, we must estimate these two models. The estimation results, both for the base model and for the full model, are presented in Table 6.[23] Thus, from Column (1), in Table 6, we conclude that, on average, a master worker has a wage premium of 2.09%, compared to a worker who has only completed a bachelor's degree or equivalent, and who is otherwise similar. This result is significant for all usual confidence levels.

The results for the full model are shown in column (2) in Table 6.

[22] We mainly want to know to what extent the worker's occupation and level of social skills can affect the performance of the wage premium.

[23] The Gelbach decomposition was also conducted for each of the age groups. For more information, see Annex 2.

Table 6 – POLS Results of wage regressions, Portugal, 2010-2018

Variables	Coefficients (1)	Coefficients (2)
Education levels (omitted category: bachelor)		
Master	0,02094*** (-0,00224)	0,03999*** (-0,00077)
Type of occupations by task intensity (omitted category: non-routine interactive occupations)		
Non-routine manual occupations		-0,10678*** (0,00140)
Routine cognitive occupations		-0,14301*** (0,00064)
Routine manual occupations		-0,20181*** (0,00197)
Non-routine abstract occupations		-0,05010*** (0,00078)
Interaction between type of occupations by task intensity and high level of social skills (omitted category: non-routine interactive occupations)		
Non-routine manual occupations*High level of social skills		-0,03267*** (0,00492)
Routine cognitive occupations*High level of social skills		0,12673*** (0,00206)
Non-routine abstract occupations*High level of social skills		0,09414*** (0,00074)
Worker's characteristics		
Female		-0,11571*** (0,00045)
Age		0,03325*** (0,00019)
Square of Age		-0,00021*** (0)
Seniority		0,01960*** (0,00009)
Square of Seniority		-0,00030*** (0)
Firm characteristics		
Logarithm of firm size (number of workers)		0,05284*** (0,00011)
Region Dummies (NUTS II)		Yes
Industry Dummies (1 digit)		Yes
Qualification levels (omitted category: Senior Management)		Yes
Time Dummies	yes	Yes
constant	2,31470*** (0,00103)	1,29329*** (0,00458)
R-squared	0,00770	0,55550
Root MSE	0,60386	0,40417

Notes: Robust cluster (workers), standard errors in parenthesis. ***, ** and * denote statistical significant at 1%, 5% and 10%, respectively. The interaction term "Routine manual occupations * High level of social skills" does not contain any observations. The total number of observations equals 3,833,399.

In the full model, where we include the set of variables omitted in the base regression, the coefficient of the "master" variable is higher, that is, by controlling for an extensive set of characteristics of workers and their firms, on average, a master worker, with similar characteristics, earns a wage premium almost 4% higher than that earned by a worker who only has a bachelor's degree, almost 2 percentage points more than in the base model.

Furthermore, looking at the occupations of workers, we notice that, compared to non-routine interactive occupations, all others have, on average, a lower wage premium. As might be expected, routine occupations have a lower wage premium, both manual and cognitive, with a gap in the order of 20% and 14%, respectively. Manual non-routine occupations also have, as expected, a lower wage premium by about 11 percent, as do abstract non-routine occupations, though on a milder magnitude (5 percent).

Looking at the interaction terms between the dummies for occupations and the dummy for social skills, we conclude that in routine cognitive occupations that require a high level of social skills, the wage gap relative to a worker who is in a non-routine interactive occupation is drastically reduced. Thus, a worker in a routine cognitive occupation earns 14% less than a similar worker employed in non-routine interactive occupations. However, if the former is simultaneously employed in a routine cognitive occupation highly intensive in social skills the differential is only 2%. This phenomenon is even more relevant if we analyze workers who are employed in non-routine abstract occupations. As we have seen, their wage premium for these workers is, on average, 5% lower than that of a worker who is in a non-routine interactive occupation. However, if this worker is employed in an abstract occupation that requires high social skills, the differential becomes positive, with a wage premium of more than 4%.

Regarding the control variables for the characteristics of workers and companies, the estimates show the usual signs: on average, a more unfavorable wage premium for female workers; a wage premium that is higher, though at decreasing rates, as the worker has more experience (proxy measure by age) and more seniority in the company, as indicated in the literature; workers in higher hierarchical positions in companies have a higher premium. As for the characteristics of the firms, large size firms pay, on average, higher wages; there is evidence of regional asymmetries, reflected in the higher average wage premium earned by workers operating in companies headquartered in the "Lisboa e Vale do Tejo" region compared to the other regions; as would be expected, there are industries that, on average, pay their workers substantially higher wages than others.

Table 7 presents the results of the Gelbach decomposition, that is, the estimates of the contribution of the sources of the wage differential between masters and bachelors. The difference in the estimate of the "master" dummy variable from the base model to the full model equals -0.019 (0.02094-0.03999). [24]

Table 7 – Decomposition of the sources of the master wage premium, Portugal, 2010-2018

Groups of variables	Coefficients results
Female	0,00798*** (0,00011)
Age	-0,05946*** (0,00029)
Seniority	-0,03535*** (0,00020)
Qualification levels	0,04576*** (0,00038)
Type of occupations by task intensity	0,00740*** (0,00012)
Interaction between type of occupations by task intensity and high level of social skills	0,00263*** (0,00009)
Logarithm of firm size	-0,00155*** (0,00023)
Location	0,00208*** (0,00011)
Industry	0,01146*** (0,00021)
Change in the coefficient of master dummy	-0,01905*** (0,00085)

Notes: This table reports the contribution of each set of variables for the observed change in the estimates of the "master" dummy from the base to the full model computed according to the procedure described in subsection 6.1. The total number of observations equals 3,833,399.

Figure 20 allows us to clarify the results obtained with the decomposition of the sources of the wage differential between masters and bachelors and draw some conclusions. The first is that, compared to bachelor workers, on average, master workers have less experience and less seniority. This can be due to two factors: the additional years of schooling, which result in a later entry into the labor market of master workers, compared to bachelors – usually around a year and a half to two years apart; Master workers are still mostly very young workers, with less work experience, which negatively impacts their wage premium.

[24] Gelbach decomposition has the advantage of not being conditioned by the order of introduction of the variables in the model. Thus, the contribution of each variable or groups of variables is revealed consistently.

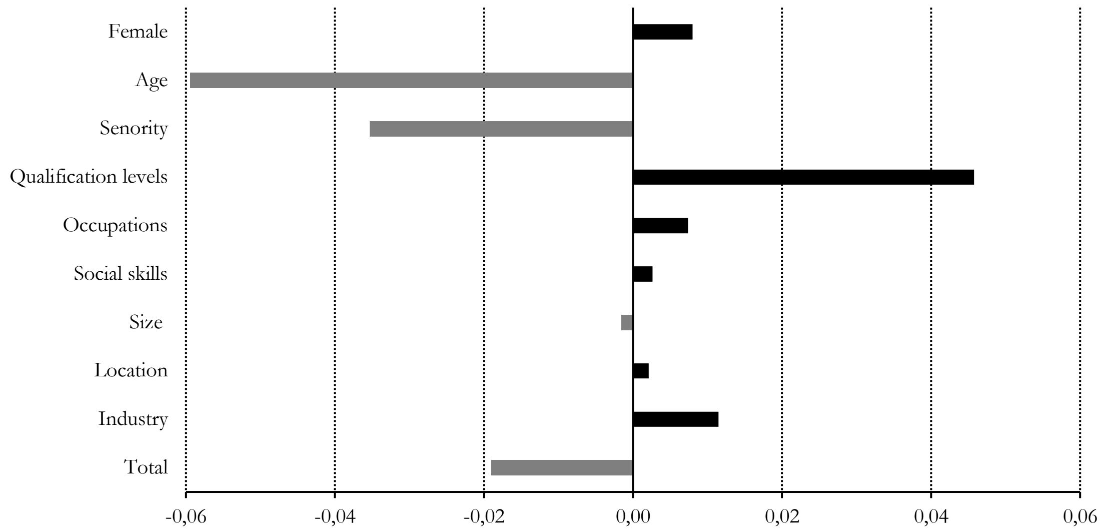

Figure 20 - Gelbach decomposition: the sources of wage differential, Portugal, 2010-2018

The second is that certain characteristics of jobs and companies where they work are especially favorable to master workers. The qualification level stands out, which reflects the hierarchical position they occupy in the company, that is, the masters tend to be in higher hierarchical positions and, therefore, earn a higher wage. Other job characteristics such as industry, and occupation - particularly relevant in our analysis - are favorable to master workers. That is, master workers tend to be in occupations that pay better to their workers - potentially those that require more skills, such as non-routine abstract and interactive occupations. It is also worth noting that master workers tend to be in occupations that, in addition to remunerating their employees better, require a high level of social skills.

Annex 3 presents the Gelbach decomposition for the four age cohorts. We concluded that as we move towards the more aged cohorts, the difference in the estimate of the "master" dummy variable from the base model to the full model decreases. Aspects such as experience[25] and seniority[26] are no longer the main sources of the wage differential.

In the estimates obtained for the four cohorts, the highest hierarchical position of the masters is the factor that contributes the most to the wage differential, although it tends to

[25] However, the impact of the lesser experience of young master workers on their wage premium is still very relevant, particularly in the 20–34-year-old cohort.

[26] In the analysis by cohorts, seniority contributes to the wage differential as much as the occupation performed by the individual.

be smaller as we move towards the older cohorts. Additionally, while younger master workers (cohort aged 20-34) tend to be employed in industries that pay higher wages, older master workers (cohort aged 55-66) tend to be employed in smaller firms.

7. Conclusion

The labor market has changed dramatically in recent decades. The improvement in the educational levels of Portuguese workers, with the growing number of graduates and postgraduates (which represent more than a fifth of workers in 2018), significantly changed the structure of supply in the labor market. This trend should persist in the coming years as the supply will tend to be increasingly composed of highly qualified workers.

On the demand side, the rapid development of new technologies, especially concerning automation and artificial intelligence, promise to contribute to a permanent update of the concept of "routine work"(Autor, 2015a). In this way, technological development tends to affect recruitment patterns, which are increasingly demanding, rewarding complementarity with technology, and accelerating the phenomena of polarization of employment and wages (Acemoglu, 2002; Autor & Dorn, 2013; Autor et al., 2006; Beaudry & Green, 2005; Dustmann et al., 2009; Goos & Manning, 2007; Katz & Murphy, 1992).

Our data showed that less-educated workers are less represented in routine cognitive occupations, now replaced by bachelors and to some extent graduate workers.

Masters, however, continue to be proportionately more represented in non-routine abstract and interactive occupations. These are the occupations with the highest wage bonus, between 10% and 20% higher, compared to other occupations.

Despite the decline in the wage premium to higher education in Portugal in recent years, we observe a slight increase in the wage premium for masters relative to graduates. This wage premium is particularly high for the 20-34 age cohort, reaching, on average, 5.9 % in the 2010-2018 period.

The decomposition of the sources of the raw wage gap between masters and bachelors showed that differences in experience and seniority, as well as employment in top hierarchical positions and in industries that pay higher wages, offer postgraduates with a master degree a wage advantage over graduates with a bachelor degree.

Finally, the econometric results show that workers employed in routine cognitive occupations and abstract occupations that require a high level of social skills benefit from a wage bonus compared with similar workers who are employed in routine cognitive and abstract occupations that do not require high social skills. This reveals the importance given by employers to these skills, which range from Social Perceptiveness, Coordination, Persuasion, Negotiation to Instructing and Service Orientation.

As already mentioned, the increase in the number of postgraduates (masters) is crucial to the strengthening of these trends, particularly to better understand the role that occupations and social skills will have in explaining the wage premium of these workers. The expansion of areas where technology operates is a permanent challenge to these workers. The development and enhancement of social skills are of utmost importance and perhaps education systems need to address some gaps to promote and enhance these skills. Above all, it remains to be seen to what extent the social skills required by employers are or are not conditioned by the pace of technological development.

Bibliographic references

Acemoglu, D. (2002). Directed Technical Change. *The Review of Economic Studies, 69*(4), 781-809. doi:10.1111/1467-937x.00226

Acemoglu, D., & Autor, D. H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In D. Card & O. Ashenfelter (Eds.), *Handbook of Labor Economics* (Vol. 4, pp. 1043-1171): Elsevier.

Acemoglu, D., & Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review, 108*(6), 1488-1542. doi:10.1257/aer.20160696

Asheim, B. T., & Coenen, L. (2006). Contextualising Regional Innovation Systems in a Globalising Learning Economy: On Knowledge Bases and Institutional Frameworks. *The Journal of Technology Transfer, 31*(1), 163-173. doi:10.1007/s10961-005-5028-0

Autor, D. H. (2015a). Polanyi's Paradox and the Shape of Employment Growth. In *Re-Evaluating Labor Market Dynamics* (pp. 129-179). Kansas City: Federal Reserve Bank of Kansas City.

Autor, D. H. (2015b). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives, 29*(3), 3-30. doi:10.1257/jep.29.3.3

Autor, D. H. (2017). *How Long Has This Been Going On? A Discussion of "Recent Flattening in the Higher Education Wage Premium: Polarization, Skill Downgrading, or Both?" by Robert G. Valletta*. Paper presented at the NBER Conference on Research and Income in Wealth, Royal Sonesta Hotel.

Autor, D. H., & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review, 103*(5), 1553-1597. doi:10.1257/aer.103.5.1553

Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The Polarization of the U.S. Labor Market. *The American Economic Review, 96*(2), 189-194. doi:10.1257/000282806777212620

Autor, D. H., Katz, L. F., & Kearney, M. S. (2008). Trends in U.S. Wage Inequality: Revising the Revisionists. *The Review of Economics and Statistics, 90*(2), 300-323. doi:10.1162/rest.90.2.300

Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing Inequality: Have Computers Changed the Labor Market? *The Quarterly Journal of Economics, 113*(4), 1169-1213. doi:10.1162/003355398555874

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics, 118*(4), 1279-1333. doi:10.1162/003355303322552801

Beaudry, P., & Green, D. (2005). Changes in U.S. Wages, 19762000: Ongoing Skill Bias or Major Technological Change? *Journal of Labor Economics, 23*(3), 609-648. doi:10.1086/430288

Beaudry, P., Green, D. A., & Sand, B. M. (2016). The Great Reversal in the Demand for Skill and Cognitive Tasks. *Journal of Labor Economics, 34*(S1). doi:10.1086/682347

Berman, E., Bound, J., & Griliches, Z. (1994). Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers. *The Quarterly Journal of Economics, 109*(2), 367-397. doi:10.2307/2118467

Blinder, A. S. (2006). Offshoring: The Next Industrial Revolution? *Foreign Affairs, 85*(2), 113-128. doi:10.2307/20031915

Blinder, A. S., & Krueger, A. B. (2013). Alternative Measures of Offshorability: A Survey Approach. *Journal of Labor Economics, 31*(2), S97-S128. doi:10.1086/669061

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: work, progress, and prosperity in a time of brilliant technologies* (1 ed.). New York: W.W. Norton & Company.

Camerer, C., Loewenstein, G., & Prelec, D. (2005). Neuroeconomics: How Neuroscience Can Inform Economics. *Journal of Economic Literature, 43*(1), 9-64. doi:10.1257/0022051053737843

Centeno, M., & Novo, Á. A. (2014). When supply meets demand: wage inequality in Portugal. *IZA Journal of European Labor Studies, 3*(1), 23. doi:10.1186/2193-9012-3-23

Cooke, P., Urange, M. G., & Etxebarria, G. (1997). Regional innovation systems: Institutional and organisational dimensions. *Research Policy, 26*(4), 475-491. doi:10.1016/S0048-7333(97)00025-5

Deming, D. J. (2017). The Growing Importance of Social Skills in the Labor Market. *The Quarterly Journal of Economics, 132*(4), 1593-1640. doi:10.1093/qje/qjx022

Deming, D. J. (2021). The Growing Importance of Decision-Making on the Job. *National Bureau of Economic Research Working Paper Series, No. 28733*. doi:10.3386/w28733

Deming, D. J., & Kahn, L. B. (2018). Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals. *Journal of Labor Economics, 36*(S1), 337-369. doi:10.1086/694106

Dustmann, C., Ludsteck, J., & Schönberg, U. (2009). Revisiting the German Wage Structure. *The Quarterly Journal of Economics, 124*(2), 843-881. doi:10.1162/qjec.2009.124.2.843

Ebenstein, A., Harrison, A., McMillan, M., & Phillips, S. (2014). Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys. *The Review of Economics and Statistics, 96*(4), 581-595.

Eurostat. (2016). Glossary: Knowledge-intensive services (KIS).

Eurostat. (2018). Glossary: High-tech classification of manufacturing industries.

Figueiredo, H., Portela, M., Sá, C., Silva, J. C., Almeida, A., & Lourenço, D. (2017). *Benefícios do Ensino Superior*. Lisbon: Francisco Manuel dos Santos Fundation.

Fonseca, T., Lima, F., & Pereira, S. C. (2018a). Job polarization, technological change and routinization: Evidence for Portugal. *Labour Economics, 51*, 317-339. doi:10.1016/j.labeco.2018.02.003

Fonseca, T., Lima, F., & Pereira, S. C. (2018b). Understanding productivity dynamics: A task taxonomy approach. *Research Policy, 47*(1), 289-304. doi:10.1016/j.respol.2017.11.004

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254-280. doi:10.1016/j.techfore.2016.08.019

Gelbach, J. B. (2016). When Do Covariates Matter? And Which Ones, and How Much? *Journal of Labor Economics, 34*(2), 509-543. doi:10.1086/683668

Goos, M., & Manning, A. (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *The Review of Economics and Statistics, 89*(1), 118-133. doi:10.1162/rest.89.1.118

Goos, M., Manning, A., & Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *The American Economic Review, 104*(8), 2509-2526. doi:10.1257/aer.104.8.2509

Griliches, Z. (1957). Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica, 25*(4), 501-522. doi:10.2307/1905380

Johnson, G. E. (1997). Changes in Earnings Inequality: The Role of Demand Shifts. *The Journal of Economic Perspectives, 11*(2), 41-54. doi:10.1257/jep.11.2.41

Juhn, C., Murphy, K. M., & Pierce, B. (1993). Wage Inequality and the Rise in Returns to Skill. *Journal of Political Economy, 101*(3), 410-442. doi:10.1086/261881

Katz, L. F., & Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *The Quarterly Journal of Economics, 107*(1), 35-78. doi:10.2307/2118323

Levy, F., & Murnane, R. J. (1992). U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations. *Journal of Economic Literature, 30*(3), 1333-1381. doi:10.3386/w7684

Levy, F., & Murnane, R. J. (2012). *The New Division of Labor*: Princeton University Press.

Lindley, J., & Machin, S. J. (2016). The Rising Postgraduate Wage Premium. *Economica, 83*(330). doi:10.1111/ecca.12184

Malerba, F. (2002). Sectoral systems of innovation and production. *Research Policy, 31*(2), 247-264. doi:10.1016/S0048-7333(01)00139-1

Mihaylov, E., & Tijdens, K. G. (2019). Measuring the Routine and Non-Routine Task Content of 427 Four-Digit ISCO-08 Occupations. *Tinbergen Institute Discussion Paper, 2019-035/V*. doi:10.2139/ssrn.3389681

Mincer, J. (1974). *Schooling, Experience, and Earnings*: National Bureau of Economic Research.

National Center for O*NET Development. (May 25, 2021). The O*NET® Content Model. Retrieved from https://www.onetcenter.org/content.html

National Center for O*NET Development. (May 25, 2021). Skills - O*NET 25.3 Data Dictionary. Retrieved from https://www.onetcenter.org/dictionary/25.3/excel/skills.html

Song, J., Price, D. J., Guvenen, F., Bloom, N., & von Wachter, T. (2018). Firming Up Inequality. *The Quarterly Journal of Economics, 134*(1), 1-50. doi:10.1093/qje/qjy025

Spitz-Oener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure. *Journal of Labor Economics, 24*(2), 235-270. doi:10.1086/499972

Valletta, R. G. (2019). Recent Flattening in the Higher Education Wage Premium Polarization, Skill Downgrading, or Both? In R. H. Charles & A. R. Valerie (Eds.), *Education, Skills, and Technical Change* (pp. 313-354): University of Chicago Press.

Weinberger, C. J. (2014). The Increasing Complementarity between Cognitive and Social Skills. *The Review of Economics and Statistics, 96*(5), 849-861. doi:10.1162/REST_a_00449

World Bank. (2016). *World Development Report 2016: Digital Dividends*. Washington, DC: World Bank. Licence: Creative Commons Attribution CC BY 3.0 IGO.

Annexes

Annex 1

Definition of variables used in the econometric models

Variables	Description
Education levels	
secondary and post-secondary education	= 1 if the individual has secondary and post-secondary education
bachelor	= 1 if the individual has a bachelor or equivalent level
master	= 1 if the individual has master or equivalent level
Types of occupations	
routine cognitive occupations	= 1 if the individual has an occupation intense in routine cognitive tasks
routine manual occupations	= 1 if the individual has an occupation intense in routine cognitive tasks
non-routine manual occupations	= 1 if the individual has an occupation intense in non-routine manual tasks
non-routine abstract occupations	= 1 if the individual has an occupation intense in non-routine abstract tasks
non-routine interactive occupations	= 1 if the individual has an occupation intense in non-routine interactive tasks
Qualification levels	
senior management	= 1 if the individual belongs to senior management
middle management	= 1 if the individual belongs to middle management
supervisors, foremen, and team leaders	= 1 if the individual belongs to supervisors, foremen, and team leaders
highly qualified professionals	= 1 if the individual belongs to highly qualified professionals
qualified professionals	= 1 if the individual belongs to qualified professionals
semi-qualified professionals	= 1 if the individual belongs to semi-qualified professionals
unqualified professionals	= 1 if the individual belongs to unqualified professionals
trainees	= 1 if the individual belongs to trainees
ignored	= 1 if the individual belongs to the ignored category
Social skills levels	
high social skills	= 1 if the individual has an occupation intense in high social skills
Worker's characteristics	
female	= 1 if the individual is female
age	age in years
seniority	seniority in years
Firms' characteristics	
Ln size	logarithm of the number of workers in the firm
Region Dummies (NUTS II)	
Norte	=1 if Norte
Centro	=1 if Centro
Lisboa e Vale do Tejo	=1 if Lisboa e Vale do Tejo
Alentejo	=1 if Alentejo
Algarve	=1 if Algarve
Açores	=1 if Açores
Madeira	=1 if Madeira
Industry Dummies (CAE-1 letter)	
CAE_1L_01	= 1 if Agriculture, forestry, and fishing
CAE_1L_02	=1 if Mining and quarrying
CAE_1L_03	=1 if Manufacturing
CAE_1L_04	=1 if Electricity, gas, steam, and air conditioning supply
CAE_1L_05	=1 if Water supply; sewerage, waste management and remediation activities
CAE_1L_06	=1 if Construction
CAE_1L_07	=1 if Wholesale and retail trade; repair of motor vehicles and motorcycles
CAE_1L_08	=1 if Transportation and storage

CAE_1L_09	=1 if Accommodation and food service activities
CAE_1L_10	=1 if Information and communication
CAE_1L_11	=1 if Financial and insurance activities
CAE_1L_12	=1 if Real estate activities
CAE_1L_13	=1 if Professional, scientific, and technical activities
CAE_1L_14	=1 if Administrative and support service activities
CAE_1L_15	=1 if Education
CAE_1L_16	=1 if Human health and social work activities
CAE_1L_17	=1 if Arts, entertainment, and recreation
CAE_1L_18	=1 if Other service activities
CAE_1L_19	=1 if Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
CAE_1L_20	=1 if Activities of extraterritorial organisations and bodies
Time Dummies	
2010	=1 if the year is 2010
2011	=1 if the year is 2011
2012	=1 if the year is 2012
2013	=1 if the year is 2013
2014	=1 if the year is 2014
2015	=1 if the year is 2015
2016	=1 if the year is 2016
2017	=1 if the year is 2017
2018	=1 if the year is 2018

Annex 2

Table 2.01 – POLS Results of wage regression, by workers with 20-34 years old

Variables	Coefficients (1)	Coefficients (2)
Education levels (omitted category: bachelor)		
Master	0.13587*** (0.00105)	0.05865*** (0.00081)
Type of occupations by task intensity (omitted category: non-routine interactive occupations)		
Non-routine manual occupations		-0.04701*** (0.00150)
Routine cognitive occupations		-0.09416*** (0.00075)
Routine manual occupations		-0.11350*** (0.002112)
Non-routine abstract occupations		0.01764*** (0.00094)
Interaction between the type of occupations by task intensity and high level of social skills (omitted category: non-routine interactive occupations)		
Non-routine manual occupations*High level of social skills		-0.04118*** (0.00525)
Routine cognitive occupations*High level of social skills		-0.07582*** (0.00249)
Non-routine abstract occupations*High level of social skills		0.00127 (0.00091)
Worker's characteristics		
Female		-0.08338*** (0.00054)
Age		-0.02325*** (0.00132)
Square of Age		0.00075*** (0.00002)
Seniority		0.03561*** (0.00025)
Square of Seniority		-0.00198*** (0.00003)
Firm characteristics		
Logarithm of firm size (number of workers)		0.03898*** (0.00013)
Region Dummies (NUTS II)		
Industry Dummies (1 digit)		
Qualification levels (omitted category: Senior Management)		yes
Time Dummies	yes	yes
constant	2.06841*** (0.00098)	2.03337*** (0.01911)

Notes: (i) Robust cluster (workers), standard errors in parenthesis. (ii) ***, ** and * denote statistical significant at 1%, 5% and 10%, respectively. (iii) The interaction term "Routine manual occupations * High level of social skills does not contain any observations. (iv) The total number of observations equals 1,714,617.

Table 2.02 – POLS Results of wage regression, by workers with 35-44 years old

Variables	Coefficients (1)	Coefficients (2)
Education levels (omitted category: bachelor)		
Master	0.11699*** (0.00208)	0.05466*** (0.00154)
Type of occupations by task intensity (omitted category: non-routine interactive occupations)		
Non-routine manual occupations		-0.13187*** (0.00263)
Routine cognitive occupations		-0.17147*** (0.00107)
Routine manual occupations		-0.25008*** (0.00368)
Non-routine abstract occupations		0.07602*** (0.00129)
Interaction between the type of occupations by task intensity and high level of social skills (omitted category: non-routine interactive occupations)		
Non-routine manual occupations*High level of social skills		-0.04880*** (0.00897)
Routine cognitive occupations*High level of social skills		0.13250*** (0.00332)
Non-routine abstract occupations*High level of social skills		0.11109*** (0.00124)
Worker's characteristics		
Female		-0.13184*** (0.00075)
Age		0.04473*** (0.00391)
Square of Age		-0.00032*** (0.00005)
Seniority		0.01978*** (0.00020)
Square of Seniority		-0.00049*** (0.00001)
Firm characteristics		
Logarithm of firm size (number of workers)		0.05619*** (0.00019)
Region Dummies (NUTS II)		
Industry Dummies (1 digit)		
Qualification levels (omitted category: Senior Management)		yes
Time Dummies	yes	yes
constant	2.47036*** (0.00166)	1.06955*** (0.07658)

Notes: (i) Robust cluster (workers), standard errors in parenthesis. (ii) ***, ** and * denote statistical significant at 1%, 5% and 10%, respectively. (iii) The interaction term "Routine manual occupations * High level of social skills does not contain any observations. (iv) The total number of observations equals 1,416,762.

Table 2.03 – POLS Results of wage regression, by workers with 45-54 years old

Variables	Coefficients (1)	Coefficients (2)
Education levels (omitted category: bachelor)		
Master	0.10836*** (0.00407)	0.04512*** (0.00294)
Type of occupations by task intensity (omitted category: non-routine interactive occupations)		
Non-routine manual occupations		-0.22899*** (0.00539)
Routine cognitive occupations		-0.19246*** (0.00221)
Routine manual occupations		-0.33509*** (0.00740)
Non-routine abstract occupations		-0.15118*** (0.00258)
Interaction between the type of occupations by task intensity and high level of social skills (omitted category: non-routine interactive occupations)		
Non-routine manual occupations*High level of social skills		-0.05373* (0.01981)
Routine cognitive occupations*High level of social skills		0.22296*** (0.00696)
Non-routine abstract occupations*High level of social skills		0.21078*** (0.00244)
Worker's characteristics		
Female		-0.13995*** (0.00144)
Age		0.02415*** (0.00920)
Square of Age		-0.00012 (0.00009)
Seniority		0.02199*** (0.00027)
Square of Seniority		-0.00050*** (0)
Firm characteristics		
Logarithm of firm size (number of workers)		0.07165*** (0.00036)
Region Dummies (NUTS II)		
Industry Dummies (1 digit)		
Qualification levels (omitted category: Senior Management)		yes
Time Dummies	yes	yes
constant	2.78270*** (0.00334)	1.53451*** (0.22580)

Notes: (i) Robust cluster (workers), standard errors in parenthesis. (ii) ***, ** and * denote statistical significant at 1%, 5% and 10%, respectively. (iii) The interaction term "Routine manual occupations * High level of social skills does not contain any observations. (iv) The total number of observations equals 523.378.

Table 2.04 – POLS Results of wage regression, by workers with 55-66 years old

Variables	Coefficients (1)	Coefficients (2)
Education levels (omitted category: bachelor)		
Master	-0.01508* (0.00860)	-0.03131*** (0.00599)
Type of occupations by task intensity (omitted category: non-routine interactive occupations)		
Non-routine manual occupations		-0.21333*** (0.01134)
Routine cognitive occupations		-0.14616*** (0.00497)
Routine manual occupations		-0.29213*** (0.01563)
Non-routine abstract occupations		-0.15011*** (0.00527)
Interaction between the type of occupations by task intensity and high level of social skills (omitted category: non-routine interactive occupations)		
Non-routine manual occupations*High level of social skills		0.05138 (0.04009)
Routine cognitive occupations*High level of social skills		0.19677*** (0.01741)
Non-routine abstract occupations*High level of social skills		0.24636*** (0.00476)
Worker's characteristics		
Female		-0.12629*** (0.00293)
Age		0.01309*** (0.01651)
Square of Age		-0.00109*** (0.00014)
Seniority		0.02252*** (0.00040)
Square of Seniority		-0.00040*** (0.00001)
Firm characteristics		
Logarithm of firm size (number of workers)		0.09077*** (0.00070)
Region Dummies (NUTS II)		yes
Industry Dummies (1 digit)		yes
Qualification levels (omitted category: Senior Management)		yes
Time Dummies	yes	yes
constant	2.88576*** (0.00614)	-1.61047** (0.49180)

Notes: (i) Robust cluster (workers), standard errors in parenthesis. (ii) ***, ** and * denote statistical significant at 1%, 5% and 10%, respectively. (iii) The interaction term "Routine manual occupations * High level of social skills does not contain any observations. (iv) The total number of observations equals 178,638.

Annex 3

Table 3.01 – Decomposition of the sources of the master wage premium for the 20-34 years old cohort, Portugal, 2010-2018

Groups of variables	Coefficients results
Female	0.00850*** (0.00011)
Age	-0.01282*** (0.00018)
Seniority	-0.01471*** (0.00016)
Qualification levels	0.06099*** (0.00042)
Type of occupations by task intensity	0.01177*** (0.00017)
Interaction between the type of occupations by task intensity and high level of social skills	-0.00038*** (0.00005)
Logarithm of firm size	0.00237*** (0.00021)
Location	0.00246*** (0.00011)
Industry	0.01905*** (0.00024)
Change in the coefficient of the master dummy	0.07722*** (0.00072)

Notes: This table reports the contribution of each set of variables for the observed change in the estimates of the "master" dummy from the base to the full model computed according to the procedure described in subsection 6.1. The total number of observations equals 1,714,617.

Table 3.02 – Decomposition of the sources of the master wage premium for the 35-44 years old cohort, Portugal, 2010-2018

Groups of variables	Coefficients results
Female	0.00777*** (0.00024)
Age	-0.00419*** (0.00020)
Seniority	-0.01193*** (0.00025)
Qualification levels	0.04970*** (0.00076)
Type of occupations by task intensity	0.00868*** (0.00026)
Interaction between the type of occupations by task intensity and high level of social skills	0.00580*** (0.00021)
Logarithm of firm size	-0.00333*** (0.00047)
Location	0.00210*** (0.00026)
Industry	0.00773*** (0.00042)
Change in the coefficient of the master dummy	0.06233*** (0.00141)

Notes: This table reports the contribution of each set of variables for the observed change in the estimates of the "master" dummy from the base to the full model computed according to the procedure described in subsection 6.1. The total number of observations equals 1,416,762.

Table 3.03 – Decomposition of the sources of the master wage premium for the 45-54 years old cohort, Portugal, 2010-2018

Groups of variables	Coefficients results
Female	0.00844*** (0.00043)
Age	0.00037 (0.00022)
Seniority	-0.01264*** (0.00053)
Qualification levels	0.05158*** (0.00143)
Type of occupations by task intensity	0.01049*** (0.00054)
Interaction between the type of occupations by task intensity and high level of social skills	0.00976*** (0.00644)
Logarithm of firm size	-0.00814*** (0.00103)
Location	0.00298*** (0.00045)
Industry	0.00038 (0.00079)
Change in the coefficient of the master dummy	0.06324*** (0.00284)

Notes: This table reports the contribution of each set of variables for the observed change in the estimates of the "master" dummy from the base to the full model computed according to the procedure described in subsection 6.1. The total number of observations equals 523,378.

Table 3.04 – Decomposition of the sources of the master wage premium for the 55-66 years old cohort, Portugal, 2010-2018

Groups of variables	Coefficients results
Female	0.00175* (0.00067)
Age	-0.00048*** (0.00013)
Seniority	-0.01466*** (0.00121)
Qualification levels	0.04510*** (0.00287)
Type of occupations by task intensity	0.01035*** (0.00078)
Interaction between the type of occupations by task intensity and high level of social skills	0.00385*** (0.00135)
Logarithm of firm size	-0.02510*** (0.00240)
Location	0.00360*** (0.00076)
Industry	-0.00818*** (0.00155)
Change in the coefficient of the master dummy	0.01623** (0.00581)

Notes: This table reports the contribution of each set of variables for the observed change in the estimates of the "master" dummy from the base to the full model computed according to the procedure described in subsection 6.1. The total number of observations equals 178,638.

Figure 3.05 – Decomposition of the sources of the master wage premium for the four cohorts, Portugal, 2010-2018