Technological Change and Wage Inequality in Portugal

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***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

I. Introduction

Technology is replacing workers who perform routine tasks, leading to unemployment and reduced wages for those employees (Acemoglu & Autor, 2011). Machines can perform certain tasks more efficiently and cost-effectively than human labour, resulting in lower wages. Conversely, workers who are supported by technology can perform tasks faster and may have better prospects for higher-paying jobs (Vannutelli et al., 2022). The RBTC theory suggests that technology substitutes routine tasks and complements technology supported tasks, which promotes productivity (Goos et al., 2014).

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).

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.

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.

The aim of this study is to assess the impact that routinisation, had on wage inequality in Portugal between the years of 2002 and 2017. Measures of wage inequality were identified (Magda et al., 2021; J. M. Pereira, 2021; Sonora, 2022), and applied, such as the Gini coefficient and the 80/20 percentile ratio.

The questions that will be addressed are as follows:

- 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?

Therefore, it was used information from *Quadros de Pessoal* to analyse the relation between routinisation and wage inequality within firms in Portugal, between the years of 2002 and 2017.

In order to carry out this study I conducted a literature search on wage inequality, routinisation, and technological change, and how they can relate. Performed a descriptive analysis, defined the methodology, and analysed the results using Stata, achieving the final conclusions.

The analysis of the Gini coefficient showed that higher levels of routinisation are associated with increased wage inequality. However, the results were inconsistent when examining the 80/20 percentile ratio, which measures different segments of the wage distribution.

Furthermore, I considered the interaction terms method using the Gini coefficient as dependent variable. The results suggested that within low technology/knowledge-intensive firms, higher routinisation is linked to lower inequality. Conversely, within high technology or knowledge-intensive firms, higher routinisation is associated with greater inequality.

II. LITERATURE REVIEW

2.1. Wage Inequality

Wage inequality has become a concern with significant implications for economic and social well-being which occurred over the years and in different countries (Autor et al., 2006; Magda et al., 2021). (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).

I analysed several measures of wage inequality throughout the literature, such as the Gini coefficient, the percentile ratios, the Theil Index etc. (Magda et al., 2021; J. M. Pereira, 2021; Sonora, 2022), as well as reasons for the increase in wage inequality. 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).

2.2. Routinisation and Technology

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

The Skilled-Biased Technological Change theory (Autor et al., 2003, 2008), considers that technology favours skilled over unskilled workers. This theory is not unanimously accepted (Beaudry & Green, 2005; Card & DiNardo, 2002).

One 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, promoting a U-shape of the occupational distribution (Acemoglu & Autor, 2011; Cortes, 2016; Goos et al., 2014).

Firstly, routinization tends to disproportionately affect workers engaged in routine and repetitive jobs. 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. Additionally, low-skilled moved from routine tasks to service occupations, which are harder to automate (Autor & Dorn, 2013).

Secondly, technological change creates a higher demand for workers with expertise in managing new technologies. Occupations that require creativity, problem-solving, complex decision-making, and interpersonal skills are less vulnerable to automation. 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.

III. DATA CHARACTERIZATION

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. We 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.

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 analyse the data.

3.2. Variables Definition

Some of the variables that were used in the analysis, are the Gini Coefficient and the 80/20 percentile ratio (which are the dependent variables). Additionally, we analysed the RTI and the knowledge or technology intensity variables. Also, we considered variables such as the age, education, tenure, gender, etc.

3.2.1. The 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 study, 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 1. The line of perfect equality assumes, by definition, the value of 0.5 (U.S. Census Bureau, 2021).

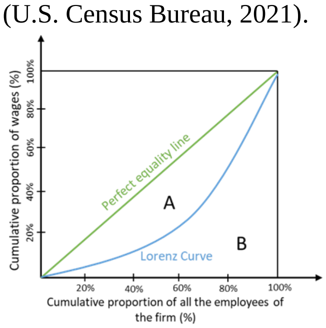

Figure 1 *- Graphical representation of Gini coefficient (firms).*

The formula to calculate the Gini coefficient is shown below:

$$Gini\ coefficient = \frac{A}{A+B} \quad (1)$$

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.

To measure wage inequality, I applied the 80/20 percentile ratio, an alternative method. This ratio involves dividing the 80th percentile of wages (the top 20%) by the 20th percentile of wages (the bottom 20%). Essentially, the ratio calculates the average ratio of workers who earn more versus those who earn less. However, it does not provide insight into wage distribution within the middle range, making it a complementary analysis to the Gini coefficient. Several authors, such as Asongu et al. (2019), Pereira (2021) and, Sonora (2022), have pointed out that the Gini coefficient concentrates its analysis on the middle range of wage or income distribution.

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. Consequently, the 80/20 ratio seems more suitable, offering a more balanced analysis approach. The increase in routinisation seems to increase wage inequality, however, different wage inequality measurements led to different results.

3.2.2. Routinisation Task Intensity (RTI)

To measure the intensity of routinisation, the literature proposes the Routine Task Intensity. This concept, introduced by Autor & Dorn (2013) and employed by Goos et al., (2014), allows for the ranking of occupations based on their levels of 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:

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

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:

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

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 serves as a way for assessing the influence of technology on tasks, as advancements in technology often lead to increased levels of routinisation. By examining the level of routinisation, it becomes possible to evaluate the extent of technological change that a particular firm may undergo. This allows for a deeper understanding of the potential impact of technology and its potential to drive routinisation within a firm.

3.2.3. Technological or Knowledge Intensity (Industry)

Firms were classified 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 is included the high-tech and medium-tech manufacturing, as well as the KIS (Knowledge Intensive Services). In the category of lower knowledge/technology intensive firms it is included 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 1 summarises this classification.

Table 1 *- Aggregation by NACE Rev.2 of the indicators on High-Tech industry and KIS/LKIS.*

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

IV. Descriptive Analysis

4.1. Gini Coefficient

Figure 2 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.

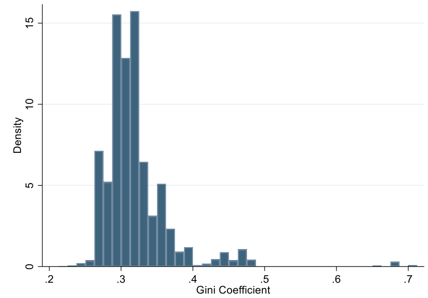

Figure 2 *- Density histogram of Gini coefficient variable (last observation of each firm).*

"Routine companies" were classified as those with an RTI value higher than the average of the RTI variable, while "non-routine companies" are those that present an RTI value lower than the average of the RTI variable (Vannutelli et al., 2022).

Figure 3 illustrates that, throughout the analysed period, with the exception of 2013, "routine companies" presented a higher inequality, when compared to companies defined as "non-routine". This observation aligns with the finding in the literature, which indicate that workers performing routine tasks display a higher level of inequality. Hence, firms with a larger proportion of employees engaged in routine tasks also tend to exhibit higher levels of wage inequality.

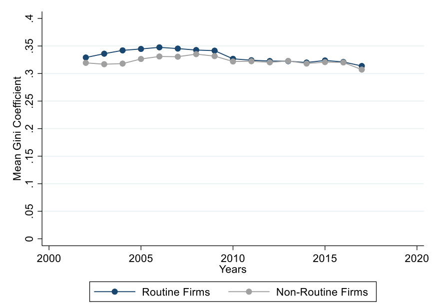

Figure 3 *- "Routine" and "Non-Routine firms" versus the mean of the Gini coefficient, between 2002-2017 (whole sample).*

4.2. 80/20 Percentile Ratio

I conducted a brief descriptive analysis of the 80/20 percentile ratio variable. 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, I applied the logarithmic function, and the results can be visualized in Figure 4, 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.

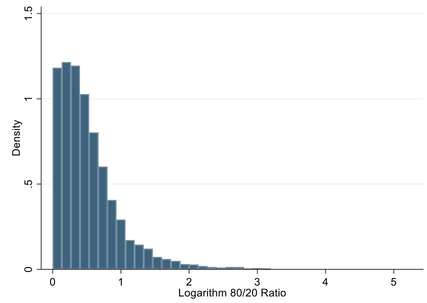

***Figure 4** - Density histogram of Log 80/20 Ratio variable (last observation of each firm).*

It can be observed in Figure 5, that in all the analysed period, “non-routine firms” presented higher inequality when compared to firms defined as “routine firms”, which contradicts the conclusions drawn from the Gini coefficient. The conclusion is distinct from what has been found and analysed in the literature, since it was found that the higher the routinisation the higher the wage inequality. This is also an indication that both inequality measurements lead to different conclusions.

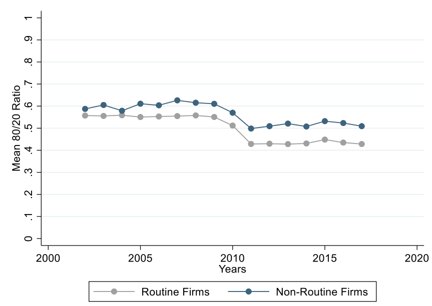

***Figure 5** - “Routine” and “Non-Routine firms” versus the mean of the 80/20 ratio, between 2002-2017 (whole sample).*

V. METHODOLOGY

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.

The analysis focused 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.

5.1. 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:

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

5.2. Fixed-Effects Method

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).

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

$$\bar{y}_i = \alpha_i + \beta_1 \bar{x}_i + \cdots + \bar{u}_i \qquad (6)$$

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

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

5.3. Random-Effects Method

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):

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

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:

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

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

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

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.

5.4. 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.

VI. 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.

6.1. Baseline Models

Table 2 - 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	0.06**	0.02***	0.02**	0.02**	0.05**	0.05**	0.05**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Technology Knowledge Intensity					1.75***	1.75***	1.75***
					(0.37)	(0.37)	(0.37)
Others – Technology Knowledge Intensity					-5.41***	-5.41***	-5.41***
					(0.39)	(0.39)	(0.39)
Age	-0.05***	0.00	0.00	0.00	-0.05***	-0.05***	-0.05***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Education	-0.2	-0.03***	-0.03***	-0.03***	-0.02	-0.02	-0.02
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Tenure	0.02	0.01	0.01	0.01	0.02*	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Males	-0.00	-0.00*	-0.00	-0.00*	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Plants			-0.01***	-0.02***		-0.02***	-0.02***
			(0.00)	(0.00)		(0.00)	(0.00)
FDI				0.20			0.44**
				(0.13)			(0.22)
% Foreign Equity				-0.00			-0.00
				(0.00)			(0.00)
% Top 3 Hierarchy				0.00			0.00
				(0.00)			(0.00)
Monthly Salary				-0.00			-0.00
				(0.00)			(0.00)
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%.

Several models were analysed, applying the fixed-effects method using the Gini coefficient as inequality measurement. Table 2 shows the results for each model.

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 analysed in Table 2.

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” indicates that firms that classified as “Other” in terms of technological and knowledge intensity tend to have, 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 a consistent relationship with wage inequality when the Gini coefficient is considered as the dependent variable. The same reasoning was also reached for the random-effects and pooled OLS methodologies. Other variables related to worker or firm characteristics do not seem to be as consistent in explaining wage inequality.

For this study, we opted for the fixed-effects method to conduct the analysis. This method was chosen because of all the reasons mentioned in the methodology 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. This method was used since the Hausman test is inappropriate when using clustered standard errors.

It was conducted an econometric analysis, considering the 80/20 percentile (dependent variable). The logarithmic function was applied to the 80/20 percentile ratio. 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.

Several models were analysed applying the fixed-effects method using the 80/20 percentile ratio as inequality measurement.

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.

6.2. Interaction Terms

Table 3 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 varies with the firm technological or knowledge intensity level.

Applying this model is interesting due to the lower significance of the RTI variable found in the fixed-effects models, when including the firm's technology/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. 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".

Table 3 *- Interaction Terms applying the Fixed-Effects method and the Gini Coefficient as dependent variable.*

Variables	Model 1	Model 2	Model 3
RTI	0.19345***	0.19230***	0.19179***
	(0.04671)	(0.04668)	(0.04673)
High Technology or Knowledge intensity	7.05611***	7.03860***	7.03847***
	(0.52675)	(0.52700)	(0.52718)
Low Technology or Knowledge intensity	4.84268***	4.84144***	4.84017***
	(0.37846)	(0.37847)	(0.37835)
Interaction Term (High Technology or Knowledge intensity & RTI)	-0.00586	-0.01300	-0.01401
	(0.10239)	(0.10283)	(0.10286)
Interaction Term (Low Technology or Knowledge intensity & RTI)	-0.23238***	-0.23165***	-0.23170***
	(0.05035)	(0.05038)	(0.05044)
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%.

In Table 3 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.

6.3. 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 was negative.

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.

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).

6.4. 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. Additionally, 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.

In Portugal, workers have lower salaries compared to other European countries, and so, 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 development 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. 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.

VII. 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 the Gini coefficient as dependent variable, the RTI and the technological/knowledge intensity variables have a positive and significant contribution in all models. It may indicate that the higher the RTI or the technological/knowledge intensity of a firm the higher the wage inequality.

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

When considering as dependent variable the 80/20 percentile ratio, different results were obtained. 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.

Addressing wage inequality requires an approach that includes both skill development for workers vulnerable to displacement, as well as policies promoting inclusive growth and fair distribution of the benefits arising from technological advancements.

Taking into consideration the impact that technology seems to have on wage inequality, 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. 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 it was not analysed the time interval where the COVID-19 pandemic started and the years following it.

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