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Technological Change and Wage Inequality in Portugal

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Declaração

Declaro que o presente documento é um trabalho original da minha autoria que cumpre todos os requisitos do Código de Conduta e Boas Práticas da Universidade de Lisboa.

Declaration

I declare that this document is an original work of my own authorship and that it fulfils all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

Resumo

O avanço tecnológico pode ter um impacto seja ao nível das variações de incidência de trabalhadores em certos tipos de empresas, indústrias, tarefas ou ocupações, ou ao nível da distinção dos salários para diferentes trabalhadores. Os impactos referidos podem gerar polarização salarial e laboral, onde os trabalhadores com qualificações altas (tarefas abstratas) e qualificações baixas (tarefas manuais) apresentaram um aumento ao longo dos anos, e os trabalhadores de qualificações médias (tarefas rotineiras) sofreram comparativamente um decréscimo.

A teoria *Routine-Biased Technological Change (RBTC)* explica como a tecnologia substitui tarefas rotineiras e também complementa os trabalhadores que executam tarefas apoiadas pela tecnologia (não-rotineiras), promovendo um aumento da produtividade. Espera-se que os trabalhadores que não desempenham tarefas rotineiras ganhem salários mais elevados do que os trabalhadores que desempenham tarefas rotineiras, pois por exemplo, há mais procura no mercado de trabalho, o que pode causar um aumento da desigualdade salarial. Assim, a rotinização poderá se relacionar com o nível salarial dos trabalhadores.

Esta dissertação tem como objectivo estudar qual a relação que existe entre a rotinização e as desigualdades salarias dentro das empresas em Portugal, utilizando dados de 2002 a 2017. Para esse efeito, utilizámos dados da base de dados Quadros de Pessoal, onde aplicámos os modelos *fixed-effects*, *random-effects* e *pooled OLS*.

Os resultados tendo em conta todos os modelos e a variável de desigualdade (coeficiente de Gini) parecem indicar que, quanto maior a rotinização (RTI), maior as desigualdades salariais dentro das empresas. O rácio 80/20 foi analisado, tendo-se obtido uma conclusão oposta.

Palavras-chave: Avanço tecnológico, Desigualdade Salarial, Rotinização, *RBTC*, Polarização laboral, RTI

Abstract

Technology change can have an impact either in terms of variations in the prevalence of employees in certain types of firms, industries, tasks, occupations or in terms of the distinction of wages for different employees. These impacts may generate wage polarisation and job polarisation, where high-skilled (abstract tasks) and low-skilled (manual tasks) workers increase throughout the years, and middle-skilled (routine tasks) workers decrease.

The Routine-Biased Technological Change (RBTC) theory explains how technology substitutes routine tasks, and also, its use to complement workers performing tasks supported by technology (non-routine), promoting an increase in productivity. Non-routine workers are expected to earn higher wages than workers performing routine tasks because, for example, there is more demand in the labour market, which may cause wage inequality to increase. Thus, routinisation may relate to the wage level of workers.

This dissertation aims to study the relationship between routinisation and wage inequality within Portuguese firms using data from 2002 to 2017. For this purpose, we used data from the *Quadros de Pessoal* database, where we applied the fixed-effects, random-effects, and pooled OLS models.

The results, considering all models and the inequality measurement (Gini coefficient), seem to indicate that the greater the routinisation (RTI), the greater the wage inequality within firms. The 80/20 percentile ratio was analysed and a opposite conclusion was obtained.

Keywords: Technological Change, Wage Inequality, Routinisation, RBTC, Job Polarisation, RTI

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List of Acronyms

FDI – Foreign Direct Investment.

INE – Instituto Nacional de Estatística.

IT – Information Technology.

KIS – Knowledge Intensive Services.

LKIS – Less-Knowledge Intensive Services.

NACE – Statistical Classification of Economic Activities in the European Community.

NPC – Número de Pessoa Coletiva, a unique number, issued by the Portuguese state, which represents each Portuguese legal entity.

OECD - Organisation for Economic Co-operation and Development.

OPEC – Organization of the Petroleum Exporting Countries.

RBTC – Routine-Biased Technological Change.

R&D – Research and Development.

RTI – Routinisation Task Intensity.

SBTC – Skill-Biased Technological Change.

STEM – Science, Technology, Engineering and Mathematics.

US – United States (of America).

1. Introduction

1.1. Overview

Wage inequality has become a concern with significant implications for economic and social well-being which occurred over the years and in different countries. (Fonseca et al., 2018) analysed the progression of wages in Portugal, where a pronounced increase in wage inequality in the 90s was found. The top wages grew sharply, and the middle and bottom of the wage distribution faced a minor increase.

The hollowing out of certain type of job activities can promote inequalities in the labour market, more precisely leading to job polarisation (Acemoglu & Autor, 2011). Job polarisation refers to a phenomenon in which employment grow significantly for both low-skilled and high-skilled occupations, while the middle-skilled occupations do not experience the same upward trend (Acemoglu & Autor, 2011; Autor et al., 2003, 2006; Autor & Dorn, 2013). Additionally, in the United States, wage polarisation seems to occur side by side with job polarisation (Autor et al., 2006). Wage polarisation corresponds to the increase of wages for the low-skilled and high-skilled (Autor & Dorn, 2013).

We identified several measures of wage inequality throughout the literature such as the Gini coefficient, the percentile ratios, the Theil Index etc., as well as reasons for its increase. The literature does not unanimously conclude that technology is the principal factor that leads to wage inequality. Besides technological change (Greiner et al. 2004) and automation (Acemoglu & Restrepo, 2020), other reasons that impact wage inequality could be outsourcing (Hijzen, 2007), offshoring (Coveri & Pianta, 2022), unionization and minimum wages (Kristal & Cohen, 2016), personal characteristics (age, education [Machado & Mata 2001]) and firm heterogeneity (Biewen & Seckler, 2019).

Over the years, technology has become increasingly prevalent in various aspects of human life, including the labour market.

The Skilled-Biased Technological Change (SBTC) theory (Acemoglu, 2002; Acemoglu & Autor, 2011; Autor et al., 2003, 2008), considers that technology favours skilled over unskilled workers. However, this theory is not unanimously accepted throughout the literature. Other authors identified that the tendency of SBTC is not constant throughout the years (Beaudry & Green, 2005; Card & DiNardo, 2002; Lemieux, 2006, 2007).

Another perspective to understand the impact of technology is through the concept of routinisation hypothesis, as proposed by (Autor et al., 2003). According to this hypothesis, technology replaces workers who perform routine tasks. Another theory, known as Routine Biased Technological Change (RBTC), has also been mentioned in the literature (Acemoglu & Autor, 2011; Goos et al., 2014; Vannutelli et al., 2022). RBTC suggests that technology substitutes workers performing routine tasks while complementing workers performing tasks supported by technology, thereby promoting increased productivity. RBTC has a polarizing effect on the labour market, promoting a U-shape of the occupational distribution (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Cortes, 2016; Goos et al., 2014). While routinisation brings productivity gains and efficiency, it also has implications for wage distribution and employment opportunities.

Additionally, Antonczyk et al. (2018), that performed an analysis for the case of Germany, concluded that, although it is noticeable that RBTC lead to job polarisation, it was not clear that the same happened in the case of wage polarisation.

Firstly, routinisation tends to disproportionately affect workers engaged in routine and repetitive jobs. This relationship can occur since using machines to do a certain type of task could be cheaper and more efficient when compared with human labour, resulting in lower wages. These jobs, often characterized by lower skill requirements, are more susceptible to automation. As technology replaces these positions, workers may face displacement or lower wages (Acemoglu & Autor, 2011). This contributes to a widening wage gap between high-skilled and low-skilled workers.

Secondly, technological change creates a higher demand for workers with advanced skills and expertise in managing new technologies. Occupations that require creativity, problem-solving, complex decision-making, and interpersonal skills are less vulnerable to automation. Consequently, workers in these roles may encounter increased demand and higher wages, further exacerbating wage inequalities. In fact, workers performing non-routine tasks are expected to have higher wages than workers performing routine tasks, thus increasing wage inequality (Vannutelli et al., 2022).

In summary, one factor that can contribute to wage inequality is routinisation, which is closely connected with technological change. As technology advances, it has the potential to automate routine and repetitive tasks, leading to changes in the demand for different types of skills in the labour market.

In the literature, the concept of Routine Task Intensity (RTI) formula has been applied to calculate the level of routinisation intensity of a certain task (Autor & Dorn, 2013), that could also be implemented for other realities, e.g., firms (Fonseca et al., 2018).

Measures of technological intensity were also analysed and identified. Ang (2008) analysed the ratio of R&D expenses and embodied technology to measure technology. Munier (2006) measured the intensity of the R&D (direct or indirect). In addition, Garcés-Galdeano et al. (2016) used the nomenclature of the Spanish Bureau of Statistics to evaluate if an industry is high, medium, or low in terms of technology intensity. Lepak (2003) used capital intensity, research & development (R&D) to measure the technological intensity.

1.2. Scope and Context

Multiple studies have examined the concept of routinisation and its impact on wage inequality. Vannutelli et al. (2022), found that workers engaged in routine tasks experience larger wage gaps across the wage distribution range. The author used the concept of RTI. Fonseca et al. (2018) confirmed that routinisation is responsible for job and wage polarisation in Portugal. Pereira (2021) identified labour market polarisation as a significant cause of increased wage inequality. Lee & Wie (2015) analysed technological change and concluded that it led to higher wage inequality, benefiting high-skilled workers.

Although, to our knowledge, there is a limited number of studies that relate routinisation with wage inequality at the firm-level. Gini coefficient, the decile dispersion ratio, and the income quantile share ratio are not commonly used measures for assessing wage inequality in these studies.

Analyses of the impact of routinisation on wage inequality can be carried out at the firm, industry, or skill level. Researchers highlighted the significance of firm-level factors in understanding wage inequality. Abowd et al. (1999), confirmed the importance of industry and firm level wage differentials for the analysis of wage inequality. Barth et al. (2016), found that the variation in average wages across firms contributed significantly to the increase in wage inequality in the US. One factor that could impact wages and employment is the power that institutions have to define wages (Machin & Van Reenen, 1998).

An increase in wage inequality happened due to a boost in the dispersion of wages between firms in the US between 1970-2010 (Barth et al., 2016). The firm-level characteristics performed an important role in defining changes in wage inequality (Lemieux, 2007). Increased heterogeneity between firms is considered and important factor in the rise of wage inequality (Barth et al., 2016; Card et al., 2013; Song et al., 2019). Changes in the labour market institutions also contribute to wage inequality (Lemieux, 2007), with estimates suggesting that institutional changes account for about one-third of wage inequality. Analysing wage inequality at the firm level is therefore relevant.

1.3. Objectives

The aim of this dissertation is to assess the impact that routinisation, had on wage inequality in Portugal between the years of 2002 and 2017. Routinisation is linked to technological change because the advancement of technology promotes the routinisation of various types of tasks.

The questions that we will aim to answer are the following:

- Does an increase in routinisation at the firm-level, lead to the increase in wage inequality in Portugal?
- Does the industry's technological/knowledge intensity influence the relationship between routinisation and inequality at the firm level?

The objective of this dissertation is to analyse the impact of routinisation in wage inequality for Portuguese firms', and so, the key explanatory variable is the RTI (routinisation). If in fact technology, increases wage inequality, organizations and the country's government should implement measures to overcome or minimise the issue. For example, by providing incentives for the population to invest in education and training in fields that may be more necessary due to technological change.

1.4. Organization of Chapters

This dissertation is organized into six chapters, summarised as follows.

Introduction

This chapter presents the reasons for conducting this analysis and a general contextualisation of the issue under analysis as well as a background for the study. The objective of this dissertation is also specified. The dissertation's organisation is also defined.

Literature Review

This chapter analyses the literature information regarding the topics of inequality, technological change, routinisation, and other relevant topics.

Data Characterization

This chapter describes the variables of the study and performs a statistical characterization of the dataset and descriptive analysis.

Methodology

This chapter defines the methods used, more precisely the econometric models that are going to be applied to the data.

Results

After running the econometric models in Stata software, the results obtained will be discussed to understand the impact that technology (in form of routinisation) had on wage inequality. Additionally, the analysis of the interaction between terms will also be analysed.

Conclusion

The conclusions of this dissertation are identified, and some ideas will be presented in order to minimize possible wage inequality.

2. Literature Review

A literature review was conducted concerning the two main topics of this dissertation, which are wage inequality and technological change. Firstly, it was considered and analysed whether wage inequality occurs, in what circumstances, and how these inequalities can be measured. Furthermore, it was evaluated how occupations, skills and tasks are defined in the context of the labour market. Finally, the impacts of technology on the labour market and its consequences are identified, one of them being the impact on worker's wages.

2.1. Inequality

2.1.1. Wage Inequality

Inequality, more particularly, wage inequality, has been widely discussed over the years in the literature. The different reasons why wage inequality occurs, and the methods to analyse those inequalities, are crucial to better understand the background and trends of this phenomenon.

Wage inequality increased at a rapid pace during the 80s and occurred across the entire wage distribution in the US (Autor et al., 2006). In that period, the demand and wages of low-skilled workers decreased in multiple OECD countries, which could also lead to wage polarisation (Berman et al., 1998). Wage polarisation corresponds to the increase of wages for the low-skilled and high-skilled (Autor & Dorn, 2013). Before 1998, in the US, it was recognized by Acemoglu (1998), that wages of high-skilled workers had increased compared to low-skilled workers. This tendency, therefore, promotes wage inequality. A continuous increase in wage inequality was also observed between 1980-2000 (Acemoglu & Autor, 2011; Autor et al., 2008; Lemieux et al., 2009). Additionally, between 1980-1990, wage inequality increased in many countries, such as the US and the United Kingdom, whereas countries such as France and Germany did not experience a so pronounced increase (Lemieux, 2007).

Between 2000-2014, wage inequality decreased in nearly all Central and Eastern European countries (Magda et al., 2021). As mentioned before, the US and the United Kingdom felt an inequality increase from 1985 to 2000. However, wage inequality declined after that (Van Reenen, 2011), which goes in line with what happened in the Central and Eastern European countries.

Vannutelli et al. (2022) analysed the reality of Italy and concluded that technology had an impact on the fact non-routine employees (high-skilled) earned more than routine employees (middle-skilled) and that, therefore, technology usage increased wage inequality.

Regarding the particular case of Portugal, Cardoso (1998) observed, by using the Gini coefficient, that among all the countries of Continental Europe in the 80s, Portugal is one of the countries that had more economic inequality. In addition, Machado & Mata (2005) and Pereira (2021) concluded that wage inequality was not the same throughout the wage distribution range. Between 1985-1995 and in the private sector, inequality grew at the bottom and the top of the wage distribution range, with a pronounced increase at the top. After 1995, it started to decline at the bottom of the wage distribution range. However, the top of the wage distribution range continued to increase, and finally, between 2005-2010 to 2017, wage inequality began declining at the top of the wage distribution range (Pereira, 2021).

In order to evaluate wage inequality in Portugal, Fonseca et al. (2018) analysed the progression in cumulative changes in wages, assessed by percentiles 90th, 50th, and 10th, applying the same reasoning as Acemoglu & Autor (2011). The authors observed a high increase in wage inequality in the 90s, when the higher wages increased a lot, and the middle and bottom wages had a slight increase. The logarithmic wage change by percentile for the first period, that is, before the 90s, and the second period, that is, after the 90s, was analysed. For the first period, an increase in inequality across the wage distribution range was identified. In the second period a U-shape curve was observed by the authors, in resemblance with the case of the US, where it confirms that from 1995 onwards wage polarisation occurred. Thus, by analysing the Gini coefficient and the Theil index, wage inequality displays an increase between 1985-2017 (Pereira, 2021). Moreover, Pereira & Galego (2015) analysed the situation of Portugal between 1995-2005 and performed a quantile decomposition method which was capable of determining that wage inequality increased in some regions of Portugal and decreased in others (heterogeneous wage inequality). The authors mentioned acknowledged that there was a lack of empirical research studying wage inequality in Portugal and other European countries.

There is substantial evidence in the literature regarding wage inequality over a very differentiated time spectrum, and for several countries, e.g., the US, Europe, and Portugal, the latter being the focus of this dissertation. In the case of Portugal, it is clear that these inequalities have existed over the years, more or less accentuated depending on the years being analysed, and with different trends in different regions.

2.1.2. Measuring Wage Inequality

Methodologies to measure wage inequality have also been identified in the literature. Pereira (2021) displayed the evolution of wage inequality in Portugal between 1985-2017, by applying the Gini coefficient of real hourly wages, which was also applied by Alesina & Rodrik (1994), for several countries, and Magda et al. (2021), for Central and Eastern European countries. Magda et al. (2021), used several methods to analyse wage inequality, such as the Theil index, the logarithmic wage gap differences, the 90/10 income inequality ratio or, as is mentioned in the literature, the decile dispersion ratio. Nevertheless, other ratios like the 80/20 and the 90/50 could be also applied and follow the same reasoning as the 90/10 ratio, which is calculated by dividing both percentiles to obtain a ratio. However, for example, the 90/50 ratio has a different meaning, compared to the 90/10 ratio, since it is evaluating the middle class compared to the wealthier class and not the extremes of the wage distribution range. Moreover, Sonora (2022), used two different wage inequality measurements to evaluate the relationship between energy consumption and income inequality in Italy. The author applied the Gini coefficient and the Palma ratio, the latter of which is evaluated by dividing the 10% richest by the 40% poorest.

Additionally, Magda et al. (2021) used the variance of logarithmic real hourly wages as a measure of wage inequality, which is stated by the authors to be a conventional statistical measure of dispersion and decomposable into between-firm and within-firm components. Barth et al. (2016, 2018) investigated, for the case of the US, the extent to which workers' wages rely on where they work. Barth et al. (2018) analysed the logarithmic wages of individual workers for nine US states between 1992-2007 and also decomposed the total variance of wages between-firms and a portion to variations in employees' wages within-firms. These decomposable analyses cannot be performed using a single index such as the Gini coefficient or the 90/10 ratio. Nevertheless, it has the disadvantage of hiding changes at the extremities of the wage distribution range, and so, Magda et al. (2021) decided to analyse other inequality measurements, as was previously stated. The alternative measurements mentioned, and the variance approach, showed a similar conclusion. However, different ways of measuring inequalities do not always lead to the same conclusions.

Pereira & Galego (2015) analysed wage inequality in different regions of Portugal between 1995-2005, using a quantile-based decomposition method inspired by Melly (2005). The authors refer that the quantile-based decomposition method has more advantages compared to the Gini coefficient and the Theil index measures, because it allows for the analysis of inequality across the entire wage distribution. Besides, single index measures can produce different inequality conclusions as they measure different parts of the wage distribution range (Pereira & Galego, 2015; Pereira, 2021), which is always something important to consider.

Moreover, Card et al. (2013) analysed the standard deviation of logarithmic wages, by observing the gap in logarithmic wages between the 80^{th} and 20^{th} percentiles, between the 80^{th} and 50^{th} percentiles, and between the 50^{th} and 20^{th} percentiles.

To review some of the methods mentioned in the literature and also to analyse other considerations mentioned by the OECD (2011), The World Bank, the US Census Bureau (2021a), and the US Census Bureau (2021b), we can use Table 1.

Table 1 *- Methods to measure inequality and the respective characterization.*

Method	Characterization
Theil Index	○ Developed by Henri Theil. Generalized entropy measure, that varies between 0 and infinite, where 0 represents an even distribution, and greater values correspond to a higher intensity of inequality.
Gini Coefficient	○ Developed by Corrado Gini. Analyses the area between the Lorenz curve and a uniform distribution. If there is not a variation, the coefficient equals 0 (perfect equality), although if they show a very large distance, the coefficient equals 1 (complete inequality). ○ Disregards the extremes of the wage distribution range and focus on the middle wage distribution. ○ Does not analyse demographic variations between subgroups within the wage distribution range.
Atkinson Index	○ Developed by Anthony Atkinson. Assesses the aversion to inequality. If it is sensitive to changes at the lower side of the wage range the distribution turns out to be near to 1. If inequality aversion falls to near 0, it is more sensitive to changes in the upper side.
Decile Dispersion Ratio	○ Ratio of the average wage of the richest 10 percent which corresponds to the 90th percentile and the poorest 10 percent which corresponds to the 10th percentile. ○ Articulates the wage of the richest as multiples of the poorest. ○ Simple and popular measure of inequality. ○ Disregards details about wages in the middle of the wage distribution range.
Percentile Ratio	○ The Palma ratio, which translates into the richest 10% divided by the poorest 40%. ○ Additionally, we have the 90/10, 80/20, 50/20 percentile ratios, along with others, which measure different parts of the wage distribution range.
Variance of Log Wages	○ Common statistical measure of dispersion, which is decomposable into the between-firm and the within-firm component. ○ Hides changes at the extremities of the wage distribution range.

2.1.3. Drivers of Wage Inequality

Several reasons have been found in the literature to explain the increased incidence of wage inequality. Firstly, automation was mentioned in the literature as one of the main causes of wage inequality (Acemoglu & Restrepo, 2020), and it was concluded that automation generates a positive productivity effect (Acemoglu & Restrepo, 2018). Furthermore, the data of the US since 1970 was analysed and it was concluded that automation is an important driving force to explain the changes in wage inequality throughout the years and it also contributed to lowering the real wages of low-skilled and high-skilled workers (Lankisch et al., 2019). However, Borrs & Knauth (2021) concluded that automation has no significant repercussion on the inequality of German industries and, besides that, causes a displacement effect for low-skilled workers, which corresponded to a decrease in inequality.

Secondly, technology, being a broader concept compared to automation, is mentioned as a very relevant component that changed the distribution of wages. Greiner et al. (2004) define, as main factors that have an impact on wage inequality, the rate of technological change, also defined by Juhn et al. (1993), and the technological spill-over effect, which happens when companies obtain indirect technological benefits from the technological development efforts of other companies. Moreover, for the United Kingdom, the main reason for wage inequality, between 1993-1998, was technological change; however, international outsourcing also contributed significantly (Hijzen, 2007). Winchester & Greenaway (2007) observed that technology was one of the main factors that caused wage inequality in the United Kingdom, between 1980-1997, and mentioned the interesting fact that the population was more willing to accept it as a cause of wage inequality compared to other reasons.

Coveri and Pianta (2022) analysed data for six European countries between 1994-2014 and also for 38 manufacturing and service sectors and realized that technology has a significant impact on the wages of workers and that. Additionally, offshoring, and international production seemed to have the same importance.

Returning to the US, between 1975-2008, Cavenaile (2021) observed that computerization and offshoring were key aspects that leveraged wages. More precisely, between 1975-1990, computers are distinctively the main reason. Since 1990, globalization (offshoring) turned out to be the main cause. The causes of increased wage inequality in the private sector, in the US between 1988-2012, are attributable in 44% to a decrease in unionization, in 15% to computer technologies and the remaining percentage has little expression (Kristal & Cohen, 2016). Also, between 1969-2012, the decrease in unionization and the minimum wage was responsible for a 50% increase in wage inequality and the increase in computer technology was responsible for an additional 28%. Between 1995-2010, Biewen & Seckler (2019) analysed the reasons behind the increase in wage inequality and concluded that other studies downplayed the de-unionization as a factor for the increase in wage inequality in Germany while the authors considered that it is the main factor for wage inequality. They also indicated personal characteristics, i.e., age and education, firm heterogeneity, and task changes as reasons for wage inequality.

Machado & Mata (2001) analysed wage distribution using quantile regressions for the case of Portugal between 1982-1994. They concluded that education positively affects wages in the whole wage distribution range. However, firm typology and their size can also influence wage inequality since bigger firms usually offer better salaries to workers with the same attributes. US workers experienced a substantial growth in wage variance in larger firms compared to smaller firms (Song et al., 2019). This was prompted by the decrease in the wage premium in large firms for median and lower wage employees and by increased wages for the top of the workforce.

Pereira (2021) verified that, in Portugal between 1985 and 2017, a period which saw changes in the wage inequality situation, there was a profound change in workforce constitution, with the main driving factors being the sharp increase in the average educational level, the increase in the average age level and also that there was a greater share of employed women.

It is possible to conclude that, besides technology and automation, other reasons that play an important role in the development of wage inequality are outsourcing, offshoring (globalization), unionization and de-unionization, personnel characteristics, age, education, firm heterogeneity, firm size, firm typology, and firm characteristics. There is a lot of information in the literature on this topic and many other reasons that may influence wage inequality can be found.

2.1.4. Firms, Industry, Occupations and Wage Inequality

Evidence shows that a significant share of the growth in inequality has happened at the firm-level, and so, it is very relevant to evaluate the workplace to investigate wage inequality. Abowd et al. (1999), confirmed the key importance of industry-level and firm-level wage differentials for the analysis of wage inequality. Also, Barth et al. (2016), found that for the US, an increase in the variation in average wages across firms justifies half of the increase in wage inequality from 1970 to 2000. Indeed, one factor that could impact wages and employment is the power that institutions have to define wages (Machin & Van Reenen, 1998).

An increase in wage inequality happened due to a boost in the dispersion of wages between firms in the US between 1970-2010 (Barth et al., 2016) . The firm-level characteristics performed a crucial role in establishing changes in wage inequality (Lemieux, 2007). Several authors affirmed that the increased heterogeneity between firms is an important factor to consider when searching for reasons for the increase in wage inequality (Barth et al., 2016; Card et al., 2013; Song et al., 2019).

Another reason that contributes to wage inequality are the changes in the labour market institutions (Lemieux, 2007), where the author refers that some estimates suggest that institutional changes can correspond to about one-third of wage inequality.

Krueger & Summers (1988) acknowledged that some firms could pay differently independently of both workers having the same skills, and the distribution of wages is affected by differences in wage premiums by firms. In fact, firm's wage premiums increased dispersion and the increase in diversity between employees has contributed to an increase in wage inequality in West Germany between 1985-2009 (Card et al., 2013).

Technological advancements could also affect the labour market and the organizational structure of firms, which could impact the labour market policies that also have an important role in wage distribution (Acemoglu, 2002). Lemieux et al. (2009) concluded that more companies are offering pay-for-performance contracts, which results in more wage inequality among workers who are paid for performance. Since technological changes can impact performance levels due to the productivity effect, pay-for-performance contracts could exacerbate wage inequality.

The impact of technological change on wage inequality in Indonesia, between 1990-2009, was analysed by Lee & Wie (2015) and it was concluded that between-industry and within-industry changes in labour demand benefited the high-skilled and simultaneously potentiated the increase of wage inequality. Kristal & Cohen (2016) analysed the situation in the US, both for between-industry inequalities and within-industry inequalities and concluded that an increase in inequality happens mainly within industries. Also, when analysing the situation in the United Kingdom, results clearly show that the majority of changes in employment and wages, and the movement towards skilled labour, occurred within industries, over the period of 1979 to 1990 (Taylor & Driffield, 2005).

To assess the technological impact and its effect on wage inequality it is important to consider the tasks and occupations assigned to the workforce. Their distinctions and particularities will be discussed in more detail in section 2.5. Autor et al. (2003) argues that to be able to recognize the effect of technical change, it is required to analyse the task objective for each identified occupation. Acemoglu & Autor (2011) also agreed that the task-based approach is recommended to analyse the relation of tasks with technology rather than simply analyse workers' skills.

2.2. Technology and Labour Market

2.2.1. Defining Skills, Tasks and Occupations

It is relevant to define what skills, tasks, and occupations are, how they are defined in the labour market and how to define the different occupations in categories that correspond to a set of tasks.

A task is a unit of work that generates an output, and it could be either services or goods. The skills of individuals are assigned to different tasks and those sets of tasks correspond to an occupation.

The relationship between education, skills, and technology, which translates into the rise of the skills premium and the conclusion that technological changes have increased inequality by changing the demand for different skill groups, has been widely studied in the literature and could be visualized in the well-known paper of Acemoglu & Autor (2011).

Regarding the tasks and occupations, Autor et al. (2003) defined a task model framework that facilitated the assignment of an occupation category to a group of tasks. Occupations were defined by the authors along two dimensions of the characteristics of performed tasks, namely analytic versus manual and routine versus non-routine. Five occupational groups were established, namely routine manual, non-routine manual, routine cognitive, non-routine analytical, and non-routine interactive task (Autor et al., 2003; Spitz-Oener, 2006). Also, the authors used the US Department of Labor's Dictionary of Occupational Titles (DOT) to study and assign to workers the task measures connected to their occupations. The successor of DOT is the Occupational Information Network (O*NET) used by Acemoglu & Autor (2011). Taking into consideration the O*NET framework, Acemoglu & Autor (2011) divided and classified the tasks into non-routine cognitive (analytical), non-routine cognitive (Interpersonal), routine cognitive, routine manual, and non-routine manual physical. Fonseca et al. (2018) depicted the O*NET descriptors in a more simplified way than Acemoglu & Autor (2011), differentiating between non-routine cognitive (abstract/analytical), routine cognitive, routine manual, and non-routine manual physical.

Cortes et al. (2020) have defined the same categories and went further to better analyse the STEM and non-STEM occupations, sub-dividing the non-routine cognitive category. With a different approach, Harrigan et al. (2021) aggregated occupations within broad categories that are meaningful in terms of the tasks and jobs they represent, i.e., business owners, professionals, managers, techies, other white-collar, office workers, unskilled workers, and service workers.

Some of the categories of skills, tasks, and the respective characteristics of occupations found in the literature, are summarized as shown in Figure 1.

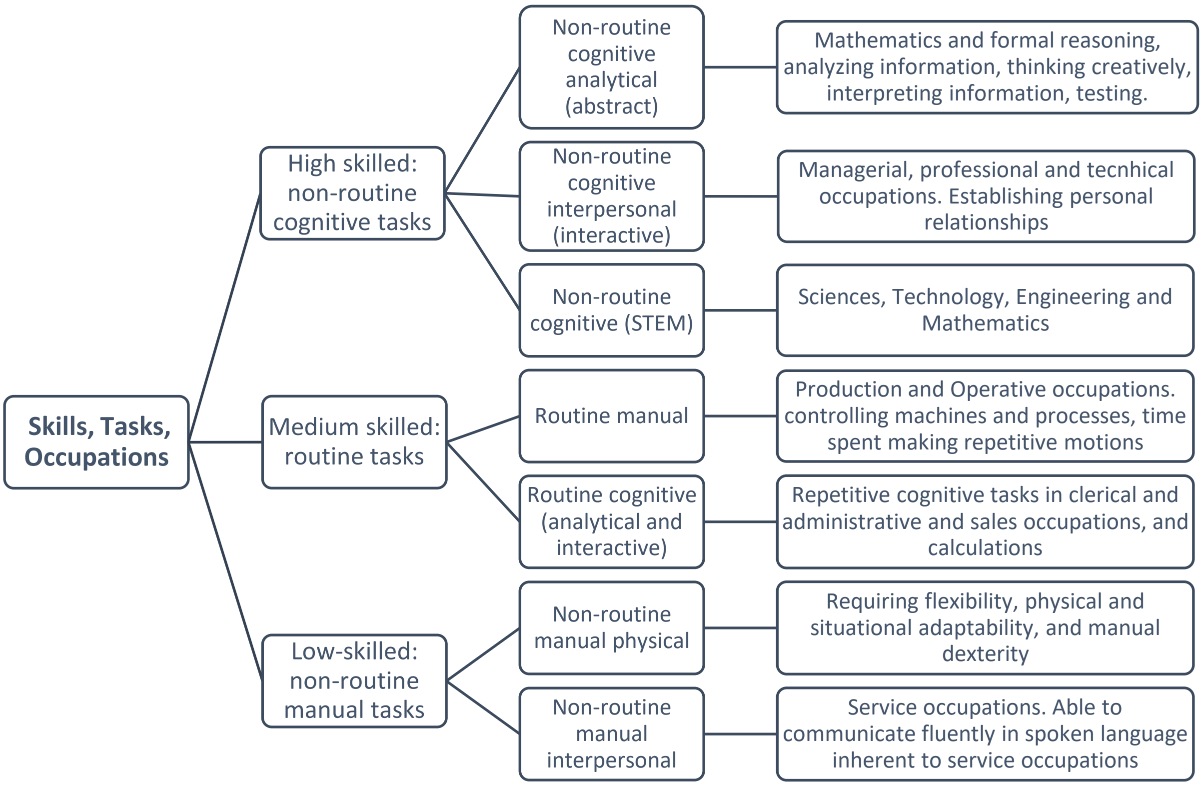

Figure 1 *- Skills, Tasks, Occupations.*

Figure 1 displays a combination of information compiled for this Dissertation, based on Acemoglu & Autor (2011), Autor et al. (2003), Autor & Dorn (2013), Cortes et al. (2020), Fonseca et al. (2018).

2.2.2. The Effect of Technology in the Labour Market

The evolution of technology is noticeable, both in terms of computerization and robotization, among other technological utilities. All these developments promote changes in people's daily lives, and in the labour market. Consequently, it is undeniable that technology has an impact in the labour market.

As was previously mentioned in section 2.3, technology was defined as one of the main factors that impact wage inequality. Two theories related to technological change were identified in the literature.

Technology can lead to the phenomena of SBTC (Skill-Biased Technical Change), where technology usage favours skilled over unskilled workers, which increases their relative productivity and the demand for skilled workers (Acemoglu & Autor, 2011). The SBTC theory was proven by Acemoglu & Autor, (2011); Autor et al., (2003, 2008). The authors stated that technology can have a factor-augmenting form, which can complement both high and low-skilled workers. Additionally, it can either decrease or increase wage inequality between certain types of workers with a set of particular skills. It was found that SBTC is a major contributing factor for increased wage inequality (Autor et al., 2008; Lee & Wie, 2015). Thus, Acemoglu (2002) concluded that the 20th century was driven by the SBTC because of the fast growth of the supply of skilled workers, which also saw their skill potentiated by complementary technologies, and that the change that was seen is not related to the rate of technology change, but, instead, the type of technologies that were implemented.

It was also concluded that SBTC increased the relative demand for skilled workers in the US and six OECD countries using a measure of technical change (R&D intensity) (Machin & Van Reenen, 1998).

Nevertheless, SBTC has some particular disadvantages, such as the impossibility of accounting for the increase in wages and demand for low-wage occupations, that is considered by many a relevant reason for the increase in wage and job polarisation (Acemoglu, 1998). Several authors do not agree that the SBTC theory is a driver of wage inequality. Beaudry & Green (2005) analysed the reasons that altered the wage distribution in the US between the years 1976-2000 and stated that SBTC is not a relevant reason for the alterations in wage distribution. Card & DiNardo (2002) also observed that SBTC is an intermittent theory, while, at the same time, computer technology and technological change, as well as wage inequality, have grown steadily in the analysed period. Lemieux (2006, 2007) considers that the extent and timing of the increase in residual wage inequality does not offer enough proof of widespread growth in demand for skills due to SBTC. Accordingly, compositional, and institutional alterations, such as de-unionization, and alterations in the minimum wage are referred to as the main causes for the increase in wage inequality (Card & DiNardo, 2002; Lemieux, 2006, 2007). Finally, it was stated that SBTC is not the primary reason for wage inequality in the US and that, instead, the reason was minimum wage's reduction in real value (Autor et al., 2016; Kristal & Cohen, 2016).

Additionally, as was possible to previously verify, automation that is driven by technological change is stated by some authors as one of the main factors that foster wage inequality among workers. Given this fact, it is important to understand the routinisation hypothesis theory. The notion of the routinisation hypothesis was firstly mentioned by Autor et al. (2003), and it consists of the reduction of routine tasks and the rise in non-routine cognitive tasks in the labour market. In addition, the routinisation hypothesis, was identified as the main factor responsible for the polarisation phenomena in Portugal between 1995-2007 (Fonseca et al., 2018), where an increase in employment and wage premium for jobs requiring non-routine cognitive tasks in detriment of routine tasks, was noticed. The author focuses his analysis on the wage premium.

Technological change also leads to a theory that is widely found in the literature, namely the Routine Biased Technological Change (RBTC), which is a technological based justification that impacts the labour market (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Goos et al., 2014; Goos & Manning, 2007). The RBTC theory argues that computers, robots, and technology have reduced the demand for routine and repetitive tasks and that these activities are concentrated on middle-wage workers (Acemoglu & Autor, 2011; Autor et al., 2003; Goos et al., 2009). Thus, RBTC has a polarizing effect on the labour market, promoting a U-shape of the occupational distribution (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Cortes, 2016; Goos et al., 2014). Autor & Handel (2013), for the reality of the US and Vannutelli et al., (2022), for the reality of Italy, explained how RBTC, which leads to job polarisation, also leads to wage polarisation. Vannutelli et al., (2022) concluded that there is a U-shaped wage gap between non-routine and routine workers, which is robust regardless of the various methodologies applied. However, Antonczyk et al. (2018), that performed an analysis for the case of Germany, concluded that, although it is noticeable that RBTC lead to job polarisation, it was not clear that the same happened in the case of wage polarisation.

Moreover, it is important to understand what effect routinisation might have in terms of wage inequality. Vannutelli et al. (2022), stated that workers that mainly perform routine tasks earn lower salaries when compared with workers that mainly perform non-routine tasks. The author uses the concept of RTI to draw those conclusions. Regarding the Portuguese reality, Fonseca et al. (2018) verified, using an employer-employee dataset from *Quadros de Pessoal*, that the regression results confirm that routinisation is the cause of the job market polarisation phenomenon. However, workers of the routine cognitive type do not seem to follow the same trend (wage premium level). Thus, it is possible to conclude that, the greater the routinisation (presence of the RBTC), the greater the wage inequality.

To evaluate the impact of technological change, it is necessary to understand ways of measuring technological intensity. Ang (2008) measured the technology intensity in Singapore and classified industries as high, medium-high, medium-low, and low technology-intensity based on rules created in 1997 by OECD (1997). These rules were built on the ratio of R&D expenses and embodied technology, where embodied technology stands for the indirect technology streams in the R&D processing.

Furthermore, Garcés-Galdeano et al. (2016) measured the technology intensity as a dummy variable that holds the value of 1 when the firm belongs to an industry classified as a medium-high or high-tech industry, and 0 if not. The authors took into consideration the nomenclature of the Spanish Bureau of Statistics to evaluate if an industry is high, medium, or low in terms of technology intensity.

Lepak (2003) measured the technological intensity by using capital intensity, research, and R&D indicators. The capital intensity was measured by dividing capital expenditure by sales and R&D intensity was measured by dividing total R&D expenditure by sales. Munier (2006) used OECD's rules of 1994, which measure the industrial technological intensity and rely on the intensity of the R&D (direct or indirect), and classified the industries as being high, medium-high, medium-low, and low.

Autor & Dorn (2013) and (Goos et al., 2014) introduced the routinisation task intensity (RTI) formula, which measures the routinisation task intensity of an occupation.

In addition to all that has already been mentioned, technological change is one of the factors found in the literature that can positively or negatively impact the gender wage gap. Cortes et al. (2020) analysed data from Portugal and the US and concluded that technological change is task-biased, where women's and men's jobs have different task content, and that it could translate into occupational segregation.

Moreover, in the US, between 1980-2000, it was identified that women have accelerated their cognitive and general skills acquisition comparatively to men's and that it, consequently, reduced the gender wage gap (Yamaguchi et al., 2016). Thus, Delaney & Devereux (2019) concluded that men have a higher incidence on STEM careers (Science, Technology, Engineering, and Mathematics) compared to women but that, however, a higher quantity of the gender wage gap happens in cases where both genders had chosen the same education and had similar performances. STEM jobs have benefited men more than women, regarding employment expansion and wage growth, in Portugal and the US, between 1985-2017 (Cortes et al., 2020).

Aksoy et al. (2021) used data from twenty European countries, between 2006-2014, and concluded that robotization increases the gender wage gap, and that this event can be exacerbated in countries that have a higher initial gender wage gap. Additionally, it was identified that is not necessarily true that the evolution of technological change can reduce the gender wage gap (Cortes et al., 2020). The authors mention that, for the period of 1985-2017, it was, in some cases, harmful to women or had almost no impact for both genders, and so, even though the employment structure may be more favourable to women, it does not mean that women experience a positive impact. On the other hand, some authors do not consider the contribution of technological change in the reduction of the gender wage gap (Blau & Kahn, 1997; Card & DiNardo, 2002). Therefore, it is clear that the literature is quite divided in topics related with the relationship that technology has with the gender wage gap.

2.2.3. Job Polarisation

Job polarisation has been identified in the literature in various countries and realities as well as in different time periods. A number of authors defined job polarisation as an occurrence where employment increased for the low-skilled and high-skilled occupations, while the middle-skilled occupations did not display the same trend (Acemoglu & Autor, 2011; Autor et al., 2003, 2006; Autor & Dorn, 2013).

Job polarisation was also identified in some European countries between 1993-2010 and it was also identified that in all the studied countries the medium-wage occupations showed a decline in the share of employment. However, the smallest decline was in Portugal (Goos et al., 2009, 2014). Which could indicate that the job polarisation phenomenon was not as pronounced in Portugal's case.

Spitz-Oener (2006) identified the event of job polarisation in West Germany and Michaels et al. (2014) analysed data between 1980-2004, for several industries from the US, Japan, and nine European countries, and also observed the existence of job polarisation. Lastly, for the years 1986-1994 and 1995-2007, Portugal seems to follow the same trend of job polarisation (Fonseca et al., 2018).

Job polarisation and its connection with technology adoption have been largely analysed and confirmed throughout the literature (Acemoglu & Autor, 2011; Autor et al., 2003; de Vries et al., 2020; Goos et al., 2009; Michaels et al., 2014; Spitz-Oener, 2006). More particularly, in the case of Europe between 1993-2006, Goos et al. (2009) indicated that technology importance is increasing for non-routine tasks and, consequently, there are more job opportunities for the high and low wage jobs. At the same time, middle wage jobs witnessed a downtrend in job availability. In the US it was identified that high-skilled workers are more prone to work on non-routine cognitive jobs while low-skilled workers usually work on non-routine manual jobs, and that this accentuates job polarisations (Cortes, 2016).

Cavenaile (2021) found that, between 1975-1990, computers are the main reason for labour market polarisation. Computerization can reduce routine manual tasks and cognitive routine tasks for the middle-skilled workers (substitution effect). Also, it can assume a complimentary role and can increase the demand for non-routine cognitive tasks (high-skilled) and non-routine manual tasks (low-skilled) (Autor et al., 2003, 2006; Goos et al., 2014; Spitz-Oener, 2006). Additionally, low-skilled workers moved from routine intensive tasks to service occupations, which are harder to automate (Autor & Dorn, 2013).

Furthermore, it was concluded that, in Portugal, and from 1995 to 2007, job polarisation and wage polarisation have happened at the same pace (Fonseca et al., 2018). Additionally, in the United States, wage polarisation seems to occur side by side with job polarisation (Autor et al., 2006).

3. Data Characterization

In this chapter, the behaviour of the data was analysed in order to obtain initial conclusions and characterize the dataset. The data characterisation section starts with the scope of the dataset (3.1) followed by the definition of the dataset variables (3.2), the formulation of the summary statistics (3.3), and finally the execution of the descriptive analysis (3.4).

3.1. Scope of the Dataset

To develop this dissertation, data was obtained from *Quadros de Pessoal*, a Portuguese longitudinal linked employer-employee dataset. This information is obtained by the Portuguese Ministry of Labour and Social Security through a mandatory national survey that happens every year. The *Quadros de Pessoal* dataset has information regarding the Portuguese private sector, and it considers firms with at least one paid employee. It excludes public administration, military, and self-employed workers. The sample dataset used for this dissertation covers a temporal interval between 2002 and 2017. It was decided to analyse the data from 2002 onwards, as it was in this year that the implementation of the Euro took place in Portugal, which caused significant structural changes in the economy and consequently in the salaries and labour market of the country.

The sample dataset has 76,000 observations that correspond to 12,066 firms. The dataset allowed us to follow the same identifier (NPC) at multiple points in time (2002-2017). Therefore, the design of the dataset is what is called longitudinal or panel data. However, it is unbalanced, since there are firms that close down throughout the years, and others that start activity after 2002.

The sample dataset corresponds to 5% of the total sample. We decided to consider this percentage since it is more computationally efficient, which raises fewer issues to properly analyse the data.

In the dataset there are 4,844 firms that never closed between 2002-2017. This number corresponds to 40.15% of the total number of firms. Therefore, 7,222 firms close between 2002-2017, which corresponds to 59.85% of total number of firms.

3.2. Variables Definition

The variables that should be considered are the ones that represent firms, workers, and technological characteristics, and that could lead to wage inequality. Regarding the characteristics of workers, several traits characterize them, such as gender, age, education level, tenure time, and the type of occupation or tasks, which are similarly defined by Autor et al. (2003), Acemoglu & Autor (2011) and Fonseca et al. (2018). Vannutelli et al. (2022), explained how much the average difference in wages between two groups (routine and non-routine) is related with worker characteristics like age, gender, education, and work experience. The authors also used firm characteristics like firm size, sector of economic activity (industry), skills and location, and job characteristics like the type of contract, job stress, job security, and training received last year.

Table 2 summarizes and describes the dataset variables used for the dissertation's analysis. The Gini coefficient and the 80/20 ratio are the dependent variables. The 20th percentile, 80th percentile, Abstract, Routine, Manual, Other Tasks and Firm Size variables were used to calculate the RTI and the 80/20 percentile ratio.

***Table 2** - Description of model variables.*

Variable	Description
Gini coefficient	Measures the dispersion of wages among the employees of the firm, goes from 0 to 1.
80/20 Ratio	Ratio that measures the dispersion of wage between the top 20% salaries of the firm and the 20% bottom salaries.
RTI	Routinisation Task Intensity by firm. Taking into consideration the four types of tasks.
Technological and Knowledge Intensity	Dummy variable that measures the technology intensity of an industry where a firm operates on, where 1 indicates high technology or knowledge intensity, 0 otherwise.
Others - Technological and Knowledge Intensity	Dummy variable that measures the technology intensity of an industry where a firm operates on, where 1 indicates the intensity of "Others", and 0 low technological or knowledge intensity.
Industry Code	NACE Code which corresponds to the firm's industry (dummy Variable).
Age	Average of firm's employee ages.
Education	Average of firm's employee level of education.
Tenure	Number of years in average that the employees worked at the firm.
Males	Percentage of males working at the firm.
Foreign Equity	Percentage of employees with non-Portuguese nationality.
FDI	Dummy variable, where 1 indicates that the firm has Foreign Direct Investment (FDI), 0 otherwise.
Top 3 Hierarchy	Percentage of employees at the firm's hierarchy top three positions.
Plants	Number of plants owned by the firm.
Salary	Average gross monthly salary in the firm.
20th Percentile	Corresponds to 20% of the lowest average salaries at the company.
80th Percentile	Corresponds to 20% of the highest average salaries at the company.
Abstract	Percentage of employees that perform Abstract tasks.
Routine	Percentage of employees that perform Routine tasks (Cognitive & Manual).
Manual	Percentage of employees that perform Manual tasks.
Other Tasks	Percentage of employees that perform a task that is neither Abstract, Manual or Routine.
Firm Size	Number of all the employees that work at the firm.

3.2.1. Gini Coefficient and the 80/20 Ratio

The Gini coefficient analyses the area between the Lorenz curve and the uniform distribution. If there is no difference between the curves, the coefficient equals 0 (perfect equality). If the Lorenz curve and the uniform distribution show a very large gap, the coefficient equals 1 (complete inequality). In other words, when the index equals 0 it represents perfect equality, where each employee's payment share is the same; whereas 1, corresponds to perfect inequality, where one of the employees receives all the income distributed by the firm (US Census Bureau, 2021a). Conducting this analysis, it is possible to obtain a measurement of the wage inequality within each firm.

For the specific case of this dissertation, the Gini coefficient can be graphically represented by the Lorenz curve, which can define wage distribution by specifying the proportion of all the employees of the firm on the horizontal axis and the cumulative wages on the vertical axis. This representation can be visualized in Figure 2. The line of perfect equality assumes, by definition, the value of 0.5 (U.S. Census Bureau, 2021).

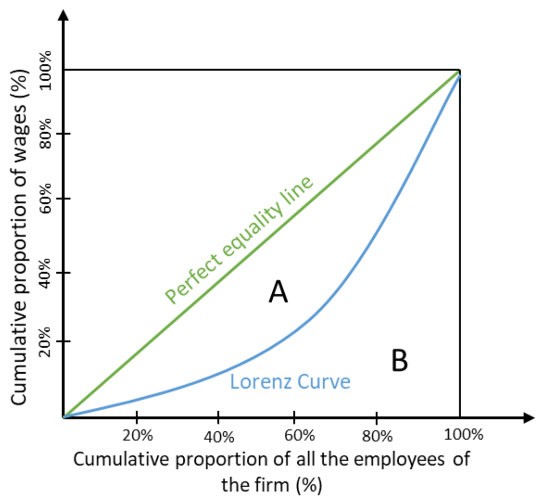

Figure 2 *- Graphical representation of Gini coefficient (firms).*

The formula to calculate the Gini coefficient is shown below (1):

$$Gini\ coefficient = \frac{A}{A+B} \tag{1}$$

By having access to the Gini coefficient data of each company, which is based on the wage distribution of its employees, it is possible to ascertain the inequality/equality present within each firm.

The 80/20 percentile ratio, which is another way to measure wage inequality will also be used. The 80/20 percentile ratio is obtained by dividing the 80th percentile of wages (top 20%) by the 20th percentile of wages (bottom 20%). In other words, we divide the average ratio of workers that earn more by the average of workers that earn less. However, it disregards details about wages in the middle of the wage distribution range, and so, can be used as an inequality analysis alternative to the Gini coefficient, since the latter concentrates its analysis on the middle wage or income distribution range as has been stated by multiple authors, e.g., Asongu et al. (2019), Pereira (2021) and, Sonora (2022). Another alternative that could be studied is the 90/10 percentile ratio. However, since it only considers the extremities of the wage distribution range and, therefore, covers a smaller percentage, it is considered an extreme inequality analysis. For that reason, the 80/20 ratio seems more suitable and a rather balanced analysis.

3.2.2. Routinisation Task Intensity (RTI)

To measure the intensity of routinisation, the literature proposes the Routine Task Intensity, presented by Autor & Dorn (2013) and used by Goos et al., (2014), to rank the occupations by the highest and lowest routine intensity. RTI is considered by many in the literature to be a strong indicator to measure the level of routinisation and the most significant indicator to measure the presence of RBTC in the labour market. The formula defined to measure the routine task intensity by occupation, that was implemented by Autor & Dorn (2013), is represented by equation 2:

$$RTI_k = \ln\left(\mathrm{T_{k,year}}^{\mathrm{R}}\right) - \ln\left(\mathrm{T_{k,year}}^{\mathrm{M}}\right) - \ln\left(\mathrm{T_{k,year}}^{\mathrm{A}}\right) \qquad (2)$$

Each argument between brackets corresponds respectively to the routine, manual and abstract task inputs (T_k^R, T_k^M, T_k^A) and “k” represents the occupation in a “year”. The author linked tasks to occupations and produced an aggregated categorization of three task types, i.e., manual, routine, and abstract (Autor & Dorn, 2013).

The formula that defines the routinisation task intensity of a firm considers employees and type of tasks that they perform can be defined in equation 3:

$$RTI_{F\ year} = \log\left(E^R{}_{F\ year}\right) - \log\left(E^M{}_{F\ year}\right) - \log\left(E^A{}_{F\ year}\right) - \log\left(E^O{}_{F\ year}\right) \qquad (3)$$

Each argument between brackets corresponds respectively to the number of employees working on a routine, manual and abstract occupation (E_F^R, E_F^M, E_F^A) for each firm (“F”) in a year. Besides abstract, routine and manual tasks, there is another category that contains all the other tasks and is represented by (E_F^O) . The higher the RTI, the higher the company's routinisation and, the lower the routinisation value, the lower the company's routinisation. This reasoning is similar to the one employed by Fonseca et al., (2018), in which the authors calculated the share of employees in each type of task at the start of the time period.

The RTI (routinisation) measures the impact of technology because the evolution of the latter causes tasks to become more routinary and consequently it is possible to evaluate the technological change that a certain firm could experience in the form of routinisation.

3.2.3. Industry Code and Technological or Knowledge Intensity (Industry)

The code that classifies the industry in which the firm is categorized can be visualized in Table 3. This categorization is part of the NACE code (*Eurostat*, 2023), which is the industry standard classification system applied in the European Union. Thus, the industry code variable assumes the value of 1 or 0 (dummy variable), in order to identify the industry to which a certain firm belongs.

Table 3 - *Industry Code Descriptions.*

Industry Code	Description
A	Agriculture, Forestry and Fishing
B	Mining and Quarrying
C	Manufacturing
D	Electricity, Gas, Steam and Air Conditioning Supply
E	Water Supply; Sewerage; Waste Management and Remediation Activities
F	Construction
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles
H	Transporting and Storage
I	Accommodation and Food Service Activities
J	Information and Communication
K	Financial and Insurance Activities
L	Real Estate Activities
M	Professional, Scientific and Technical Activities
N	Administrative and Support Service Activities
O	Public Administration and Defence; Compulsory Social Security
P	Education
Q	Human Health and Social Work Activities
R	Arts, Entertainment and Recreation
S	Other Services Activities
U	Activities of Extraterritorial Organizations and Bodies

We can classify firms into two categories according to the knowledge or technology intensity of the industry in which they operate. For this we used the Eurostat classification, based on the NACE codes. In the category of high knowledge or technology intensive firms we include high-tech and medium-tech manufacturing, as well as KIS (Knowledge Intensive Services). In the category of lower knowledge/technology intensive firms we include medium-low, low tech manufacturing, and LKIS (Less Knowledge Intensive Services). The "Other" category includes firms in industries that do not match any of these classifications. Table 4 summarises this classification.

Table 4 - Aggregation by NACE Rev.2 of the indicators on High-Tech industry and KIS/LKIS.

Technological or Knowledge Intensity	Eurostat indicators on High-Tech Industry and Knowledge-Intensive Services
High	High-Tech Manufacturing Medium-High-Tech Manufacturing High-Tech Knowledge-Intensive Services Market Knowledge-Intensive Services Financial Knowledge-Intensive Services Other Knowledge-Intensive Services
Low	Medium-Low-Tech Manufacturing Low-Tech Manufacturing Market Low-Knowledge-Intensive Services Other Low-Knowledge-Intensive Services
Other	Industries that do not fit in any other category

3.2.4. Age, Gender, Education, Tenure and Foreign Equity

The age value corresponds to the average age of the firm's employees. The observations that presented a value between 0 and 18 were deleted (7 observations). The minimum age to start working is 16, but even so, only under certain rules. So, observations below 16 years old were deleted, which corresponds to 6 observations. A company with an average age of employees between 16 and 18 did not seem reasonable and, for that reason, one observation was also removed. Throughout the literature, the age variable is usually limited between 18 and 64 (Vannutelli et al. 2022), which depends on the retirement age in each country. In Portugal, in 2017, the retirement age was around 66, consequently, this is the age limit that is going to be applied.

Firm employees' gender is quantified through the percentage of men working at the firm, with the remaining percentage corresponding to the percentage of women working at the firm. Additionally, education levels can be defined as level 2, corresponding to the 3rd basic education cycle, level 3, corresponding to the secondary education, level 4, corresponding to the secondary education obtained through double certification pathways, level 5, corresponding to post-secondary non-tertiary level qualification, level 6, corresponding to a bachelor's degree, level 7, corresponding to a master's degree, and finally level 8, that corresponds to doctoral degree (DGES - Direção-Geral do Ensino Superior, 2022).

Tenure corresponds to the average period that employees have worked in the firm, measured in years. The age to start working, considering the definition of age previously mentioned, is 18 years old, and at most, an employee works until the age of 66. Consequently, working more than 48 years at the same firm is not plausible. Accordingly, we deleted all observations presenting a value greater than

48 years, i.e., 31 observations. The observations with a tenure of 0 were kept, corresponding to a company that has started its activity and therefore does not have workers with more than 0 years of service, or most of the workers left the firm and the company hired new ones.

The percentage of foreign workers represents the percentage of the firm's workers that do not have the Portuguese nationality.

3.2.5. FDI and Top 3 Hierarchy

The FDI variable is a dummy variable that takes the value of 1 if there is foreign capital invested in the firm, and 0 otherwise.

Quadros de Pessoal identifies each workers' position in the company's hierarchy, in eight distinct levels. The classification reflects the type of tasks performed at the company, the degree of responsibility, and the qualifications of the worker. The top 3 hierarchy variable represents the percentage of workers that are in the top three positions in the firm's hierarchy.

3.2.6. Salary

The values obtained for wages correspond to the average monthly wage of the firm's employees for that year (gross wage). The elements of wages that were considered are the base salary and regular bonuses. Irregular bonuses were not included. The wages data represents all types of contracts, such as full-time, part-time, traineeship, and others. In the case of Portugal, there used to be unpaid traineeships, which may lead to workers being paid the value of zero.

3.2.7. Tasks

The type of tasks that are performed by employees can be visualized in Table 5, and they could be categorized as manual, abstract, and routine tasks.

Table 5 *- Description of each defined task.*

Tasks	Skills	Decomposition of type of task	Description
Abstract	High-skilled	Non-routine cognitive analytical (abstract) or non-routine cognitive interpersonal	Formal reasoning, analysing information, thinking creatively, testing, managerial, and technical occupations. Establishing personal relationships.
Routine	Medium-skilled	Routine Manual or Routine Cognitive	Production and operative occupations, controlling machines and processes, time spent making repetitive motions. Repetitive tasks in clerical, administrative and sales occupations.
Manual	Low-skilled	Manual physical or Manual Interpersonal	Requiring flexibility, physical and situational adaptability. Service occupations, able to communicate, fluent in spoken language.

3.3. Descriptive Analysis

This section analyses and describes the dataset, performing a descriptive analysis of the variables defined in section 3.2. Most of the analyses carried out during the descriptive analysis are limited to one observation per firm. It was decided to apply this approach because firms that exist in larger quantities in the dataset, i.e., firms that function for larger periods of time, can make the conclusions and analysis biased towards older, more successful, firms. Analyses, that take into consideration the evolution over time, were analysed taking into consideration the whole sample.

3.3.1. Gini Coefficient

Figure 3 shows the density distribution of the Gini coefficient variable, where it considers the last observation of each firm. It is possible to visualize that between 0.2 and 0.3, which accounts for significant equality within the firms, there is a relative high density of observations. Between 0.3 and 0.4, which corresponds to reasonable equality, is where most of the observations of the sample are found. Furthermore, between 0.4 and 0.5 which corresponds to large wage inequality, some prevalence of observations can be observed, however much less significant. Between 0.5 and 0.6, there are no observations. However, approximately between 0.6 and 0.7, which represents severe wage inequality, there is a marginal number of firms. It is possible to conclude that most of the firms present low to moderate inequality, i.e., values for inequality are between 0.2 and 0.4.

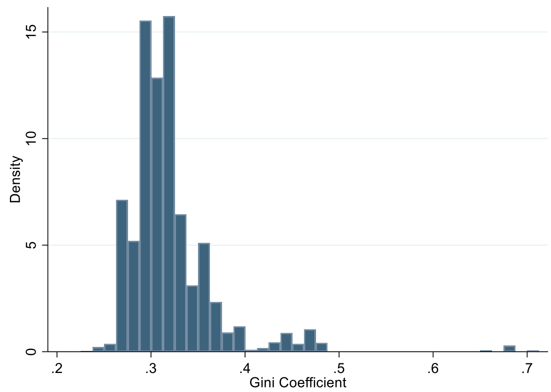

***Figure 3** - Density histogram of Gini coefficient variable (last observation of each firm).*

“Routine companies” were defined as those that present an RTI value higher than the average of the RTI variable, and “non-routine companies” are those that present an RTI value lower than the average of the RTI variable (Vannutelli et al., 2022). It is possible to visualize in Figure 4, that in all the analysed period, except in 2013, “routine companies” presented a higher inequality, when compared to companies defined as non-routine, which is consistent with the literature, where it has been found that workers performing routine tasks display a higher level of inequality. Thus, firms that have more workers performing routine tasks also have a higher level of wage inequality.

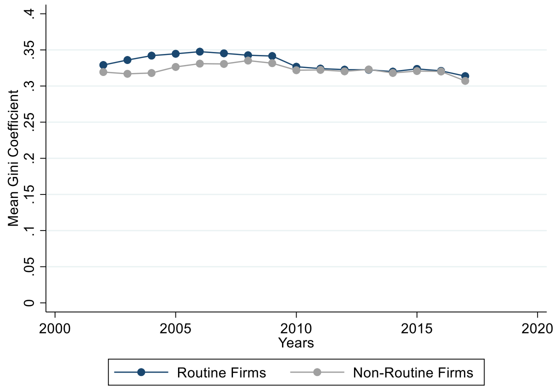

***Figure 4** - "Routine" and "Non-Routine firms" versus the mean of the Gini coefficient, between 2002-2017 (whole sample).*

3.3.2. Tasks and the Routinisation Task Intensity

In Figure 5 we can see that the sample suggests that between the years 2002 and 2005 there was a higher percentage of workers in routinary tasks in Portugal and that this trend slightly decreases from 2005 onwards. From 2005 to 2009 there were more workers performing manual tasks, but only with a slight difference in relation to routinary tasks. However, from 2009 onwards, there is a considerable decrease in manual tasks, until 2017, where routinary tasks prevalence increased slightly. In contrast, between 2002 and 2017, abstract tasks increased very slightly, with the variation ranging approximately from 12% to 18%.

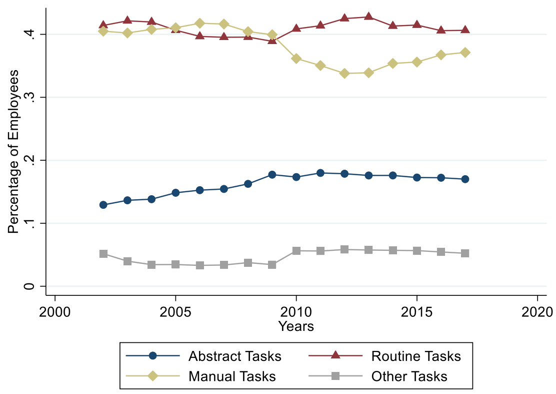

***Figure 5** - Percentage of employees for each type of task, between 2002-2017 (whole sample).*

Regarding the RTI variable, most of the firms display a RTI between -5 and 0, followed by 0 and 5, as we can observe in Figure 6. Thus, between -10 and -5, it is possible to visualize a low density. The sample dataset has a higher number of firms with a lower routinisation, between -10 and 0.

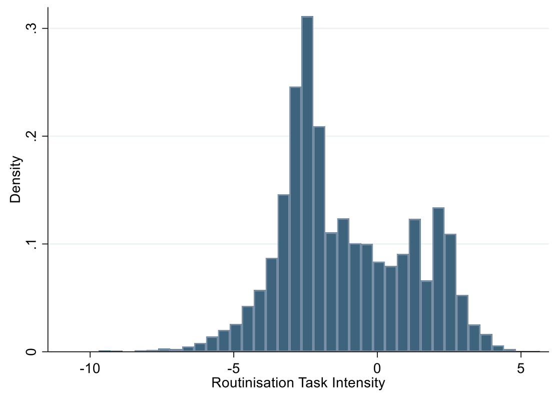

Figure 6 *- Density histogram of the RTI variable (last observation of each firm).*

In Figure 7, the average routinisation for the Gini coefficient range of 0.2-0.3, corresponds to the lowest, -1.58, which means that for the firms where inequality is lower, routinisation on average is also lower. For the case where the Gini coefficient is higher than 0.6, which is already considered high inequality, it represents the highest average routinisation in the firm. For the intermediate Gini coefficient intervals, the values do not present a pattern. The pattern is only visible by analysing the extremities of the Gini coefficient. Between 0.3 and 0.4, where it is possible to analyse reasonable equality, the routinisation values are the second interval with more routinisation. On the other hand, the values between 0.4 and 0.5, have the second lowest routinisation value. Therefore, the most interesting conclusions are found at the extremities of the inequality spectrum, where more routinisation corresponds to more inequality. And that less routinisation corresponds to less inequality.

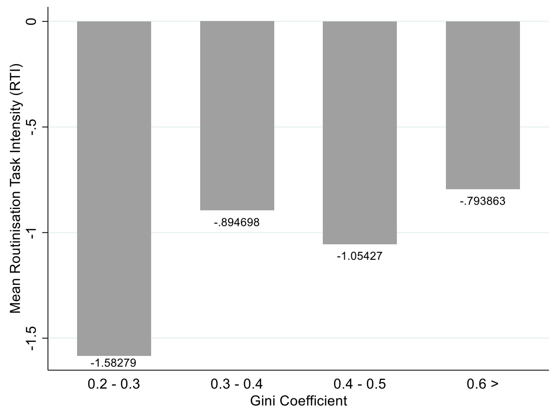

Figure 7 *- Bar chart of the mean RTI versus the Gini coefficient (last observation of each firm).*

3.3.3. Technological Intensity in Industries

In Figure 8 we can observe that firms that are in industries that have the highest Gini coefficient and consequently higher inequality are the high technological or knowledge intensive ones. This suggests that the higher the technological or knowledge intensity of a firm, the greater the inequality within that firm. However, the difference in inequality between the low tech/knowledge intensive industries and the high tech/knowledge intensive industries, is low. Firms with an RTI higher than the average are considered high, the remaining are considered low.

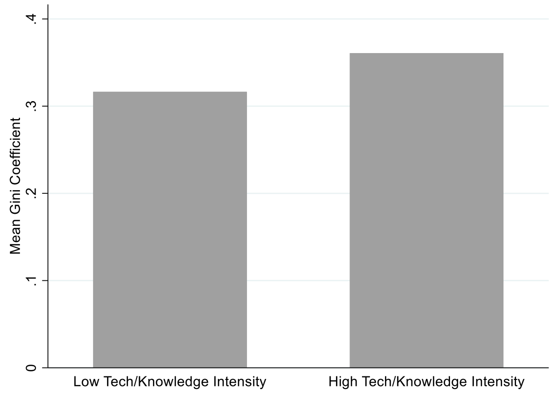

Figure 8 *- Bar chart of the technology intensity of industries by Gini coefficient (last observation of each firm).*

3.3.4. Employee Characteristics

As was previously mentioned, employee characteristics such as age, gender, education, and nationality are important characteristics to consider when evaluating wage inequality.

Age

In Figure 9 it is possible to observe that the age range that has more prevalence in the sample is 35 to 45 years, approximately. The histogram follows a normal distribution, with the values at the centre displaying a higher tendency.

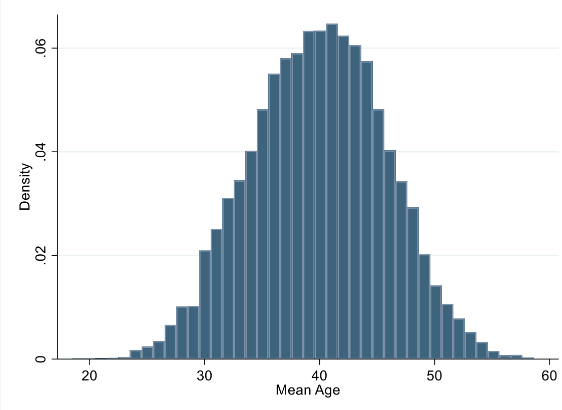

Figure 9 *- Density histogram of the Age variable (last observation of each firm).*

Also, it is possible to visualize in Figure 10 that workers with a higher routinisation index are younger when compared to the older workers. The relationship between the Gini coefficient and the age of workers does not display any particular tendencies.

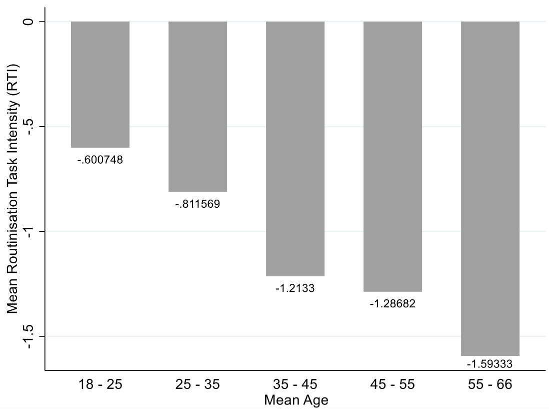

Figure 10 *- Distribution of age by the routinisation task intensity (last observation of each firm).*

Gender

Figure 11 shows that firms with more employed women, with respectively 60%, 70%, 80% and 90% of prevalence, have a lower routinisation index, when compared with firms which employ more men. There is therefore a substantial difference between the two genders when considering the routinisation of the tasks that both perform.

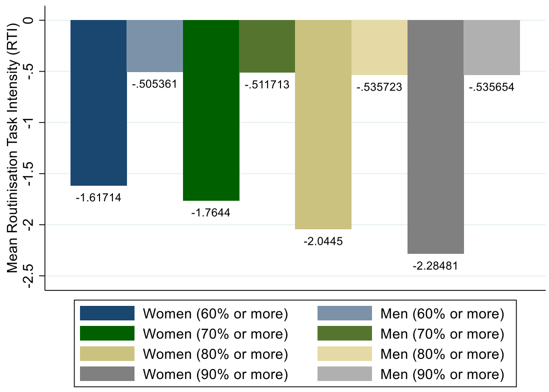

Figure 11 *- Bar chart of the routinisation by gender for different percentages of gender (last observation of each firm).*

Education

Most companies' employees have an average education level between 1 and 2, followed by level 2 and 3, and finally, level 3 and 4. The sample presents a considerably low level of average education. Figure 12 shows that, as the average level of education rises, average wages also rise. Each point of the graphic represents the mean of each year.

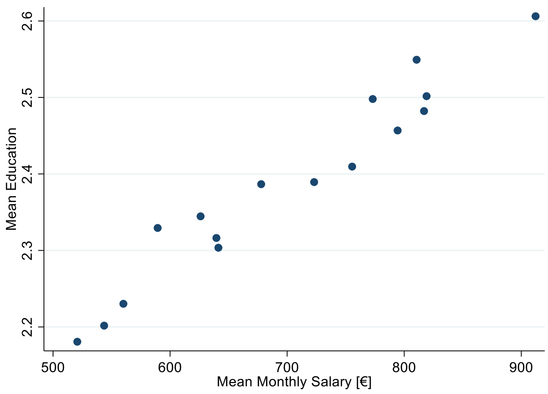

Figure 12 *- Mean Education by Mean Salary (last observation of each firm).*

Regarding the relation between education and the routinisation index, in Figure 13 we can observe that the highest average level of education has a lower routinisation index, and that the higher routinisation index corresponds to education levels 2 and 3. Figure 13 indicates an obvious conclusion, namely that the more an individual studies (firms with higher levels of education) the more he/she is expected to work in jobs that are less routinized and that require more cognitive ability.

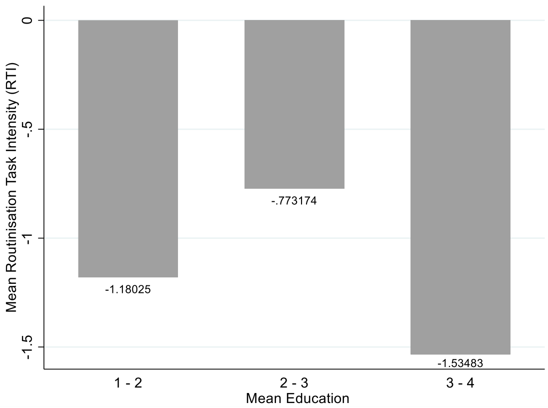

Figure 13 *- Bar chart of the routinisation task intensity by education level (last observation of each firm).*

3.3.5. Salary

Figure 14 shows that both the 10th percentile, the 90th percentile, the average wage and the median wage have increased over the years. However, from 2011 onwards, the increase stops and stagnates. The 10th percentile in 2017 reached an average salary of 500€/month, while the 90th percentile is around 1400€/month. In terms of average and median, it is close to 1000€/month.

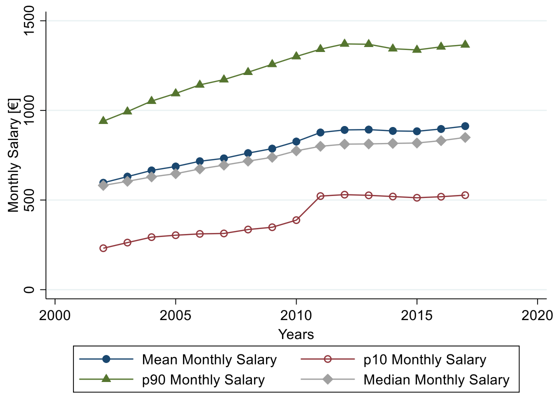

Figure 14 *- Tendency of monthly salaries in terms of percentile 10, 90, mean and median for each year (whole sample).*

Figure 15 shows that most firms (4,797) pay their workers on average between 500 and 750 euros per month. This trend is in line with the fact that, in Portugal, there is a large number of workers earning the minimum wage, that varies between 406€/month and 649€/month (2002-2017) (*Eurostat*, 2022).

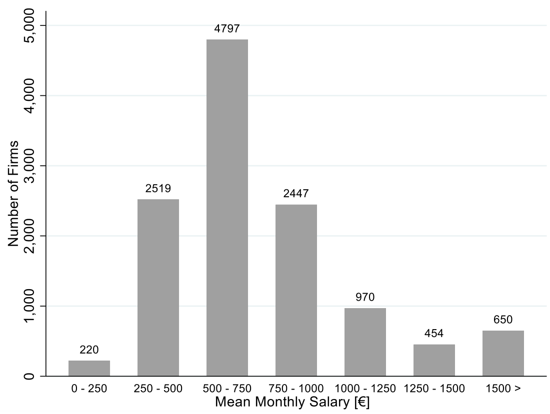

Figure 15 *- Bar chart of the distribution of firms per different salary intervals (last observation of each firm).*

3.3.6. 80/20 Percentile Ratio

A brief descriptive analysis of the 80/20 percentile ratio variable was conducted. The dependent variable, 80/20 percentile ratio, is mostly distributed at a lower value, showing several values that are considered outliers. To achieve a better behaviour, we applied the logarithmic function, and the results can be visualized in Figure 16, where they are right-skewed. However, no extreme outliers are depicted. There is a higher quantity of observations between 0 and 1, followed by 1 and 2. Analysing the interval between 0 and 1, it is possible to see that there is a higher density closer to 0. When approaching the value of 1 the density starts to drop considerably.

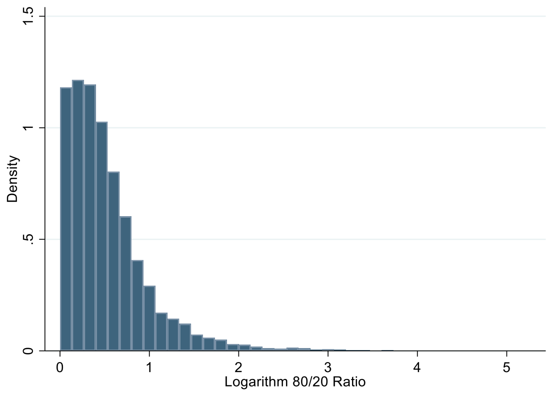

Figure 16 *- Density histogram of Log 80/20 Ratio variable (last observation of each firm).*

It is possible to visualize in Figure 17, that in all the analysed period, "non-routine firms" presented higher inequality when compared to firms defined as "routine firms", which is the contrary conclusion when comparing with the Gini coefficient inequality measurement. The conclusion is distinct from what has been found and analysed in the literature, since it was observed that the higher the routinisation the higher the wage inequality. This is also an indication that both inequality measurements lead to different conclusions.

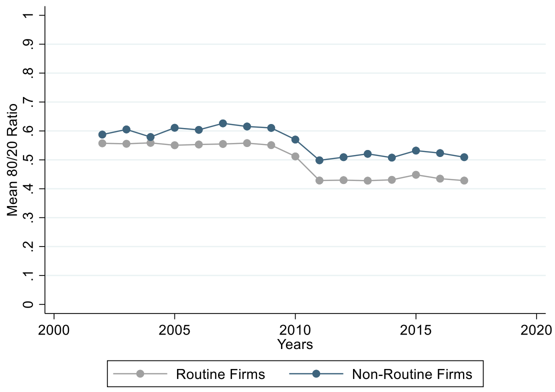

Figure 17 *- "Routine" and "Non-Routine firms" versus the mean of the 80/20 ratio, between 2002-2017 (whole sample).*

3.4. Summary Statistics

Table 6 presents the descriptive statistics of the main variables under analysis. From the initial data sample, we deleted a total of 38 observations. Therefore, the final dataset is composed of 75,962 observations, that correspond to 12,057 firms. In order to analyse the statistics summary, we only considered the last observation of each firm, since, by accounting all the observations, the outcomes would become biased. The bias occurs because firms with a higher number of observations would have a higher impact on the average, and the reason for those firms to be prevalent throughout the years could be because of the success that they had throughout time.

Firstly, when we analyse Table 6, we see that the Gini coefficient has a mean of 31.98. This shows that, on average, the firms present in the dataset have a reasonable wage equality and, also, that the standard deviation, which equals 4.74 (almost 15% of the mean), corresponds to a considerable variation around the mean. Finally, we also observe that the minimum value present on Table 6 is 21.27 and the maximum value is 71.25. It is important to refer that the Gini coefficient was multiplied by 100, in order to achieve higher values when running the regressions. For that reason, the analysis is going to be performed in percentage points.

The logarithmic 80/20 percentile ratio displays an average value of 0.5302 and a standard deviation of 0.4735. Thus, the minimum value corresponds to 0 and the maximum value corresponds to 5.33, which, considering that the average value is 0.5302, demonstrates that most of the firms have a lower wage inequality. Also, since the standard deviation is around 5.49, this indicates that probably there are some outliers, and, for that reason, the values are not so spread out around the mean. The RTI value has an average value of -1.14, with a standard deviation of 2.30. The minimum value corresponds to -10.94 and the maximum to 5.66.

The mean values of the different industrial technological and knowledge intensity categories can be also visualized, and it is possible to conclude that the market LKIS (Less Knowledge Intensity Services), other type of industrial intensity, and low-tech manufacturing, have the highest number of observations. This conclusion was reached because, for categorical variables, the mean represents the proportion of firms in each category. These categories also display a larger standard deviation which means that a large portion of the data is not clustered around the mean. The industries that display a higher technological/knowledge intensity have a lower standard deviation, and therefore, most of the data is clustered around the mean.

Additionally, the average age of employees is 39.89 years, and the maximum age is 58.64. In terms of level of education, the sample falls between levels 2 and 4, which corresponds to the 3rd cycle of basic education and to the senior high school, respectively. The education level mean is 2.46, and it does not display a higher standard deviation, corresponding to 0.75, which means that the values are pretty much around the mean.

The average length of employment (tenure) is 6.22 years, with a standard deviation of 5.61, which translates into a slightly high standard deviation. The smaller value encountered is 0, which could translate into firms that do not hold employees long enough, i.e., employees stay for less than 1 year; or it could just mean that, for example, the company has started operating recently. Finally, the maximum encountered value is 47.6.

Additionally, in terms of gender, 40.74% corresponds to the male sample. Consequently, the percentage of women corresponds to an average of 59.26%, corresponding to a larger quantity of women. It displays a considerable standard deviation of 32.00%.

The FDI assumes a value of 0 or 1, has a mean value of 0.04, and a standard deviation of 0.20. Since FDI is a dummy variable, the value represents the proportion of firms that practice FDI and, consequently, since the FDI variable displays a low mean, there are a lot of firms in the dataset that do not practice FDI. The average percentage of foreign employees is 1.90%, which implies that a lot of firms have no foreign employees. The same reasoning occurs with the variable of the top 3 hierarchy, which has a mean value of 5.50%. The number of plants a firm holds has an average value of 1.58, and a standard deviation of 3.13, the minimum value is 1 and the maximum value is 148.

The average monthly wage corresponds to 768.66€, and its minimum and maximum, ranges from 5.65€ to 17,075.54€. Also, the standard deviation equals 482.65€, which suggests moderate variation around the mean. The mean of the firm size equals 30.76 and has a minimum of 10 and a maximum of 7,604 employees, and also has a high standard deviation, 108.67. It might be feasible for a firm to exist with 10 employees, if considering small firms, such as start-ups, therefore it has been considered.

In terms of the tasks that the employees perform it is possible to visualize that for routine tasks the mean is 35.77%, for manual tasks it is 41.59%, for abstract tasks it is 15.45%, and for other tasks it equals 7.20%. It is important to note that the standard deviation for all the different types of tasks is high, corresponding to 34.29% to routine tasks, 35.86% to manuals tasks, 21.41% to abstract tasks, and 16.14% to other tasks.

Finally, the number of firms that closed down between 2002-2017, corresponds to 7,246 firms, which translates into 60.10% of the firms in the dataset.

***Table 6 -** Summary statistics for the main variables.*

Variables	Mean	Standard Deviation	Min	Max
Gini coefficient [x100]	31.98	4.7	21.27	71.25
Log 80/20 Ratio*	0.530	0.474	0	5.33
RTI	-1.14	2.30	-10.94	5.66
High-Tech Manufacturing	0.002	0.046	0	1
Medium-High-Tech Manufacturing	0.019	0.137	0	1
High-Tech KIS	0.017	0.129	0	1
Market KIS	0.053	0.224	0	1
Financial KIS	0.008	0.090	0	1
Other KIS	0.093	0.290	0	1
Medium-Low-Tech Manufacturing	0.061	0.238	0	1
Low-Tech Manufacturing	0.161	0.367	0	1
Market LKIS	0.341	0.474	0	1
Other LKIS	0.019	0.137	0	1
Other Type of Industrial Intensity	0.227	0.419	0	1
Age [years]	39.89	5.84	18.5	58.64
Education	2.46	0.75	1	4
Tenure [years]	6.22	5.61	0	47.6
Males [%]	40.74	32.00	0	100
FDI (Dummy Variable)	0.04	0.20	0	1
Foreign Equity [%]	1.90	10.35	0	100
Top 3 Hierarchy [%]	5.50	15.91	0	100
Plants	1.58	3.13	1	148
Monthly Salary [€]	768.66	482.65	5.65	17,075.54
Percentile 20^{th} – Monthly Salary [€]	546.51	300.43	0	4,275.92
Percentile 80^{th} – Monthly Salary [€]	963.87	666.58	0	16,366.55
Routine Tasks [%]	35.77	34.29	0	100
Manual Tasks [%]	41.59	35.86	0	100
Abstract Tasks [%]	15.45	21.41	0	100
Other Tasks [%]	7.20	16.14	0	100
Firm Size	30.76	108.67	10	7,604
Number of Observations				75,962
Number of Firms				12,057
Firms that closed between 2002-2017				7,246
Firms that closed between 2002-2017 [%]				60.10%

- Statistics computed using the last observation of each firm. For categorical variables the mean represents the proportion of firms in each category.

* The dependent variable has a total of 72,360 observations instead of 75,962 since the division between the 80^{th} percentile and the 20^{th} percentile leads to values of 0. Since the logarithm of 0 is not defined, those observations were removed from the analysis. The total of firms equals 11,473.

4. Methodology

In this chapter, we define the methodology that will be applied to the previously mentioned data. As was previously explained, the dataset design corresponds to an unbalanced panel or longitudinal dataset. Several econometric methods can be applied to find a relationship between wage inequality and routinisation. It is therefore necessary to analyse which independent variables have an influence on the dependent variable, which is the wage inequality measurement. For this purpose, we defined distinct econometric models that are going to be applied to the data previously characterized in section 3.

All the topics mentioned in this chapter were studied and analysed in (M.Wooldridge, 2018a) for the Pooled OLS, Fixed-Effects, and Random-Effects methods and in (M.Wooldridge, 2018b) for the interaction terms method.

By studying the literature that measured wage inequality relation with other issues apart from technology, we concluded that the authors often used the fixed effects method, for example, the study of Barth et al. (2016), where the dispersion of earnings across establishments in the USA was analysed. The authors also used the Pooled OLS method. Additionally, Sonora (2022) analysed the relationship between income inequality and the energy consumption of a country, and for that, the author used the Gini coefficient, the fixed effects method and the instrumental variables method. Furthermore, Taylor & Driffield (2005) studied the impact that multinationals have in wage inequality, also using the fixed effects method. To a lesser extent, random effects were used, for example, throughout the study of Jaumotte et al. (2013), where the relationships between income inequality (Gini coefficient) and technology, trade, and globalization, were analysed. In rare cases, instrumental variables were applied (Ge & Zhou, 2020; Harrigan et al., 2021). Fonseca et al. (2018) used the fixed effects methodology, although the author did not focus on inequality measurements like the Gini coefficient. To our knowledge, there are no studies that analyse the relationship between routinisation and firm-level wage inequality, using the Gini coefficient measurement, and applying methods such as the fixed-effects, random-effects, pooled OLS, and the instrumental variables.

Nevertheless, we focused the analysis on the fixed-effects method since it can address the issue of biased estimates. In this method it is assumed that u_{it} (idiosyncratic error term) is uncorrelated with all x_{itj} (independent variable), making the estimates unbiased (assumption of exogeneity on the independent variables). On the other hand, the random-effects method allows some estimates to be biased, which can be problematic.

4.1.1. Pooled Ordinary Least Squares method (Pooled OLS)

The Pooled Ordinary Least Squares method calculates the coefficients of a linear regression for a panel dataset. The composite error, that is defined by $v_{it} = \alpha_i + u_{it}$, must be uncorrelated with x_{it}, to prevent biased estimates. The α_i stands for the unobserved time-constant effect, and u_{it} corresponds to the idiosyncratic error term, which takes into consideration all the factors that were not considered in the regression. The definition of the Pooled OLS model is represented in equation 4:

$$Y_{it} = \beta_0 + \beta_1 X_{it1} + \beta_2 X_{it2} + \cdots + \beta_k X_{itk} + v_{i,t} \tag{4}$$

4.1.2. Fixed-Effects Method (FE)

The fixed-effects method can also be called the within transformation method. By employing it, it is possible to eliminate the unobserved effect α_i. The unobserved effect, α_i, is fixed over time, so, by subtracting equation (6) to equation (5), it is possible to end up with a time-demeaned data on *y*, on the error term and on the explanatory variable, as can be observed in equation (7). In equation (8), it is possible to see that the unobserved time-constant effect was eliminated. With this transformation, we now only need to assume that u_{it} is uncorrelated with all x_{itj}. In conclusion, a time demeaning is performed on the dependent variable and each independent variable, and a pooled OLS regression is performed using all time demeaned variables. The time demeaned equation for each *i* corresponds to equation (8).

$$Y_{it} = \alpha_i + \beta_1 X_{it1} + \beta_2 X_{it2} + \cdots + \beta_k X_{itk} + u_{i,t}, t = 1,2, \dots , T \tag{5}$$

$$\bar{y}_i = \alpha_i + \beta_1 \bar{x}_i + \cdots + \bar{u}_i \tag{6}$$

$$y_{it} - \bar{y}_i = \beta_1 (x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i, t = 1,2, \dots , T \tag{7}$$

$$\ddot{y}_{it} = \beta_1 \ddot{x}_{it1} + \beta_2 \ddot{x}_{it2} + \cdots + \beta_k \ddot{x}_{itk} + \ddot{u}_{it}, t = 1,2, \dots , T \tag{8}$$

4.1.3. Random-Effects Method (RE)

The unobserved effects model, as previously mentioned in the fixed-effects model, can be visualized in equation 9 (this equation could be simplified by using the composite error):

$$Y_{it} = \alpha_i + \beta_1 X_{it1} + \beta_2 X_{it2} + \cdots + \beta_k X_{itk} + u_{i,t}, t = 1,2, \dots , T \tag{9}$$

For the random-effects method, the goal is not to correct biased estimates, but instead to achieve higher efficiency. If α_i is uncorrelated with the explanatory variables in each time-period, using a transformation to eliminate α_i will result in inefficient estimators. In the random-effects method, it is assumed that the unobserved effect α_i is uncorrelated with each explanatory variable. Hence, the method follows the following rule:

$$Cov(x_{itj}, \alpha_i) = 0,\ t=1,2,\ldots,T;\ j=1,2,\ldots,k \tag{10}$$

To calculate the random-effects model estimates, the GLS (weighted OLS with weight *Θ*) is used to solve the serial correlation problem, (equation 11):

$$\Theta = 1 - [\sigma_u^2/(\sigma_u^2 + T\sigma_a^2)]^{1/2} \tag{11}$$

This equation varies between 0 and 1, where when *Θ* is close to zero, α_i is not relevant and if *Θ* is close to one, α_i it is relevant because the random-effects is close to the fixed-effects method. The transformation equation taking into consideration the GLS, is shown in equation 12:

$$y_{it} - \Theta\bar{y}_i = \beta_0(1-\Theta) + \beta_1(x_{it1} - \Theta\bar{x}_{i1}) + \cdots + \beta_k(x_{itk} - \Theta\bar{x}_{ik}) + (v_{it} - \Theta\bar{v}_i) \tag{12}$$

Equation 12 represents quasi-demeaned data for each variable, since the random-effects transformation subtracts a fraction from the time average. The GLS estimators are the Pooled OLS method applied to equation 12.

4.1.4. Interaction Terms

Models with interaction terms are helpful to evaluate if the partial effects, semi-elasticity, or elasticity of the dependent variable, with relation to an explanatory variable, depend on the effect of another explanatory variable. The following model can be visualized in equation 13:

$$A = \beta_0 + \beta_1 B + \beta_2 C + \beta_3 B.C + u \tag{13}$$

The partial effect of C on B (with all other variables fixed) can be visualized in equation 14:

$$\frac{\Delta A}{\Delta C} = \beta_2 + \beta_3 B \tag{14}$$

If $\beta_3 > 0$ then it means that an additional unit of C corresponds to a higher increase in B, which in turn corresponds to an interaction effect between B and C.

However, it is possible to reparametrize the model as shown in equation 15:

$$y = \alpha_0 + \delta_1 x_1 + \delta_2 x_2 + \beta_3(x_1 - \mu_1)(x_2 - \mu_2) + u \tag{15}$$

μ_1 corresponds to the population mean of x_1 and μ_2 to the population mean of x_2. The coefficient on x_2, δ_2, is the partial effect of x_2 on y at the mean value of x_1.

The study of the model of interaction between terms is pertinent since it is interesting to assess whether the effect of routinisation (RTI) varies with the knowledge or technology intensity of the industry where the firm operates on.

5. Results

After running the econometric models in Stata software, applying the fixed-effects methodology, the results obtained will be discussed to understand the impact that routinisation had on wage inequality. Additionally, the analysis of the interaction between terms will also be analysed.

5.1. Baseline Models

Table 7 shows results for each model, when using the fixed-effects method for the Gini coefficient inequality measurement. The first model contains the main variables that are part of each subsequent model: RTI, age, tenure, males (gender), and education. These variables were maintained throughout the analysis, since they are significant, or they seem to affect the significance of other variables. The industry category variable is not considered when the technological or knowledge intensity variable is. Additionally, the first model was analysed without the industry category variable since differences were observed in the significance of some variables.

***Table 7** - Fixed-Effects estimations with clustered standard errors (Gini coefficient – Dependent variable).*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
RTI	0.056**	0.023***	0.021**	0.020**	0.050**	0.047**	0.046**
	(0.024)	(0.009)	(0.008)	(0.008)	(0.023)	(0.023)	(0.023)
Technology or Knowledge Intensity					1.751***	1.751***	1.754***
					(0.373)	(0.373)	(0.374)
Others – Technology or Knowledge Intensity					-5.409***	-5.406***	-5.405***
					(0.385)	(0.385)	(0.385)
Age	-0.047***	0.001	0.001	0.001	-0.045***	-0.046***	-0.045***
	(0.014)	(0.005)	(0.005)	(0.005)	(0.013)	(0.013)	(0.013)
Education	-0.017	-0.032***	-0.032***	-0.034***	-0.017	-0.017	-0.018
	(0.020)	(0.010)	(0.010)	(0.010)	(0.020)	(0.020)	(0.020)
Tenure	0.018	0.006	0.007	0.007	0.019*	0.020*	0.020*
	(0.012)	(0.006)	(0.006)	(0.006)	(0.012)	(0.011)	(0.011)
Males	-0.002	-0.002*	-0.002	-0.002*	-0.002	-0.001	-0.002
	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Plants			-0.015***	-0.015***		-0.019***	-0.020***
			(0.001)	(0.001)		(0.003)	(0.003)
FDI				0.202			0.439**
				(0.128)			(0.215)
% Foreign Equity				-0.000			-0.001
				(0.001)			(0.001)
% Top 3 Hierarchy				0.000			0.000
				(0.000)			(0.000)
Monthly Salary				-0.000			-0.000
				(0.000)			(0.000)
N	75,962	75,962	75,962	75,962	75,962	75,962	75,962
R^2	0.1	0.77	0.77	0.77	0.14	0.14	0.14

Note: The standard error is shown in parentheses below each coefficient. All models include year dummies. **Models 2–4 include industry dummies (not shown)**.
* significant at 10%, ** significant at 5%, *** significant at 1%.

The RTI variable, that represents the routinisation level of a firm, has a positive contribution and it is significant in all models. The positive contribution of this variable suggests that 1 unit increase in routinisation (RTI), results in an increase in wage inequality by approximately 0.05 pp or 0.02 pp, depending on the model that is being visualized in Table 7.

Additionally, the technological or knowledge intensity variable has a positive contribution in all models, and it is significant at 1%. The positive contribution of this variable suggests that, on average, a firm with high technological or knowledge intensity has 1.75 pp more wage inequality than a firm with low technological or knowledge intensity.

Moreover, the negative contribution of the variable “Other” tells us that a firm that is classified as “Other” in terms of technological and knowledge intensity, has, on average, 5.40 pp less wage inequality than a firm with a low technological or knowledge intensity.

Other variables seem to have a smaller role in explaining wage inequality at the firm level, as they are not significant in several models. The age, education, and plants variables have a negative contribution on all the models where they are statistically significant. It is clear that the education variable loses its significance when considering the technological or knowledge intensity variables in the model. The negative contribution of this variable suggests that 1 unit increase in the education level promotes the decrease in wage inequality by approximately 0.032 pp, with slight differences between the models. The males (gender) and the FDI variables have a positive contribution.

The remaining variables do not present any significance for the dependent variable considered. For that reason, other possible combinations with those variables are not presented, except for models 4 and 7, where all the variables are taken into consideration to run the model.

In conclusion, the routinisation (RTI) and the technological or knowledge intensity variables were significant on all regression models, which suggests that these variables have a consistent relationship with wage inequality. Other variables related to worker or firm characteristics do not seem to be as consistent in explaining wage inequality.

The fixed-effects method was chosen to perform the analysis of this dissertation. This method was chosen because of all the reasons mentioned in chapter 4 and because we used the Sargan-Hansen method, to compare the fixed-effects and the random-effects methods and determined that the null hypothesis should be rejected.[1]

An econometric analysis was performed considering the 80/20 percentile (dependent variable). The logarithmic function was applied to the 80/20 percentile ratio, as mentioned in chapter 3. For this reason, the interpretation is different from the Gini coefficient analysis because the dependent variable experienced a logarithmic transformation. Since the dependent variable is log-transformed, the coefficient of each independent variable is the exponential function of the coefficient, subtracted by one and multiplied by 100.

Table 8 shows the results of each regression model using the fixed-effects methodology for the 80/20 percentile ratio wage inequality measurement.

[1] The Hausman test is inappropriate when using clustered standard errors.

The first model contains the main variables that are part of each subsequent model: RTI, age, tenure, males (gender), and education. These variables were maintained throughout the analysis since they are significant, or they seem to affect the significance of other variables. The industry category variable is not considered when the technology or knowledge intensity variable is. The first model was analysed without the industry category variable and for the second model we used it, because noticeable differences were observed in the regression coefficient values for some variables, as it is possible to observe on Table 8.

Table 8 *- Fixed-Effects estimations with clustered standard errors (80/20 ratio – Dependent variable).*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
RTI	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.011***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Technology or Knowledge Intensity					-0.008	-0.008	-0.007
					(0.013)	(0.013)	(0.013)
Other - Technology or Knowledge Intensity					-0.010	-0.010	-0.011
					(0.024)	(0.024)	(0.024)
Age	0.001	0.002	0.002	0.002*	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education	0.007***	0.007***	0.007***	0.006***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Males	0.001**	0.001**	0.001**	0.000**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Plants			-0.001***	-0.001***		-0.001***	-0.001***
			(0.000)	(0.000)		(0.000)	(0.000)
FDI				0.023			0.023
				(0.015)			(0.014)
% Foreign Equity				0.000			0.000
				(0.000)			(0.000)
% Top 3 Hierarchy				0.000			0.000
				(0.000)			(0.000)
Monthly Salary				-0.000*			-0.000**
				(0.000)			(0.000)
N	72,360	72,360	72,360	72,360	72,360	72,360	72,360
R^2	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Note: The standard error is shown in parentheses below each coefficient. All models include year dummies. **Models 2–4 include industry dummies (not shown)**.
* significant at 10%, ** significant at 5%, *** significant at 1%.

By analysing Table 8, it is possible to extract several conclusions for the fixed-effects estimations. The RTI variable, that represents a firm's routinisation level, has a negative contribution and is significant for all models. The negative contribution of this variable suggests that 1 unit increase in routinisation (RTI) promotes the decrease of the 80/20 percentile ratio (decrease in wage inequality) by approximately 1% or 1.1%, depending on the model. Moreover, the technology or knowledge intensity variables are not significant in any of the models.

The age variable is only significant in one model, and it has a positive contribution. Moreover, the number of plants and the monthly salary variables have a negative contribution in some models where they are significant.

Furthermore, the education and males (gender) variables have a positive contribution and are significant in all models. The positive contribution of the education variable suggests that 1 unit increase in the education level, promotes the decrease of the 80/20 percentile ratio (decrease in wage inequality) by approximately 0.6% or 0.7%, depending on the model. Additionally, the tenure variable has a negative contribution in all models and is significant. Therefore, it could be important to explain wage inequality in addition with the education and males (gender) variables. The negative contribution of the tenure variable suggests that one unit increase in the tenure promotes the decrease of the 80/20 ratio (increase in wage inequality) by approximately 0.3%.

The RTI, education, males (gender) and tenure variables are significant in all models, and so, for the case of the fixed-effects method, using the 80/20 percentile ratio, these are the variables that seem to more impact wage inequality.

5.2. Interaction Terms

Table 9 shows the results of the fixed-effects methodology when using the interaction between terms analysis. The Gini coefficient is the dependent variable chosen for this analysis. The study of the model of interaction between terms is relevant since it is of interest to assess whether the effect of routinisation (RTI) varies with the firm technological or knowledge intensity level. Moreover, it is interesting to apply this model because in the fixed-effects models we found that the RTI variable has a lower significance when including the firm’s technology or knowledge intensity indicator. This may indicate an interaction/effect between the two variables.

To analyse the interaction between terms, two additional dummy variables were considered, besides the RTI variable (routinisation). The high technology or knowledge intensity variable and the low technology or knowledge intensity variable. For both variables, the 0 corresponds to the category "Others" mentioned in chapter 3.

__Table 9 -__ Interaction Terms (RTI and High and Low Technological and Knowledge Intensity) taking into consideration the Fixed-Effects method.

Variables	Model 1	Model 2	Model 3
RTI	0.193***	0.192***	0.192***
	(0.047)	(0.047)	(0.047)
High Technology or Knowledge intensity	7.056***	7.039***	7.038***
	(0.527)	(0.527)	(0.527)
Low Technology or Knowledge intensity	4.843**	4.841***	4.840***
	(0.378)	(0.378)	(0.378)
Interaction Term	-0.006	-0.013	-0.014
(High Technology or Knowledge intensity & RTI)	(0.102)	(0.103)	(0.103)
Interaction Term	-0.232***	-0.232***	-0.232***
(Low Technology or Knowledge intensity & RTI)	(0.050)	(0.050)	(0.050)
N	75,962	75,962	75,962
R^2	0.15	0.15	0.15

Note: Every model contains controls for the year. The standard error is shown below each coefficient in parentheses.

* significant at 10%, ** significant at 5%, *** significant at 1%.

The equation of the interaction between terms is represented as follows:

$$Gini = \beta_0 + \beta_1 \times RTI + \beta_2 \times HTKI + \beta_3 \times LTKI + \beta_4 \times RTI \times HTKI + \beta_5 \times RTI \times LTKI + \boldsymbol{\beta_n} \times Variable_n + u \quad (16)$$

The partial effect of RTI on the Gini coefficient (keeping the other independent variables fixed) is:

$$\frac{\Delta Gini}{\Delta RTI} = \beta_2 + \beta_4 \times HTKI \quad (17)$$

$$\frac{\Delta Gini}{\Delta RTI} = \beta_3 + \beta_5 \times LTKI \quad (18)$$

The coefficients of “RTI” and the “High technological or knowledge intensity (HTKI)” variables are represented separately, followed by the interaction term “RTI × High technological or knowledge intensity (HTKI)”. The same reasoning can be applied for the case of the “Low technological or knowledge intensity (LTKI)” variable. Finally, the remaining variables of the regression equation are represented as “$\boldsymbol{\beta_n} \times Variable_n$”.

In Table 9 it is possible to analyse the base coefficients (“Technology or Knowledge Intensity”), which show that the technological or knowledge intensive firms are more unequal than the “Others” category, with the inequality being 7 pp higher (Model 1). Also, the low technological or knowledge ones are also more unequal, but less, only 4.8 pp on average. Moreover, the effect of 1 unit increase in routinisation (RTI) leads to an increase in “Others” by 0.19, that is, within the firms categorized as “Others”, the more routinisation the firms have, the more unequal they are.

Furthermore, the effect of an increase of 1 unit in routinisation (RTI) on firms with low technology or knowledge intensity is 0.19 - 0.23 < 0. Therefore, at firms with low technology or knowledge intensity, 1 additional unit of RTI, decreases wage inequality. In other words, within firms with low technology or knowledge intensity, the firms that have more routinisation are less unequal. To confirm this conclusion the average marginal effects was analysed. The analysis confirms that, in firms with low technology or knowledge intensity, there is a negative average effect, although relatively small.

Additionally, the fact that the interaction term of firms with high technological or knowledge intensity is not significant tells us that the effect of routinisation in these firms is equal to firms classified as "Others" (positive contribution).

In conclusion, within firms with low technology or knowledge intensity, the ones which are more routinized, exhibit less wage inequality. On the other hand, firms with higher technology or knowledge intensity, and that present more routinisation, exhibit greater wage inequality.

5.3. Gini Coefficient and the 80/20 Percentile Ratio

The Gini coefficient and the 80/20 percentile ratio were used in order to measure wage inequality in a firm. In the literature, the Gini coefficient is one of the most widely used and mentioned methods to measure wage inequality. The 80/20 percentile ratio was also considered to be an alternative analysis to the Gini coefficient.

The conclusions for the RTI and technological or knowledge intensity variables are different depending on the dependent variable applied. When applying the Gini coefficient, the RTI and the technological or knowledge intensity variables presented a positive relation with the dependent variable for all the three econometric methods. However, when considering the 80/20 percentile ratio as the dependent variable, the RTI coefficient presented a negative relation. Also, the technological or knowledge intensity variables presented a negative relation when the fixed-effects method was applied. For the two remaining methods, it presented a positive relation, similar to what happened when considering the Gini coefficient as a dependent variable. Therefore, different wage inequality measurements resulted in different conclusions.

Pereira (2021) analysed a variety of wage inequality measurements to examine whether wage inequality increased in Portugal. The author discovered that wage inequality varied in Portugal, between 1985 and 2017. The author analysed the wage logarithm per hour and applied the 90/10, 90/50, 50/10 percentile ratios, the Gini coefficient, and the Theil Index as wage inequality measurements. It was concluded that the overall wage inequality corresponds to a decrease in wage inequality for the 90/10, 50/10 measurements. However, wage inequality increased when applying the 90/50 percentile ratio, the Gini coefficient, and the Theil index measurements. The author further claims that these differences are not surprising, as wage inequality indices consider different intervals of the wage distribution range. In addition, Sonora (2022) analysed the relationship between income inequality and energy consumption. The author analysed different countries which presented opposite conclusions depending on the measurement of wage inequality used (Palma ratio and Gini coefficient). This dissertation studies the firms' context related to routinisation, and so, Pereira (2021) and Sonora (2022) did not aim to provide the same answers as this dissertation.

To our knowledge, there is no study in the literature that uses the same wage inequality measurements applied to firms (Gini coefficient and 80/20 ratio), when taking into consideration the technology, knowledge, and routinisation of the firm. In any case, whatever the context of the analysis, it is possible that different wage or income inequality measurements will present different conclusions as was also concluded by Pereira (2021) and Sonora (2022).

One possible reason for the different conclusions could be that the Gini Coefficient takes into consideration the entire wage distribution, while the 80/20 ratio considers the extremes of the wage distribution. Single index measures can produce different inequality conclusions as they measure different parts of the wage distribution range (Pereira & Galego, 2015; Pereira, 2021).

5.4. Fixed-Effects, Random-Effects and Pooled OLS methods (Gini Coefficient)

Other methodologies were analysed, besides the fixed-effects, i.e., the random-effects and pooled OLS methods (chapter 7). For all of them we assessed whether the significant variables follow the same trend in terms of contribution (positive or negative). The RTI and the technological or knowledge intensity variables contribute positively and are significant in all the models analysed. Besides these important variables, the age, and males (gender) variables had a negative contribution on almost all regression models and methodologies. Moreover, it was not possible to find any contribution tendency on the education and top 3 hierarchy percentage variables. Finally, the tenure variable had a negative contribution on some models of the random-effects and pooled OLS methods.

Considering both the significant variables used on the three methodologies and the coefficient of each variable (higher coefficient) it is suggested that the technological or knowledge intensity, and the routinisation (RTI) variables are the ones that most impact wage inequality (positive contribution). Other variables like the FDI, age, and, to some degree, the number of plants also appear to have some importance in explaining wage inequality.

5.5. Discussion

Summarizing all the inputs mentioned before and considering the aim of this dissertation, it is possible to assume that routinisation can increase firm-level wage inequality as measured by the Gini coefficient. Also, when analysing the technological or knowledge intensity of the industry where the firm operates, we reached the same conclusion for both wage inequality measurements in most models. This conclusion is consistent with what was stated by Vannutelli et al. (2022), who mention that workers that perform non-routine tasks are expected to have higher wages than workers performing routine tasks, and that this increases wage inequality. For the author this is a consequence of the RBTC theory, previously mentioned in the literature review. Also, Fonseca et al. (2018) confirmed that routinisation is the cause of the job and wage polarisation phenomenon. Thus, the greater the routinisation, the greater the wage inequality.

Moreover, the 80/20 ratio has a different relation, where the greater the routinisation, the less the wage inequality. This may also happen because there may be more firms in the sample with a higher level of routinisation (higher percentage of routine tasks), which might imply that there are no extremes in workers' wages and that inequality is not so noticeable. One possible reason for the different conclusions could be that the Gini Coefficient takes into consideration the entire wage distribution, while the 80/20 ratio considers the extremes of the wage distribution. Single index measures can produce different inequality conclusions as they measure different parts of the wage distribution range (Pereira & Galego, 2015; Pereira, 2021).

By applying the interaction between terms, it was possible to verify that within firms with low technology or knowledge intensity, the more routinized exhibit less wage inequality. Additionally, firms with higher technology or knowledge intensity, that have more routinisation, exhibit greater wage inequality. The latter occurs because technology can complement workers that perform non-routine tasks, increasing their productivity and wages, in addition, the opposite is not true (routine tasks) (Acemoglu & Autor, 2011; Vannutelli et al. 2022). Consequently, in firms with more workers performing routine tasks and displaying a high level of technological intensity, the disparity of wages could be more accentuated, which can lead to a greater wage inequality.

It is important to note that, in Portugal, workers have lower salaries compared to other European countries, and so, sometimes it could not be as beneficial to replace workers with machines, since the alternative of applying more technology in companies may not be as financially rewarding. Additionally, Portugal's 2014 recession may have increased wage inequality, because some firms and industries may have been more affected at that time, which could impact worker’s wages differently.

It is also important to consider that services jobs have had a very high increase in Portugal (Fonseca et al., 2018), and, since they depend heavily on human labour and spoken communication skills, many jobs end up not being so dependent on technological change and routinisation (Acemoglu & Autor, 2011).

In addition, it is clear that the demand for jobs related to IT (Information Technology) has increased in Portugal throughout the years. Because, on this type of job, employees perform abstract tasks, which are not easily routinized, as has been mentioned in chapter 2. However, there is a shortage of labour force to meet the demand felt throughout the years, which causes wages for this kind of jobs to increase. Thus, several individuals have started to work remotely for countries where the wages are higher, which forces firms in Portugal to increase wages so as to try to respond to this type of competition. This phenomenon is called offshoring and was pointed out by Coveri and Pianta (2022) as being one driver of wage inequality. This kind of phenomena can also exacerbate wage inequality since workers that have this kind of activity, could earn a lot more compared to workers that perform routine jobs and that work in Portugal. However, technology can make both routine and some abstract jobs offshorable (Fonseca et al., 2018), which also can impact wage inequality to a certain extent.

6. Conclusion

Several conclusions can be drawn regarding the relationship between routinisation and wage inequality, when performing the analysis at a firm-level.

When analysing the fixed-effects method (considering all models) it was achieved that the RTI and technological or knowledge intensity variables have a positive and statistically significant contribution, when considering the Gini coefficient as dependent variable. Since the RTI and the technological or knowledge intensity variables have a positive contribution in all models, could mean that the higher the RTI (routinisation) or the technological/knowledge intensity of a firm the higher the wage inequality. The same reasoning was also reached for the random-effects and pooled OLS methodologies.

The interaction between terms method was also considered in order to analyse the impact that technology or knowledge intensity has on the relationship between routinisation and wage inequality. We concluded that within low technology or knowledge intensive firms, those with higher routinisation have lower inequality. On the other hand, within high technology or knowledge intensive firms, those with higher routinisation present greater inequality.

When considering as dependent variable the 80/20 percentile ratio, other results were obtained. The RTI variable has a negative contribution, contrary to what was achieved by using the Gini coefficient and is significant in all models. Therefore, different wage inequality measurements resulted in different conclusions for the routinisation (RTI). One possible reason for the different conclusions could be that the Gini Coefficient takes into consideration the entire wage distribution, while the 80/20 ratio considers the extremes of the wage distribution. On the other hand, the technological or knowledge intensity variable, when it is significant, has a positive contribution. Which goes in line with what was concluded for the Gini coefficient analysis. When analysing all the regression models for the three methodologies considering the 80/20 percentile ratio, the technological or knowledge intensity and the RTI variables were considered important factors that can impact wage inequality.

Taking into consideration the impact that technology seems to have on wage inequality (Gini coefficient as dependent variable), measures should be adopted to minimize its negative consequences. Some of those measures could be to create incentives for people to be more skilled in jobs that are in higher demand or have lower routinisation. In addition, jobs that tend to be more routinized tend to have lower salaries. To minimize that, firms, governments, etc., could invest in training courses for workers so that they obtain skills that cannot be routinized, like learning new languages, etc., and so make them more valuable to the labour market.

This dissertation presents some limitations such as the inexistence of a sensibility analysis applied to data variables. Moreover, more wage inequality measurements could have been analysed and not only the Gini coefficient and the 80/20 percentile ratio. As was analysed in chapter 2, there are several distinct wage inequality measurements that could be applied to enrich the study. Additionally, restructuring the categorization of task types to include only abstract, manual, and routine categories, and removing the “Others” category, would be a preferable approach.

For future work, it would be interesting to analyse the context of industries or occupations instead of only firms, since the conclusions could be different. Also, the COVID-19 pandemic led to several firms starting to adopt the remote work approach. Consequently, this could have resulted in more competition in terms of salaries between Portugal and other countries, which in some way could have forced firms that operate in Portugal to increase wages for this type of jobs (mostly abstract occupations). This fact can increase wage inequality. It could be interesting to see the impact that this reality could have in wage inequality, since this dissertation does not analyse the time interval where the COVID-19 pandemic started and the years following it.

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8. Appendix

8.1. Random-Effects and Pooled OLS using the Gini Coefficient

Table 10 shows the results of each regression model using the random-effects methodology for the Gini coefficient inequality measurement. The first model contains the main variables that are part of each subsequent model: RTI, age, tenure, males (gender), and education. These variables were maintained throughout the analysis since they are significant, or they seem to affect the significance of other variables.

Table 10 *– Random-Effects estimations with clustered standard errors (Gini coefficient – Dependent variable).*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
RTI	0.073***	0.073***	0.071***	0.071***	0.064***	0.064***	0.062***	0.063***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.018)	(0.018)	(0.018)	(0.018)
Technology or Knowledge Intensity					2.903***	2.903***	2.901***	2.856***
					(0.242)	(0.242)	(0.242)	(0.244)
Others – Technology or Knowledge Intensity					-3.915***	-3.914***	-3.910***	-3.854***
					(0.161)	(0.161)	(0.161)	(0.161)
Age	0.003	0.003	0.002	0.002	-0.031***	-0.031***	-0.032***	-0.033***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)	(0.010)	(0.009)
Education	-0.038***	-0.038***	-0.043***	-0.040***	0.060***	0.060**	0.060***	0.048**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.019)	(0.019)	(0.020)	(0.020)
Tenure	-0.014***	-0.014***	-0.013***	-0.013***	-0.013*	-0.013*	-0.012	-0.015*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)
Males	-0.015***	-0.015***	-0.015***	-0.015***	-0.011***	-0.011***	-0.011***	-0.010***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Plants			-0.013***	-0.013***			-0.015***	-0.014***
			(0.001)	(0.001)			(0.004)	(0.004)
FDI			0.288***	0.311***			0.333*	0.236
			(0.093)	(0.099)			(0.170)	(0.172)
% Foreign Equity		-0.001		-0.0010		-0.001		-0.001
		(0.001)		(0.001)		(0.001)		(0.001)
% Top 3 Hierarchy			0.001**	0.001**			-0.000	-0.000
			(0.000)	(0.000)			(0.001)	(0.000)
Monthly Salary				-0.000				0.000***
				(0.000)				(0.000)
N	75,962	75,962	75,962	75,962	75,962	75,962	75,962	75,962

Note: The standard error is shown in parentheses below each coefficient. All models include year dummies. **Models 1–4 include industry dummies (not shown)**.
* significant at 10%, ** significant at 5%, *** significant at 1%.

By analysing Table 10, it is possible to reach several conclusions for the random-effects estimations. Firstly, the RTI variable, that represents the routinisation level of a firm, has a positive and significant contribution in all models. The positive contribution of this variable suggests that 1 unit increase in routinisation (RTI) promotes the increase of the Gini coefficient (increase in wage inequality) by approximately 0.06 pp.

Additionally, the technological or knowledge intensity variable has a positive contribution in all models, and it is significant at 1%. The positive contribution of this variable suggests that, on average, a firm with high technological and knowledge intensity has 2.90 pp more wage inequality than a firm with low technological and knowledge intensity. Moreover, the negative contribution of the variable "Other" tells us that a firm that is classified as "Other", has on average, 3.90 pp less wage inequality, than a firm with a low technological or knowledge intensity.

The age, tenure, males (gender) and plants variables have a negative contribution. In addition, the males (gender) variable is significant in all models, which implies that it could be an important variable to explain wage inequality. The negative contribution of this variable suggests that 1 pp increase in the quantity of males in the firm promotes the decrease in wage inequality by approximately 0.015 pp or 0.011 pp, depending on the model. The education variable has a negative contribution in models that only consider the RTI variable, and a positive contribution in models which use both the RTI and the technology or knowledge intensity variables. There is no particular trend for the contribution of this variable.

The foreign equity percentage, the top 3 hierarchy percentage, and the monthly salary variables, display, in some models, a level of significance. However, the value of the regression coefficient is very low, and so, they are not relevant.

In conclusion, for the random-effects method, the variables that seem to have a more relevant impact on wage inequality were the RTI, technology or knowledge intensity, and males (gender) variables.

Table 11 shows the results of each model that uses the Pooled OLS for the Gini coefficient inequality measurement. The first model contains the main variables that are part of each subsequent model: RTI, age, tenure, and males (gender). The education variable was not considered as a main variable for the pooled OLS methodology. It was not significant in virtually all models, and it did not appear to influence any other model variables. For that reason, for models 2, 3, 6 and 7 the education variable was not considered. The first model was analysed without the industry category variable and on the second model we used it, since differences were observed in the significance of some variables.

Table 11 *- Pooled OLS estimations (Gini coefficient – Dependent variable).*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
RTI	0.119***	0.104***	0.104***	0.101***	0.209***	0.212***	0.211***	0.204***
	(0.007)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
Technology or Knowledge Intensity					3.648***	4.038***	4.034***	3.368***
					(0.044)	(0.042)	(0.043)	(0.044)
Other - Technology or Knowledge Intensity					-2.813***	-2.888***	-2.884***	-2.657***
					(0.048)	(0.049)	(0.049)	(0.048)
Age	-0.019***	0.013***	0.013***	0.013***	0.001	-0.014***	-0.013***	-0.003
	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Education	1.425***			-0.003	0.773***			0.566***
	(0.023)			(0.012)	(0.022)			(0.023)
Tenure	-0.033***	-0.036***	-0.037***	-0.035***	-0.077***	-0.076***	-0.076***	-0.088***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Males	0.012***	-0.014***	-0.014***	-0.014***	-0.017***	-0.017***	-0.017***	-0.012***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Plants				-0.010***				-0.000
				(0.001)				(0.002)
FDI			0.309***	0.379***			0.173**	-0.821***
			(0.035)	(0.037)			(0.072)	(0.074)
% Foreign Equity				-0.003		-0.002	-0.002	-0.001
				(0.001)		(0.002)	(0.002)	(0.002)
% Top3				0.000				-0.003***
				(0.001)				(0.001)
Monthly Salary				-0.000***				0.001***
				(0.000)				(0.000)
N	75,962	75,962	75,962	75,962	75,962	75,962	75,962	75,962
R^2	0.09	0.82	0.82	0.82	0.23	0.21	0.21	0.24

Note: Every model contains controls for the year. **Models 2, 3 and 4 include industry dummies (not shown)**. The standard error is shown below each coefficient in parentheses.
* significant at 10%, ** significant at 5%, *** significant at 1%.

The RTI variable has a positive contribution and is significant in all models, when using the Gini coefficient as a dependent variable. The positive contribution of this variable suggests that 1 unit increase in routinisation (RTI) promotes the increase of the Gini coefficient, by approximately 0.11 pp or 0.21 pp, depending on the model visualized on Table 11.

Additionally, the technological or knowledge intensity variable has a positive contribution in all models, and it is significant at 1%. The positive contribution of this variable suggests that, on average, a firm with high technological and knowledge intensity has 4 pp more wage inequality than a firm with low technological and knowledge intensity. Moreover, the negative contribution of the variable

"Other" tells us that a firm that is classified as "Other", has, on average, 2.88 pp less wage inequality, than a firm with a low technological or knowledge intensity.

The tenure and the males (gender) variables present a negative contribution and are significant in almost all models, therefore, they could be important to explain wage inequality. Also, the age, FDI and monthly salary are significant in some models and have contradictory contributions, being sometimes negative or positive. The education variable has a positive contribution in all models where it is significant. On the other hand, the plants and the top 3 hierarchy percentage variables have a negative contribution in some models that are significant.

In conclusion, the variables that seem to be more valuable to explain wage inequality are RTI, technological or knowledge intensity, tenure, and males (gender) variables.

8.2. Random-Effects and Pooled OLS using the 80/20 Percentile Ratio

By analysing Table 12, it is possible to reach several conclusions for the random-effects estimations considering the 80/20 percentile ratio inequality measurement. The first model contains the main variables that are part of each subsequent model: RTI, age, tenure, males (gender), and education. These variables were maintained throughout the analysis since they are significant, or they seem to affect the significance of other variables. The industry category variable is not taken into consideration when the technology or knowledge intensity variables are considered.

Table 12 - *Random-Effects estimations with clustered standard errors (80/20 ratio – Dependent variable).*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
RTI	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.016***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Technology or Knowledge Intensity					0.063***	0.063***	0.062***	0.051***
					(0.009)	(0.008)	(0.008)	(0.008)
Other - Technology or Knowledge Intensity					0.007	0.007	0.008	0.018*
					(0.010)	(0.010)	(0.010)	(0.010)
Age	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education	0.019***	0.019***	0.018***	0.016***	0.021***	0.021***	0.020***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure	-0.001*	-0.001*	-0.001*	-0.002***	-0.001**	-0.001**	-0.001**	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Males	-0.000***	-0.000***	-0.000***	-0.000*	-0.000*	-0.000*	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Plants			-0.001***	-0.001***			-0.001***	-0.001***
			(0.000)	(0.000)			(0.000)	(0.000)
FDI			0.057***	0.037***			0.056***	0.035***
			(0.011)	(0.011)			(0.011)	(0.011)
% Foreign Equity		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
% Top 3 Hierarchy			0.000	0.000			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)
Monthly Salary				0.000***				0.000***
				(0.000)				(0.000)
N	72,360	72,360	72,360	72,360	72,360	72,360	72,360	72,360
R^2								

Note: The standard error is shown in parentheses below each coefficient. All models include year dummies. **Models 1–4 include industry dummies (not shown).**
* significant at 10%, ** significant at 5%, *** significant at 1%.

By analysing Table 12, it is possible to reach several conclusions for the random-effects estimations. The RTI variable, that represents a firm's routinisation level, has a negative contribution in all models, when using the 80/20 percentile ratio as a dependent variable and is significant in all models. The negative contribution of this variable suggests that a 1 unit increase in routinisation (RTI) promotes the decrease of the 80/20 percentile ratio (decrease in wage inequality) by approximately 1.5% or 1.6%, depending on the model.

Additionally, the technological or knowledge intensity variable has a positive contribution and is significant in all models. The positive contribution of this variable suggests that, on average, a firm with high technological and knowledge intensity has 5.2% or 6.5% more wage inequality than a firm with low technological and knowledge intensity. Moreover, the negative contribution of the variable "Other" has a positive contribution and is significant only in one model.

The age and education variables are significant and have a positive contribution in all models. For example, the positive contribution of the age variable suggests that 1 unit increase in it promotes the increase of the 80/20 ratio (increase in wage inequality) of 0.17%, 0.20% or 0.22%, depending on the model. The same reasoning happens in the case of the education variable. Thus, the tenure, males (gender), and the plants variables, have a negative contribution in all models that are significant. However, the tenure variable is significant in all models. Also, in all the models were the FDI variable was used in the regression, it presents a positive contribution, and it is significant at 1%.

The variables that did seem to be more relevant for wage inequality were the RTI, technology or knowledge intensity, age, education, and tenure.

By analysing Table 13, it is possible to reach several conclusions for the pooled OLS estimations, considering the 80/20 percentile ratio as a dependent variable. The first model contains the main variables that are part of each subsequent model: RTI, age, tenure, males (gender), and education. These variables were maintained throughout the analysis since they are significant, or they seem to affect the significance of other variables. The industry category variable is not considered when the tech and knowledge intensity variable is. The first model was analysed without the industry category variable and for the second model we did use it, because differences were observed in the significance of some variables.

***Table 13** – Pooled OLS estimations (80/20 ratio – Dependent variable).*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
RTI	-0.020***	-0.022***	-0.022***	-0.020***	-0.016***	-0.016***	-0.017***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Technology or Knowledge Intensity					0.082***	0.082***	0.081***	0.042***
					(0.004)	(0.004)	(0.004)	(0.004)
Other - Technology or Knowledge Intensity					-0.008*	-0.008*	-0.006	0.016***
					(0.005)	(0.005)	(0.005)	(0.005)
Age	0.001***	0.002	0.002**	0.001***	0.001***	0.001***	0.001***	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.103***	0.071***	0.067***	0.040***	0.091***	0.091***	0.088***	0.053***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure	-0.000	0.000*	0.000	-0.002***	-0.000	-0.000	-0.001	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Males	-0.001***	-0.001***	-0.001***	-0.000***	-0.001***	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Plants				-0.000				0.000
				(0.000)				(0.000)
FDI			0.098***	0.007			0.097***	-0.005
			(0.007)	(0.007)			(0.007)	(0.007)
% Foreign Equity		0.001***	0.001**	0.001***		0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
% Top 3 Hierarchy				0.000***				0.000***
				(0.000)				(0.000)
Monthly Salary				0.000***				0.000***
				(0.000)				(0.000)
N	72,360	72,360	72,360	72,360	72,360	72,360	72,360	72,360
R^2	0.06	0.08	0.08	0.12	0.07	0.07	0.07	0.10

Note: The standard error is shown in parentheses below each coefficient. All models include year dummies. **Models 2–4 include industry dummies (not shown)**.
* significant at 10%, ** significant at 5%, *** significant at 1%.

When analysing Table 13 it is possible to reach several conclusions for the pooled OLS estimations. The RTI variable has a negative contribution and is significant in all models. The negative contribution of this variable suggests that 1 unit increase in routinisation (RTI) promotes the decrease of the 80/20 ratio (decrease in wage inequality) by approximately 2%, depending on the model.

Additionally, the technological or knowledge intensity variable has a positive contribution and is significant in all models. The positive contribution of this variable suggests that, on average, a firm with high technological and knowledge intensity has 4% or 8.5% more wage inequality than a firm with low technological and knowledge intensity.

The education variable has a positive contribution and is significant on all models. The positive contribution suggests that a 1 unit increase in the education variable level, promotes the increase of the 80/20 percentile ratio (increase in wage inequality) by approximately 7%, 9% and 11%, depending on the model. The age variable has also a positive contribution and is significant on almost all models. The males (gender) variable has a negative contribution and is significant in all models. The education and males (gender) variables seem interesting factors to take into consideration when analysing wage inequality. Also, the FDI, the top 3 hierarchy percentage, monthly salary, and the foreign equity percentage variables have a positive contribution when they are significant.

The variables that did seem to be more relevant for wage inequality are RTI, technology or knowledge intensity, education, and males (gender).

In conclusion, the variables that seem to be more relevant to explain wage inequality for the three methodologies are the RTI, technological and knowledge intensity, and education variables. Also, by taking into consideration the fixed-effects methodology, which is considered the main methodology, the variable that seems to have a consistent relationship with wage inequality (higher regression coefficient and significant in all models) is the RTI variable. Thus, there seems to be a relation between routinisation and wage inequality in firms.