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Does the Field of Studies Matter to the Private Returns to Higher Education? Evidence from Portugal

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By Laura Bartolomeu

Abstract: This paper investigates the private returns to education across fields of study for bachelor's and master's degrees in Portugal from 2006 to 2021, using the *Quadros de Pessoal* dataset. The analysis reveals significant variation in wage premiums by degree levels, fields of study, and gender. While bachelor's degree returns have declined over time, master's degrees maintain higher and stable premiums. IT and Health fields yield the highest returns, contrasting with Humanities and Education. Gender wage gaps remain a persistent phenomenon across many fields, even within high-return domains, highlighting the complexity of wage gaps.

JEL classification: I26

Keywords: Returns to Education, Higher Education, Wage Premiums, Fields of Study, Gender Gaps

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I. Introduction

Since the 1960s, the landscape of higher education has faced a significant transformation, marked by an exponential increase in the number of students with tertiary education. In 2021, the European Union set the target of 45% of the population aged 24-35 years attaining higher education by 2030. By 2023, this goal is just two percentage points away, with 13 countries already surpassing it. This rise in the number of graduates is expected to increase the diversity of skills, leading to different labour market outcomes among graduates with different educational backgrounds.

In Portugal, the expansion of higher education has been a key objective over recent decades. Whilst in the early 1960s, there were just over 20,000 students enrolled in higher education, by 2003 this number had increased twentyfold, exceeding 400,000, and has remained relatively stable ever since (FIGUEIREDO et al. 2017). Despite the progress achieved over the past seventy years, gender disparities persist in tertiary education enrolment. For instance, in the academic year 2021/2022, the fields with the highest feminization rates among higher education graduates were Health (77%) and Education (78%) while men predominantly graduated in IT and Engineering fields, 80% and 70%, respectively (FERNANDES, MARVÃO, and MIGUEL 2023).

As the population becomes increasingly educated, the returns to education, which is a critical determinant of individual and societal investment decisions, have become a central focus of economic research. The groundbreaking contributions of BECKER (1964) and MINCER (1974) have established the theoretical and empirical foundation, respectively, for analysing these returns, arguing that education enhances productivity, which translates into higher earnings.

The growing educational attainment of the population has been driven by high expectations of its private returns (FIGUEIREDO, TEIXEIRA, and RUBERY (2013)). As the population becomes more educated, educational decisions increasingly focus not only on the level of education to pursue but also on the specific field or path to follow.

This empirical study seeks to complement the existing literature on returns to education across different fields of study in Portugal by offering an overview of how these returns have evolved from 2006 to 2021. I use the Portuguese administrative linked employer-employee

longitudinal database, "*Quadros de Pessoal*", to estimate the wage premium not only for each degree level but also across different fields of study for bachelor's and master's degrees compared to workers with a high school diploma. Additionally, I look into the gender wage gap by examining how these wage premiums vary by gender and whether choices in specific fields of study influence such outcomes.

In summary, the results obtained in this study are the following: there is a clear decline in the wage premium to bachelor's degrees over time, whereas master's degrees consistently yield higher wage benefits, highlighting the economic value of pursuing advanced education. A. ALMEIDA et al. (2017) found similar results, showing that postgraduate education provides significantly higher wage premiums relative to graduate degrees across the wage distribution. As for the difference in expected wage gains across fields of study, an evident disparity on wage premiums is observed. Health-related fields as well as Information Technology (IT) present the highest premiums, while Humanities, Arts, and Education yield the lowest, with only marginal wage improvements even at the master's level. Regarding gender wage disparities, women remain overrepresented in lower-premium fields like Education and Humanities, while men dominate high-premium areas such as IT and Engineering. This partially contributes to the gender wage gap. Moreover, it is also observed that, within fields of study, differences in wages between women and men persist.

The paper is structured as follows. Section II reviews literature on returns to education at both the international and Portuguese levels. Section III describes the dataset and its key characteristics. Section IV presents the empirical methodology for estimating the returns to education. Section V outlines the results obtained, while Section VI concludes with future research directions.

II. Literature Review

A. International Perspective on Returns to Education

The question of whether pursuing a college degree is a worthwhile investment has been extensively discussed. Balancing the costs and benefits of enrolling in a higher education pro-

gramme is crucial for students making this decision. Existing literature does provide evidence of wage premiums to higher education (OREOPOULOS and PETRONIJEVIC 2013). Notably, educational attainment has increased globally, aligning with the observed economic benefits.

Nevertheless, while wage premiums are evident, outcomes vary significantly across different fields of study. Therefore, the decision of the area of study is also a key factor when considering pursuing tertiary education. Empirical research in countries like Germany (GRAVE and GOERLITZ 2012), France (GIRET and GOUDARD 2010), Italy (BUONANNO and POZZOLI 2009), Ireland (KELLY, O'CONNELL, and SMYTH 2010), Greece (LIVANOS and POULIAKAS 2008) and Norway (KIRKEBOEN, LEUVEN, and MOGSTAD 2016) consistently reveals major differences in wage premiums among different fields of study, with Health, Engineering and Business being the ones yielding the highest expected returns, while Humanities and Art courses providing the lowest wage benefits.

Although expected earnings play an important role when choosing a study path, they may not be the only factor. In Germany, for instance, there is a substantial share of students enrolled in low-earning courses such as Humanities and Arts. GRAVE and GOERLITZ (2012) resort to comparative advantage (PAGLIN and RUFOLLO 1990) and to non-monetary preferences (BLAKEMORE and LOW 1984) to try to explain enrolments in low-earning courses. People are not equally equipped to study all fields, thus they might tend to self-select themselves into fields where they have comparative advantages. For instance, students with high analytical skills might tend to choose degrees like Engineering or Business, while those with strong verbal abilities might be more inclined towards Social Sciences or Humanities. Similarly, DALY, JENSEN, and MAIRE (2022) show that individuals admitted to their preferred field within different broad disciplines realize higher earnings gains and align more closely with the skill demands of those fields, supporting the role of comparative advantage in shaping educational and labour market outcomes. Moreover, DE PAOLA and GIOIA (2011) add that risk aversion also influences field choice. Risk-averse students are less likely to choose Social Sciences, favouring Humanities and Engineering related courses. This might be a result of the reduced dropout risk in Humanities and lower labour market risks in Engineering. Additionally, high-ability, risk-averse students tend to choose Engineering, while the preference for Humanities decreases with ability.

Furthermore, one should consider that there are other factors that can influence expected earnings. Those include firm size and location as well as working field and occupation. Roy's model (ROY 1951) defends that earnings differentials across occupations are not just a result of differences in skills or education but also a consequence of self-selection based on individual's unique skill sets. This model is rooted in the idea that individuals' skill levels vary across different types of work and that they will choose the occupation in which they can earn the highest income, considering their abilities, thus introducing the concept of self-section bias. NEUMAN and ZIDERMAN (1991) and PEREIRA and MARTINS (2002) further highlight that the bargaining dynamics between employer and employee can be seen as another challenge. Instrumental variable methods are often used to address such biases by isolating variation in education unrelated to individual characteristics. However, applying IV in the context of multiple fields of study is challenging because it requires a specific instrument for each educational path, as noted by JAHROMI and MEAGHER (2024).

B. Returns to Higher Education in Portugal

A wide range of cross-country studies underscores the significant returns to education, particularly in Portugal, where these returns rank among the highest in the European Union (MONTENEGRO and PATRINOS 2014). For instance, VIEIRA (1999) estimated that each additional year of schooling increases earnings by approximately 7 percent, on average. A. ALMEIDA et al. (2017), provide further evidence that the returns are even higher for individuals with tertiary education. Although conventional estimates focus on mean returns, methods like quantile regressions are also commonly used, highlighting variations across the wage distribution. MACHADO and MATA (2001) estimated that returns ranged from 4% to 11% at its lower and upper part of the distribution. MARTINS and PEREIRA (2004) also used this approach finding expected returns of 6.5% and 14.5% at the bottom and top of the distribution, respectively.

When analysing returns to higher education in Portugal, it is important to consider the change in the education system in 2006, following the Bologna Process. To align the Portuguese education system with other European systems and contribute to the creation of the European Higher Education Area, a new higher education framework was introduced. This

structure established three formal level of qualifications: bachelor's, master's and PhD degrees. The restructured system standardized bachelor's degrees at 3 years and master's at 2 years. Thereupon, the combined duration of the first two study cycles (bachelor's and master's) is similar to the duration of a bachelor's degree in the pre-Bologna period (FÁTIMA and ABREU 2007). The implementation of this new education system was seen as a sign of higher quality, attracting more students to programmes structured in line with this process (CARDOSO et al. 2008). In fact, it was registered an increase in the enrolment in higher education by 19.7% from 2006 to 2007 (SULEMAN and FIGUEIREDO 2020) leading to a substantial increase in the share of master's degrees holders.

Despite the evidence of wage premium on pursuing higher education compared to secondary education, there is increasing evidence that these returns are decreasing over time. D. R. ALMEIDA et al. (2022) indicates a downward trend in the returns to college degrees, attributing this decline to the oversupply of highly skilled workers. A. ALMEIDA et al. (2017) finds a decreasing trend at the bachelor's level, while at the master's level there is a slight growth and stabilization of relative returns after 2010. It is also suggested that when examining the trends in gross real mean wages, the reduction in graduates' returns was accompanied by a decrease in their purchasing power. Additionally, the field of study emerges as a key factor in determining wage premiums. Evidence from PEREIRA and MARTINS (2002) suggests that fields like Engineering yield higher returns than Human and Social Sciences.

C. Gender Wage Disparities

The gender wage gap has been a prominent area of research within labour economics which has been highlighting persistent disparities in earnings between men and women. This gap is observed across many countries and industries, with significant implications for economic inequality and social policy.

As highlighted in the literature, an increase in female labour participation is expected to decrease gender wage disparities, as higher participation reduces the potential for selection effects to distort wages (OLIVETTI and PETRONGOLO 2008). Similarly, the improvement in women's educational attainment should contribute to narrowing the wage gap (ALTONJI and

BLANK 1999). However, disparities persist. For instance, CARDOSO et al. (2016) report that while the raw gender wage gap in Portugal declined from 32% to 20% between 1991 and 2013, the adjusted gap - controlling for observable characteristics - remained considerably constant, at around 25%. They further explain that sorting among firms and job titles accounts for about two-fifths of this gap.

Nevertheless, education in itself can also contribute to the gender wage gap. LIVANOS and POULIAKAS (2012) found that, in Greece, gender disparities in field of study choices impact wage outcomes. Women are more likely to select fields such as Humanities and Education, which offer lower wage premiums compared to fields like Engineering or Finance, where men are overrepresented. Moreover, MUSSIDA and PICCHIO (2014) analyse the Italian labour market and highlight how lower-educated women experience significant wage penalties, finding a more marked evidence of "sticky floor" and evidence of "glass ceiling" for highly educated women. In Portugal, M. CAMPOS and REIS (2017) documented that, although women achieve higher educational levels than men, their returns to schooling remain systematically lower.

III. Data

A. *Quadros de Pessoal*

The analysis of this paper relies on *Quadros de Pessoal (QP)*, a longitudinal linked employer-employee job title dataset. The information is based on a compulsory survey conducted annually by the Portuguese Ministry of Employment. Data covers every establishment paying wages in the Portuguese private sector, meaning that general government, military staff, self-employed and household employees are excluded. The questionnaire contains information for all firms with, at least, one wage earner.

This dataset includes information on gender, age, education, occupation, industry, tenure and earnings, among other dimensions. For this analysis, I use data in the period spanning from 2006 to 2021. I focus on a sub-sample made of full-time employees aged between 25 and 30 years who have attained at least a secondary level of education. The restriction to this age range is primarily done to align with the introduction of the Bologna Process in 2006. While some in-

dividuals aged 25–30 with a bachelor’s degree in the earlier years of the sample (e.g., 2006) may have completed their degree under the pre-Bologna system, by 2015, most individuals in this age range with a bachelor’s degree will have obtained a post-Bologna qualification. The dataset considers 3 groups of workers: high school educated workers, corresponding to employees with 12 years of schooling; workers with a bachelors’ degree, equivalent to 15 years of schooling; and individuals with a master’s degree, equivalent to 17 years of schooling. The reasoning for excluding PhD workers relies on the fact that jobs for doctorates often have very specific characteristics. In fact, the sample would include only about two thousand doctorate-level individuals, representing just 0.06% of the total sample. Moreover, the sample was restricted to workers with up to 10 years of work experience. Finally, in order to exclude outliers from the analysis, workers that report total wages 2.5 times above the 99th percentile were dropped (that is, monthly wages above 8,557 euros). The final sample consists of 3,172,711 observations.

Wages are defined as the total of all work-related income categories, including base salary, overtime, regular and irregular payments. Wages are adjusted to the total amount of working hours, both normal and supplementary. Additionally, real wages are calculated using the Consumer Price Index for each year, with 2012 as the base year. In addition, a variable was created to provide information on the minimum number of school years required to complete the highest reported educational level.

Moreover, to facilitate the analysis, fields of study were grouped into broader categories based on their representation¹ in the dataset and conceptual similarities². The broad fields are the following: 1) Business; 2) Health, Life Sciences and Veterinary; 3) Education; 4) Engineering, Maths and Physical Sciences; 5) Humanities and Arts; 6) Social Sciences; 7) IT; 8) Other. This approach ensures that all fields are included in the analysis while maintaining sufficiently large sample sizes for meaningful statistical evaluation. It is important to note that this division is only done for higher education, there is not a distinction between secondary school fields.

1. At the bachelor’s level, the distribution of fields of study falls into the following share intervals: [0%; 5%] – Arts, Humanities, Information and Journalism, Life Sciences, Mathematics, Physical Sciences, Law, Education, Manufacturing Industry, Architecture, Agriculture, Veterinary Sciences, Social Services, Personal Services, Environmental Protection, and Security Services; [5%; 10%] – Information Technology (IT); [10%; 20%] – Business, Engineering, and Health. At the master’s level, the distribution across these intervals remains consistent, with the exception of an increase in the share of workers with a master’s degree in Social Sciences, which moves from [0%; 5%] to [5%; 10%].

2. Refer to Table 2 for a detailed list of the narrow fields.

B. Descriptive Statistics

Table 1: Descriptive statistics of the restricted sample.

	2006	2010	2013	2015	2017	2021
N° observations						
High School	121 384	104 976	90 404	94 585	110 377	131 939
Bachelors	65 319	80 414	68 137	65 919	72 795	83 186
Masters	3 079	4 749	9 746	14 631	20 262	27 414
Gender (% of female)						
High School	51.5%	50.6%	49.9%	48.5%	46.5%	44.2%
Bachelors	61.1%	63.1%	64.6%	63.2%	62.1%	60.5%
Masters	58.2%	49.8%	49.0%	51.0%	53.5%	55.2%
Education (Mean, in years)						
High School	13.11	13.39	13.50	13.54	13.57	13.59
Tenure (Mean, in years)						
High School	3.11	2.92	3.13	2.74	2.36	2.27
Age (Mean, in years)						
High School	27.65	27.64	27.90	27.60	27.52	27.56
Modal field of study						
Bachelors	Business	Health	Health	Health	Health	Health
Masters	Business	Engineering	Engineering	Engineering	Engineering	Engineering

Notes: Source: Author's own calculations based on "*Quadros de Pessoal*".

Table 1 provides a summary of the descriptive statistics for the number of employees across each education level, highlighting several trends observed over time.

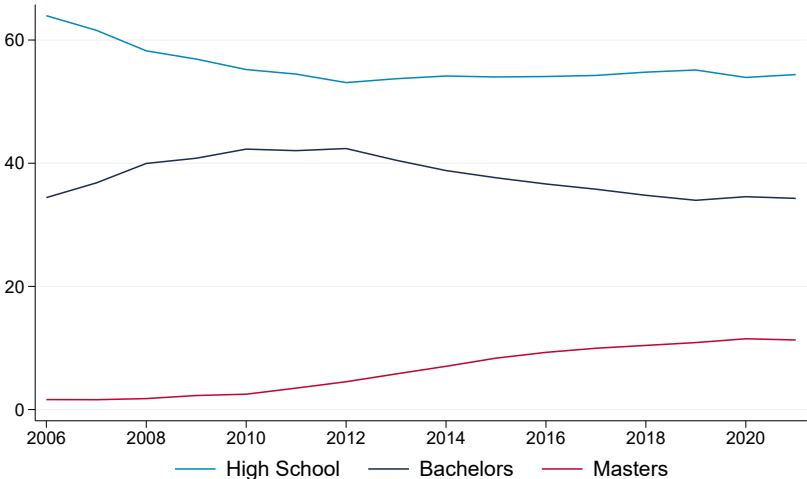
First, between 2006 and 2021, the number of employees with high school diplomas and bachelor's degrees rose, although some fluctuations occurred during this period. As for workers with a master's qualification, there has been a consistent increase over time. Moreover, the number of individuals with bachelor's and master's degrees grew at a faster pace compared to those with only high school, suggesting an upward trend in the educational attainment of the workforce. Second, the share of women across education levels exhibits distinct patterns. Among high school graduates, the percentage of women declines steadily over time, from 51% in 2006 to 44.2% in 2021. In contrast, the percentage of women with master's degrees shows a gradual increase, rising from 49.8% in 2010 to 55.2% in 2021. Additionally, average tenure decreases across the entire period and the average age remains relatively stable over the period in analysis, around 27-28 years old. Finally, the modal field of study for both bachelor's and master's degrees shifts over time. For bachelor's degrees, there is a transition from Business being the most common field in 2006 to Health by around 2010 and beyond. For master's degrees, Business was the predominant field of study in 2006. However, by approximately 2010,

Engineering-related courses emerged as the leading choice and have consistently remained the most pursued field through 2021.

C. Shifts in Educational Attainment and Field Preferences

In Figure 1, one can observe an overall increase in the proportion of workers with tertiary education over time, particularly individuals with a bachelor’s degree between 2006 and 2010. This period highlights the rapid expansion of higher education. Prior research notes that such expansion reduces the relative value of degrees, particularly at the undergraduate level. Despite the continuous growth in the supply of postgraduate individuals, as also depicted in Figure 1, the expected returns to master’s degrees have not experienced the same decline as bachelor’s programs (A. ALMEIDA et al. 2017). This trend suggests that a master’s degree increasingly functions as a mechanism to differentiate individuals in the labour market. A. ALMEIDA et al. (2017) further indicate that postgraduate qualifications help reducing substitutability in the labour market, allowing those with this qualification to access higher-paying jobs.

Figure 1: Evolution of worker’s highest education attainment over time (in percentage).



Notes: Source: Author’s own calculation based on *Quadros de Pessoal*.

Shifting focus to the evolution of employee shares within each field of study, Figures 8 and 9, in the Appendix, reveal notable trends across educational levels. At the bachelor’s level, Business degrees initially held the largest share, but have experienced a significant decline since 2010, possibly reflecting the impact of the Bologna Process. By 2020, this share was notably

lower than its peak in the early-10's. As previously explained, before Bologna, Business degrees were typically structured as four-year programs. However, after Bologna, the duration of a bachelor's degree was reduced to three years, on average, making a master's degree more necessary to achieve the same level of qualification as the one achieved in pre-Bologna programs. This structural change likely explains the increasing share of master's graduates in Business, as individuals now seek advanced degrees to meet the market demands that were previously fulfilled by a four-year bachelor's degree.

On the other hand, there was a sharp rise in the share of workers holding a bachelor's degree in Health-related areas, particularly from 2006 to 2013. This increase might reflect a growing demand for health professionals during that period, stabilizing afterwards. The share of workers holding bachelor's degrees in Education experienced initial growth but has steadily declined over time. Moreover, fields like Humanities and Arts maintain minimal shares of workers with these degrees throughout the observed period, implying a lower market labour demand of employees in these areas.

At the master's level, Figure 9 in the Appendix, there are further shifts in field dynamics. While the presence of workers with Business degrees saw a decline from 2006 to 2009, it began increasing after 2010 and stabilized from 2015 onwards. In 2006, Business was the most common area among individuals with a master's qualification, but it was soon surpassed by Engineering degrees, which grew to nearly 40% of employees with master's qualifications. This significant growth was likely due to the "Mestrado Integrado" programs in fields like engineering, where students are automatically placed in a combined bachelor's and master's track. These programs effectively require completion of a master's degree. Similarly, the health sector shows a rise in master's graduates, reflecting an increasing preference for masters' qualifications in this field. Meanwhile, fields like Education, Humanities, and Arts maintain smaller but steady shares of employees holding masters' degrees in these areas.

It is important to note, however, that the trends discussed here are based on the *Quadros de Pessoal* dataset, which only includes private sector employees. Consequently, these findings may not fully capture dynamics in public sector employment or self-employment, which could exhibit different patterns.

IV. Empirical Methodology

The pioneering work of BECKER (1964) introduced the concept of human capital. Becker argues that education is a form of an investment that enhances an individual's productivity, leading to higher earnings over time. Individuals forgo immediate benefits in favour of future gains by acquiring skills and knowledge that enhance productivity, resulting in higher future earnings. Building on Becker's theoretical framework, MINCER (1974) developed an empirical framework to quantify the returns to education. The Mincer earnings function demonstrates how earnings are influenced by years of schooling and work experience, being expressed as follows:

$$\ln y_i = \alpha + \beta S_i + \lambda_1 Exp_i + \lambda_2 Exp_i^2 + \epsilon_i \quad (1)$$

where, y_i represents earnings, S_i is the number of years of schooling, Exp_i refers the individual's work experience and Exp_i^2 captures the diminishing returns to experience. The coefficient on schooling β is typically interpreted as the percentage increase in earnings associated with an additional year of schooling.

In addition, CARD (1999) highlights that decisions regarding the level of investment in education are influenced by individual preferences. Factors such as differences in personal abilities, access to resources, or individual preferences for immediate versus future benefits play a significant role. This perspective supports a heterogenous effects framework, where the impact of various factors on wages can differ substantially across individuals.

That said, a significant challenge in estimating the returns to education arises from the potential issue of endogeneity. This occurs when unobservable individual-specific characteristics, such as ability or motivation, affect both educational attainment and earnings. These factors, some of them unobservable, are captured in the error term, ϵ , and, if correlated with years of schooling, lead to biased OLS estimators. Consequently, this leads to an inconsistent estimator of the returns to education. Since the main Mincerian equation does not account for the impact of individual's ability on wages and educational level, the estimated returns to schooling are likely to be upward biased.

To address this ability challenge, GRILICHES (1977) highlights that including measures such as IQ scores or "knowledge of the world of work" (KWW) tests can help control for unobserved ability that may correlate with both schooling and earnings. Moreover, he also notes that test scores can be treated as indicators of unobserved ability, and family background variables (e.g., parental education or occupation) can be used as instruments for test scores or schooling when addressing endogeneity concerns. Beyond these, college proximity has been employed as an instrumental variable, as it reduces the cost of attending college and thereby influences educational attainment, particularly for disadvantaged individuals (KLING 2001). Similarly, ANGRIST and KRUEGER (1991) use season of birth (quarter of birth) as an instrument, leveraging the interaction between school start age policies and compulsory schooling laws to generate exogenous variation in education.

Nevertheless, IV estimates are heavily influenced by the subset of individuals whose educational attainment is affected by the chosen instrument. Different instruments can produce varying estimates of the returns to schooling, leading to different interpretations (ANGRIST and IMBENS 1995). Moreover, this approach is difficult to implement in a context of majors, particularly because there are numerous fields of study and students can choose several unordered alternatives meaning that identification in IV requires one instrument per alternative (JAHROMI and MEAGHER 2024). In addition to traditional IV methods, A. ALMEIDA et al. (2017) highlight the potential of firm-specific controls and occupational classifications in capturing variation in educational returns. However, this study focuses on providing a broad overview of wage premiums associated with different fields of study, rather than establishing causal relationships, thus methods such as IV estimation or control functions are not employed in this analysis.

This paper examines the financial returns by using OLS to estimate different specifications of the Mincerian wage regression. The first regression is estimated with the highest completed level of schooling included as a dummy variable.

$$\ln y_i = \alpha + \sum_{j=1}^2 \beta_j E_{j,i} + \gamma \mathbf{x}_i^T + \epsilon_i \quad (2)$$

where y_i corresponds to individuals' real hourly wage, E_j , $j = 1, 2$ is an indicator variable for an individual's level of education: 1) Bachelor's Degree; and 2) Master's Degree. High School

is the category treated as the baseline for the comparison, and therefore it is omitted from the regressions. This means that each β_j represents the wage premium benefiting individuals with level j of education compared to high school educated individuals. Vector \mathbf{x}_i^T corresponds to a set of observable characteristics and the parameters in vector γ measure the respective marginal impact on $\ln(y_i)$. Firstly, the above regressions are estimated with the typical Mincer controls including tenure (in years), tenure squared and gender dummy variable (1 for male). Following that, they are re-estimated adding the logarithm of the firm size and socio-demographic variables including a dummy variable for the industry sector and another for region.

Secondly, the main regression of this study accounts for the area of study of the highest completed level of schooling as a dummy variable. By employing this specification, the analysis estimates the financial returns associated with an individual's field of study.

$$\ln y_i = \alpha + \sum_{j=1}^{18} \beta_j (Field_i * Degree_i) + \gamma \mathbf{x}_i^T + \epsilon_i \quad (3)$$

In this regression, the main variables of interest are the 18 education categories based on an interaction between the two types of tertiary education degrees and 9 fields of study. $Field_i$ includes the 9 fields of study as described in Section III. $Degree_i$ refers to Bachelors and Masters programmes, as mentioned above. Once again, High School is omitted in the regressions to serve as a comparison. Therefore, each β_j represents the wage premium of an individuals with level j of education and field of study compared to individuals with only high school. In this study, the analysis focuses exclusively on employees with three distinct levels of education—12, 15, or 17 years of schooling. Consequently, estimating returns to each additional year of education using a baseline regression is not particularly insightful, as the limited variability in educational levels does not lend itself well to such an approach.

Additionally, building on the baseline model presented in Equation 2, the analysis is expanded to explore how the gender wage gap varies when accounting for differences in fields of study and levels of education. First, an interaction between gender and level of education is introduced to examine how gender influences the wage premium associated with each degree level. Second, controls for fields of study are included to assess whether differences in field choices contribute to the gender wage gap. Finally, the model is further refined by incorporat-

ing a three-way interaction between gender, level of education, and field of study, aiming to capture differences in the gender wage gap across fields of study.

V. Results

This section presents the findings from the empirical analysis, focusing on the wage premiums associated with different degrees and fields of study in comparison to secondary education. In subsection *V.A*, the discussion focuses on the overall returns to higher education degrees, providing a general understanding of how additional schooling translates into wage premiums. Subsection *V.B* delves deeper into returns across various fields of study. Lastly, subsection *V.C*, explores gender disparities in returns to education, examining how the interaction between gender, education level, and field of study shapes observed wage differentials. The results presented in the following subsections were obtained from the regressions that include controls for firm size, region and sector. As anticipated, the estimated results are lower than those derived from the regressions without these controls, suggesting that a portion of the observed wage premiums is associated with differences in firm characteristics, economic conditions at the regional level and sector-specific effects (as shown in Table 3 panel A vs B, and Table 6 vs Table 7).

A. Returns to Higher Education

As mentioned in the methodology section, the wage equation was estimated using an OLS approach, where the coefficients of the dummy variable for bachelor's and master's degrees indicate the wage premium relative to those with only secondary education. These coefficients represent the percentage increase in income associated with each level of higher education, providing insights about the relative financial benefits of pursuing higher education over time.

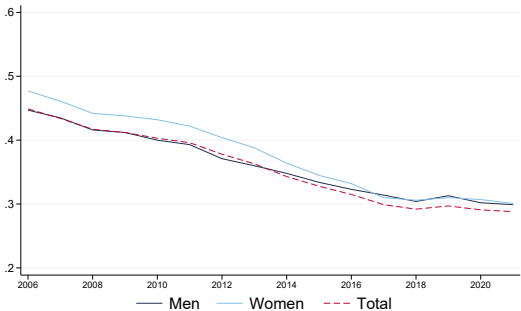
The first set of results are presented in Table 3 in the Appendix. Figure 2 shows these results over the years, divided by gender. The results for men and women are derived from separate regressions of Equation 2, representing the wage premium for individuals with a bachelor's degree compared to those with only a high school education within the respective gender. The aggregate line represents the results of Equation 2 estimated for the entire sample without

including the gender dummy, capturing the average wage benefit across the entire sample.

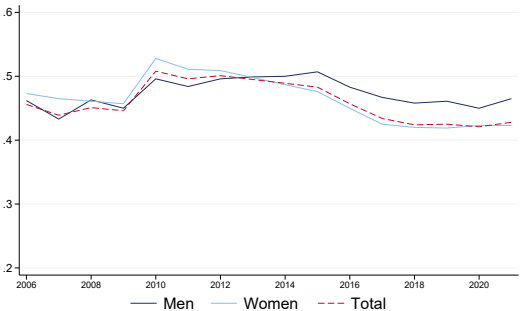
In Figure 2 (a), one can observe a consistent downwards trend from 2006 to 2020, suggesting a gradual reduction in the wage premium associated with a bachelor’s degree. This reflects the increase in educational attainment among the Portuguese workforce, as previously mentioned. This trend aligns with the theory that as more individuals obtain degrees, the premium associated with those degrees’ declines (A. ALMEIDA et al. 2017). This phenomenon is commonly referred to as the ”credential inflation” hypothesis, where the value of a degree diminishes as it becomes more ubiquitous in the workforce.

Additionally, Figure 2 (a) also shows that the wage premium from obtaining a bachelor’s degree is consistently higher for women than for men across most of the analysed period, until around 2016. This indicates that, in percentage terms, women are more compensated for pursuing higher education. However, this does not necessarily imply the absence of a gender wage gap. If men earn more than women at the high school level, a smaller wage premium for men can still result in higher absolute wages for men with a bachelor’s degree compared to women. The higher wage premiums for women may reflect the fact that women start from a lower wage baseline at the high school level, making the relative reward for pursuing higher education more substantial for women than for men, in percentage terms.

Figure 2: Estimated wage premiums to higher education by degree level for men and women with high school as the baseline.



(a) Wage premium to having a bachelor’s degree compared to high school.

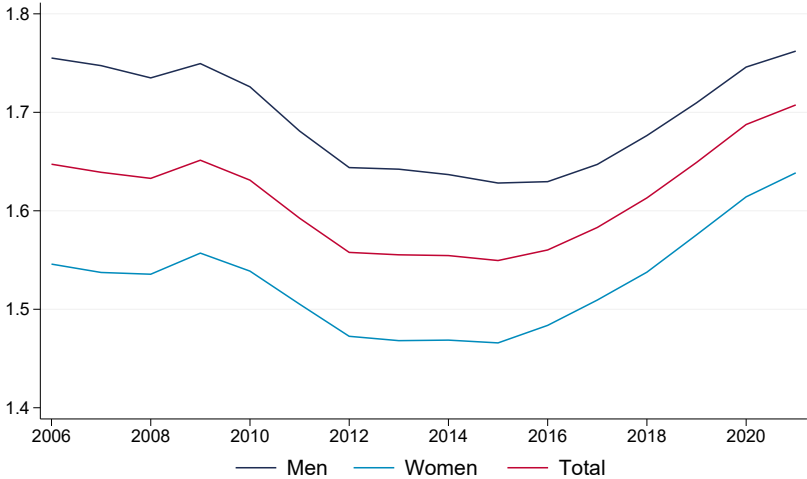


(b) Wage premium to having a master’s degree compared to high school.

Notes: The Figure displays the estimates wage premiums for individuals with a bachelor’s (a) or master’s degree (b) relative to those with only high school education, derived from Equation 2 and including controls (firm size, region and sector controls). The results for men and women are obtained from separate regressions, reflecting the wage premium within each gender. The aggregate line captures the estimated wage benefits for the entire sample, derived from Equation 2 without including a gender dummy. The detailed regression results of the average premium of the entire sample are presented in Panel B in Table 3 and the wage premium results for each gender are displayed in Table 4, in the Appendix. *Source:* Author’s own calculation based on *Quadros de Pessoal*.

In Figure 3, the average real wage per hour of employees with only a high school education is depicted. The persistent disparity on wages provides context for understanding the higher wage premiums observed for women pursuing a bachelor’s degree. The larger percentage increase for women likely reflects their lower starting point, as women with only high school earn considerable less than their male counterparts. Thus, while higher education can narrow the gap in percentage terms, there may still exist wage differentials between men and women. In Figures 10 and 11, in the Appendix, one can observe that at the bachelor’s and master’s level, respectively, women consistently earn lower average wages than men.

Figure 3: Average logarithm of real wage per hour (in euro) of employees with only high school education.



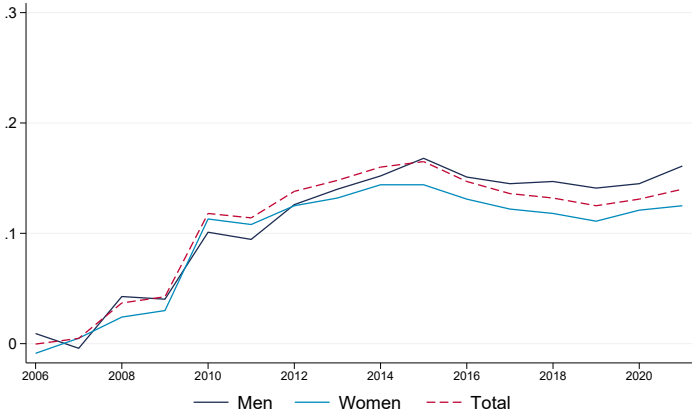
Notes: The chart depicts the average real wage per hour worked in each wave of QP (deflated using CPI, 2012 base year) *Source:* Author’s own calculation based on *Quadros de Pessoal*.

In comparison to bachelor’s degrees, returns to a master’s degree, as depicted Figure 2 (b), remain higher and more stable, reinforcing the economic value of a master degree. From the beginning of the analysis period until approximately 2013, the master’s wage premium is higher for women than for men. This suggests that, during this period, women were relatively more compensated (in percentage terms) for pursuing a master’s degree compared to men. From 2013 onwards, the wage premium for men surpassed that for women, indicating that men start to experience higher relative returns to a master’s degree compared to women in later years.

Furthermore, it is insightful to compare directly the returns to a master’s degree against those of a bachelor’s degree. Figure 4 presents these OLS regression results. From 2006 to around 2016, both men and women see an upward trend in the wage premium associated with

a master’s degree relative to a bachelor’s degree followed by a period of stabilization. This upward trend suggests, once again, that the additional financial benefits of holding a master’s degree have become more valuable over time.

Figure 4: Estimated wage premiums to having a master’s degree in comparison with an individual with a bachelor’s degree.



Notes: The Figure displays the estimates wage premiums for individuals with a master’s degree relative to those with a bachelor’s program, derived from Equation 2 and including controls (firm size, region and sector controls). The results for men and women are obtained from separate regressions, reflecting the wage premium within each gender. The aggregate line captures the estimated returns for the entire sample, derived from Equation 2 without including a gender dummy. The detailed regression results of the average returns of the entire sample are presented in Panel A, in Table 5 and the wage premium results for each gender are displayed in the same Table in Panel B and C, in the Appendix. *Source:* Author’s own calculation based on *Quadros de Pessoal*.

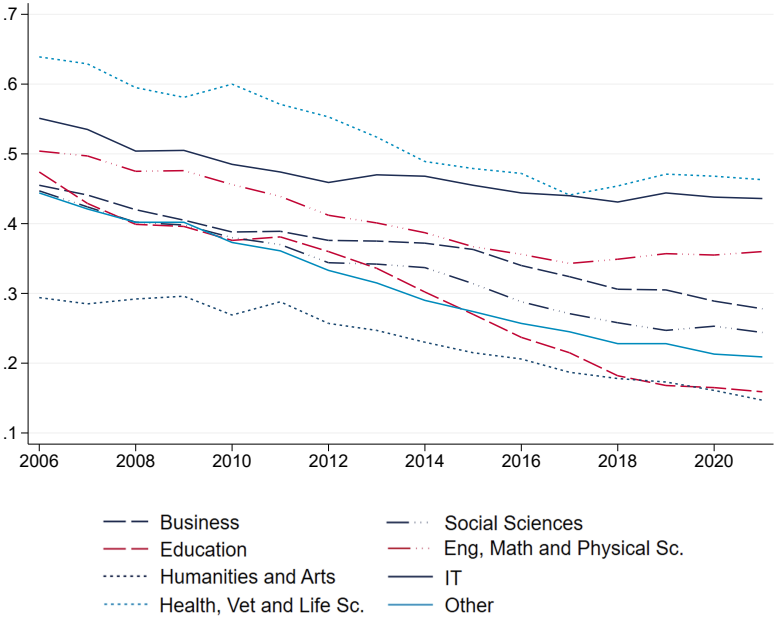
B. Returns to Higher Education across fields of study

Focusing on the analysis by field of study, the results presented in Figure 5 were calculated using a regression model that incorporates interactions between degree levels and field of study, as specified in Equation 3. This specification allows the estimation of wage premiums for individuals with a bachelor’s degree, segmented by field of study, relative to those with only high school education. Therefore, the coefficients for the interaction terms (β_j) capture the wage premium associated with each specific combination of degree level and field of study, with high school serving as the baseline for comparison.

In Figure 5, one can observe that there is a general downward trend across most fields, which reinforces the previous finding that the wage premium associated with a bachelor’s degree has diminished. Among all fields of study, Health-related degrees initially yield the highest returns, although this advantage has decrease from around 60% in 2006 to 46% in 2021. IT degrees also

offer high wage benefits with a less pronounced downward trend than in other fields, suggesting a continuous demand for technology skills. Engineering, Mathematics and Physical Sciences follow closely, also providing relatively high returns, varying from 50% in 2006 to around 35% in 2021. By contrast, Humanities and Art courses hold consistently the lowest relative returns, starting below 30% in 2006 and decreasing further to about 15% by 2021.

Figure 5: Estimated wage premiums to having a bachelor’s degree in comparison with an individual with high school across different fields of study.



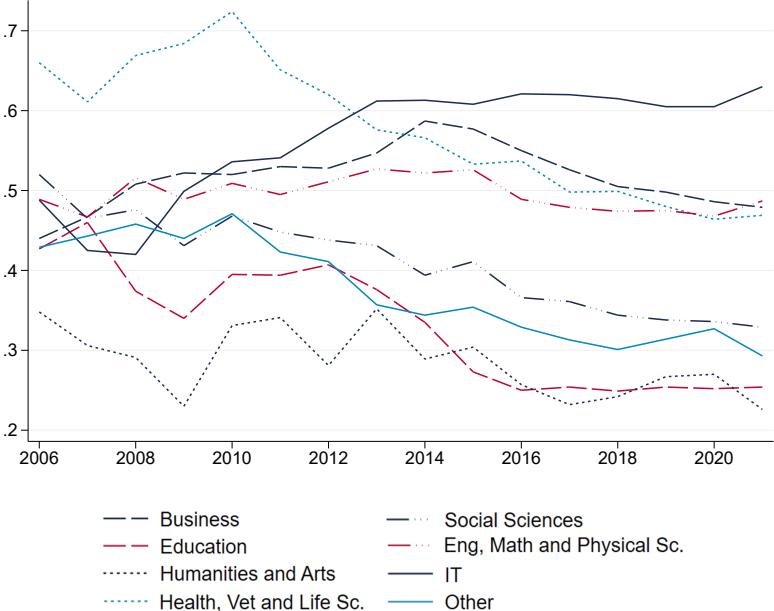
Notes: Displays the estimates wage premiums for individuals with a bachelor’s degree relative to those with only high school education across various fields of study, calculated using Equation 3, which includes interactions between degree levels and fields of study, as well as control variables (e.g., firm size, region, and sector). The detailed regression results are presented in Table 7, in the Appendix. The results are shown across the analysis period and are statistically significant. *Source:* Author’s own calculation based on *Quadros de Pessoal*.

Similarly, Figure 6 presents the wage premiums for individuals with a master’s degree relative to those with only secondary education, derived from Equation 3 that incorporates interactions between degree levels and fields of study.

At the master’s level, returns across most fields are generally higher than those at the bachelor’s level, as expected. There is an upward trend across several fields between 2006 and 2014, followed by a period of stabilization or slight decline from 2016 onwards. Moreover, some fields of study stand out among others. Firstly, Health-related degrees show the highest returns for almost half of the period, with returns starting at around 66% in 2006, peaking close to 72% in 2010, but then declining to approximately 47% by 2021. Despite this decline, the wage

premium in Health-related fields remains one of the highest, likely due to sustained demand for high skills in healthcare. Not surprisingly, IT-related degrees exhibit a consistent upward trend until around 2013, at which point they became the degrees offering the highest returns. This pattern stabilized and remained elevated through 2021, underscoring the growing demand for technology-related skills and their increasing value in the labour market. Another field that shows relatively high returns is Business. One can observe a relatively stable increase until around 2015-2016, reaching approximately 57%. Following this period, a decline in returns emerges, with a decrease of about 10 percentage points. Engineering-related master’s degrees also yield relatively high wage benefits, suffering a slight decrease around 2015, but remaining considerable stable. By contrast, Humanities and Arts consistently show the lowest returns, even at the master’s level, with wage premium declining from around 35% in 2006 to 22% by 2021. Similarly, a significant decrease in wage benefits in Education after 2010 is noticeable, highlighting limited financial benefits in this sector despite the higher level of education.

Figure 6: Estimated wage premiums to having a master’s degree in comparison with an individual with high school across different fields of study.



Notes: Displays the estimates wage premiums for individuals with a master’s degree relative to those with only high school education across various fields of study, calculated using Equation 3, which includes interactions between degree levels and fields of study, as well as control variables (e.g., firm size, region, and sector). The detailed regression results are presented in Table 7, in the Appendix. The results are shown across the analysis period and are statistically significant. *Source:* Author’s own calculation based on *Quadros de Pessoal*.

C. Gender Disparities in Returns across Fields of Study

In this subsection, the analysis focuses on the gender wage gap, a topic that has received significant attention in empirical research due to its implications for labour market equity and social policy. In the context of this study, it is important to explore how the gender wage gap varies when considering differences in fields of study and levels of education. This approach allows for a deeper understanding of whether educational choices contribute to wage disparities and how these effects evolve over time.

Firstly, the distribution of men and women across various fields of study is analysed at both levels of education (e.g., Bachelor's and Master's degrees). Figures 12 and 13, in the Appendix, provide information about the gender representativeness for the years 2006 and 2021 (graphs (a) and (b), respectively). The distribution reveals only minor changes over time, with women disproportionately represented in fields such as Health, Education, and Humanities and Arts, while men dominate areas like IT and Engineering.

As discussed earlier, female-dominated fields tend to exhibit lower wage premiums over time. For example, Education, Humanities and Arts show a particularly pronounced decline in wage benefits, while IT continues to offer high and increasing premiums. This can raise the question: to what extent does this unequal distribution of men and women across fields of study explain the observed gender wage gap? To address this, baseline results derived from Equation 2 are presented, now incorporating the gender dummy variable to account for gender-specific differences in returns to education.

Table 8 presents the baseline results. As observed in Figure 7 (a), across the analysis period, men consistently earn higher wages than women. However, the gender wage gap decreases from 17.2% in 2006 to 11% in 2021, indicating some degree of convergence in wages over time. Nevertheless, this baseline specification does not yet account for interactions with education level or fields of study, which may provide further insights into the sources of the gap.

Building on the baseline equation, Table 9 incorporates interaction terms between gender and education levels (e.g., Bachelor's and Master's degrees). This addition allows to analyse how gender influences the wage premium associated with each degree level. At the bachelor's level, the interaction term (Gender \times Bachelor) is negative across most years, indicating that

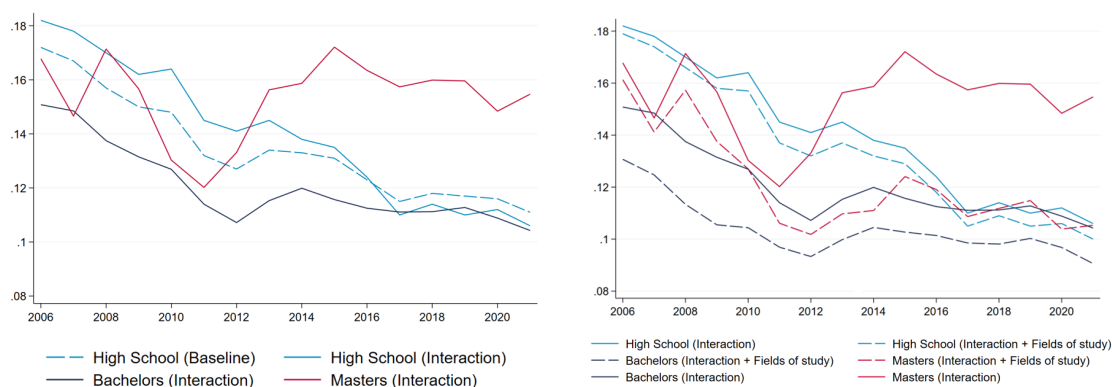
the wage premium for men with a bachelor's degree is smaller than for women. This suggests that obtaining a bachelor's degree helps narrowing the gender wage gap relative to those with only a high school education.

At the master's level, the interaction term ($\text{Gender} \times \text{Master}$) tells a more nuanced story. While it is negative in earlier years (e.g., 2006 and 2010), it turns positive around 2013 onwards, suggesting that, in later years, men with master's degrees experience a larger wage premium relative to women. In Figure 7 (a), it is, in fact, noticeable that the gender wage gap among individuals with a bachelor's degree is decreasing while for masters, it increases from 2011 to 2015 and exhibitd a slight decrease from 2016 onwards.

To deepen the analysis, controls for fields of study were added, which are presented in Table 10. This allows to examine whether differences in field choices contribute to the gender wage gap. Firstly, controlling for fields of study slightly reduces the overall gender wage gap across all years, as seen in Figure 7 (b). For instance, the coefficient for Gender (Male = 1) decreases from 18.2% in Table 9 to 17.9% in Table 10 in 2006, and from 10.6% to 10% in 2021. This reduction suggests that part of the wage gap can be attributed to differences in the fields of study chosen by men and women.

At the bachelor's level, the interaction term becomes more negative across all years when controlling for fields of study. For example, it drops from -3.1% in Table 9 to -4.8% in Table 10 in 2006, and from -0.17% to -0.94% in 2021. This indicates that differences in field choices explain part of the gender wage gap for bachelor's degree holders, as verified in Figure 7 (b). However, after accounting for these differences, although the gender wage gap decreases over time, it remains high. At the master's level, the interaction term is negative in earlier years (-1.7% in 2006) but turns positive later on. However, the magnitude of the positive difference in wage premium between gender is smaller after controlling for fields of study, as shown in Tables 9 and 10 in the Appendix. As one can observe in Figure 7 (b), the gender wage gap when controlling for fields of study becomes much smaller compared to when such fields are not included, suggesting that field choices partially explain gender wage disparities in this level of education. Nevertheless, not all coefficients of the interaction term at the master's level are statistically significant, which limits the robustness of this interpretation.

Figure 7: Estimated gender wage gap by education level.



(a) Gender wage gap estimates derived from the regression accounting for the interaction $Gender \times Degree Level$ (solid lines) and estimates from the baseline regression only accounting for the gender dummy (dashed line).

(b) Gender wage gap estimates derived from the regression accounting for the interaction $Gender \times Degree Level$ (solid lines) and estimates from the regression with the interaction term, controlling for fields of study (dashed lines).

Notes: Both graphs in the Figure display the estimated wage gender gap by level of education (e.g., high school, bachelors and masters). In graph (a), the solid line represents the baseline gender wage gap estimates from the regression in Table 8, which do not account for interactions with educational levels. The dashed lines, on the other hand, incorporate interaction terms between gender and education levels (e.g., bachelor's and master's degrees), showing how the wage gap changes when considering the impact of education level on wages. Graph (b) presents the gender wage gap after controlling for fields of study. The solid lines reflect the gender wage gap estimates when only interactions with education levels are included (Table 9), while the dashed lines represent estimates when added controls for fields of study (Table 10). Both graphs highlight the estimated gender wage gap for individuals with high school, bachelor's, and master's degrees. The gap is calculated by summing the gender dummy coefficient (the one from high school) and the interaction term coefficients for each education level. All tables mentioned are presented in the Appendix. *Source:* Author's own calculation based on *Quadros de Pessoal*.

In Table 11, the analysis is extended by adding to Equation 2 interaction terms between gender, fields of study, and educational levels. This regression aims to capture differences in the gender wage gap across fields, providing a more detailed view of how these factors interact.

At the bachelor's level, almost all interaction terms are negative, suggesting that men earn a lower wage premium than women within the same field and level of education. For example, in Health-related fields, the interaction term decreases from -13% in 2006 to -6% in 2021, indicating a narrowing of the wage premium gap. However, despite these negative interactions, the overall gender gap persists, as shown in Figure 14. In fields like IT and Engineering, the interaction terms are less negative, not contributing considerably to reducing the gender wage gap. This suggests that these male-dominated fields maintain a high gender wage disparity. At the master's level, it is important to note that many interaction terms lack statistical significance. In Health and Education-related fields, the interaction terms remain significantly negative (and

statistically significant), suggesting that women receive higher wage premiums than men in these fields. Yet, these differences are not sufficient to close the overall gender wage gap.

The analysis highlights significant gender disparities across fields of study and levels of education, with some fields reflecting high gender wage gap (e.g., Engineering and IT) while others indicate smaller wage disparities (e.g., Education and Health).

VI. Conclusion

This paper studies the private returns to education across fields of study for bachelor's and master's degrees in Portugal between 2006 and 2021, using the matched employer-employee database, *Quadros de Pessoal*. The objective was to explore the variability in wage premiums by degree level and field of study, providing insights into how higher education contributes to financial outcomes in the labour market.

The findings highlight a clear decline in returns to bachelor's degrees over time, with wage premiums dropping from approximately 50% in 2006 to around 30% in 2021. This trend reflects the increasing massification of higher education. As more individuals obtain bachelor's degrees, the wage benefit associated with this qualification decreases. Despite this decline, returns to master's degrees remain significantly higher and more stable, stabilizing around 44% by 2017, after peaking in earlier years. These results emphasize the value of advanced education, particularly master's degrees, as a differentiator in a competitive labour market.

Moreover, it is observed a clear variability in returns across fields of study. The analysis reveals different levels of incentives for pursuing a master's degree. For instance, IT-related courses consistently present higher returns for master's graduates compared to undergraduates, surpassing 60% in 2013 and remaining stable thereafter, indicating a strong incentive for advanced studies in this area. The same conclusion holds for Engineering degrees. As for Health-related fields, although expected returns have declined, both bachelor's and master's degrees offer high wage benefits, with a master's degree offering a slight advantage and continue demand in this field. A master's degree in Business provides an advantage over a bachelor's degree, remaining valuable despite the decrease in recent years. Conversely, Humanities and Arts, as well as Education, persistently exhibit the lowest returns, with master's degrees in these

fields offering premiums of just 22% and 25%, respectively, by 2021.

This work also examines gender disparities in returns to education across fields of study and levels of education, revealing persistent gender disparities with some evidence of convergence overtime. Women continue to be disproportionately represented in low-premium fields, such as Education and Humanities, while men dominate high-premium fields like IT and Engineering. This unequal distribution contributes to the gender wage gap, as controlling for fields of study reduces the gap, particularly at the master's level. Moreover, interaction effects show that, within certain fields, women earn higher wage premiums than men, especially in Health and Education, but these differences are insufficient to eliminate the overall gender wage gap, therefore being evident gender wage disparities within fields of study. The findings underscore the complex interplay between gender, educational choices, and labour market outcomes.

While this paper provides valuable insights into the higher education in Portugal, several limitations must be acknowledge. First, despite the statistical significance of the results and the extensive dataset used, the analysis only accounts for workers employed in the private sector, which limits the broader validity of the findings. Second, the study relies solely on observable characteristics of individuals. Unobservable factors such as socio-economic background of individuals or their ability are not captured, potentially influencing the estimated returns.

Future research could expand this study by examining the interaction between undergraduate and postgraduate fields of study to better understand how educational trajectories influence labour market outcomes. For instance, analysing wage differentials between individuals who pursue interdisciplinary paths—such as a bachelor's degree in Business followed by a master's degree in Law—and those who maintain continuity within a single field could provide valuable insights into the benefits of academic diversity. However, the current dataset focuses solely on the highest qualification attained, which restricts the ability to explore such pathways. To address this, future studies could incorporate surveys or leverage alternative datasets that include detailed information on individuals' complete educational trajectories. This approach would enable a more comprehensive analysis, contributing to the understanding of how combinations of fields of study affect employability and wage outcomes, particularly in an increasingly dynamic labour market.

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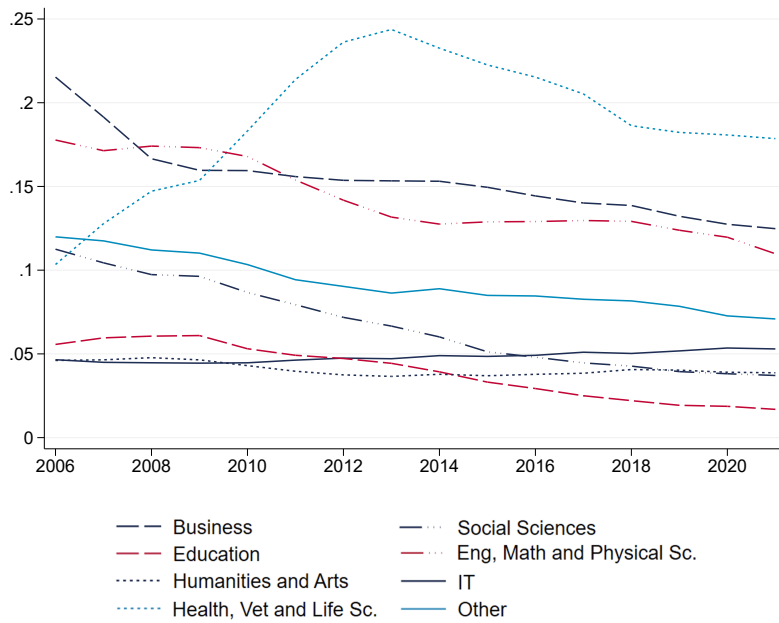
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Appendix

Table 2: Classification of Fields of Study by Narrow and Broad Categories.

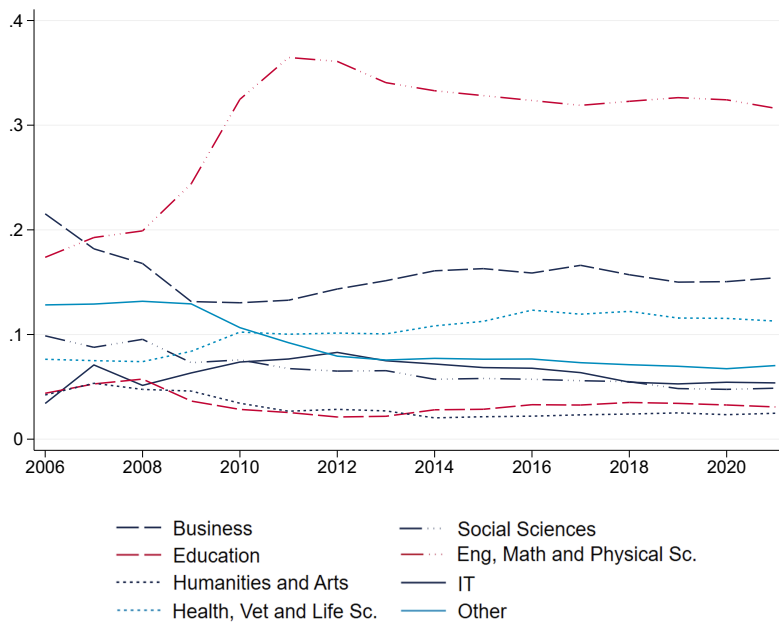
Narrow Field	Code	Broad Field	Code		
Business Sciences	34	Business	01		
Health	72	Health, Veterinary and Life Sciences	02		
Veterinary Sciences	64				
Life Sciences	42				
Teacher/Trainer Education and Education Sciences	14	Education	03		
Engineering and Related Techniques	52	Engineering, Mathematics and Physical Sciences	04		
Mathematics and Statistics	46				
Physical Sciences	44				
Arts	21	Humanities and Arts	05		
Humanities	22				
Social and Behavioural Sciences	31	Social Sciences	06		
Computer Science	48	IT	07		
Information and Journalism	32	Other	08		
Law	38				
Manufacturing Industries	54				
Architecture and Construction	58				
Agriculture, Forestry, and Fisheries	62				
Personal Services	81				
Transport Services	84				
Environmental Protection	85				
Security Services	86				
Unknown or not specified	99			Unknown or not specified	99

Figure 8: Share of individuals holding a bachelor's degree by field of study.



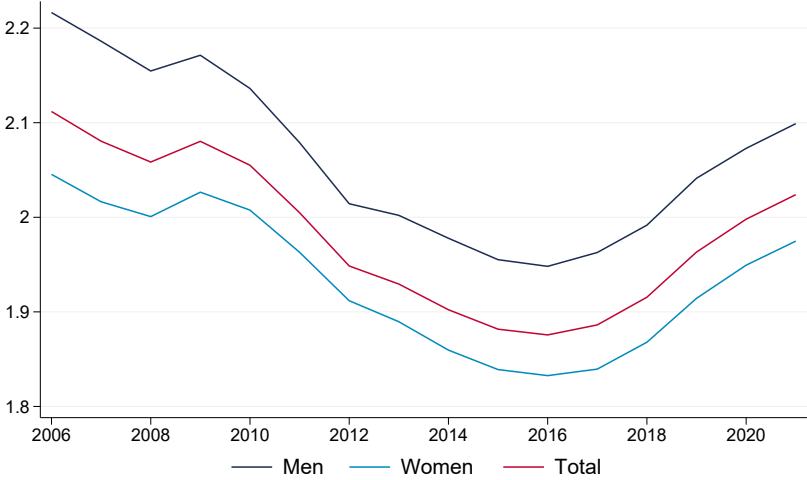
Notes: Source: Author's own calculation based on *Quadros de Pessoal*.

Figure 9: Share of individuals holding a master's degree by field of study.



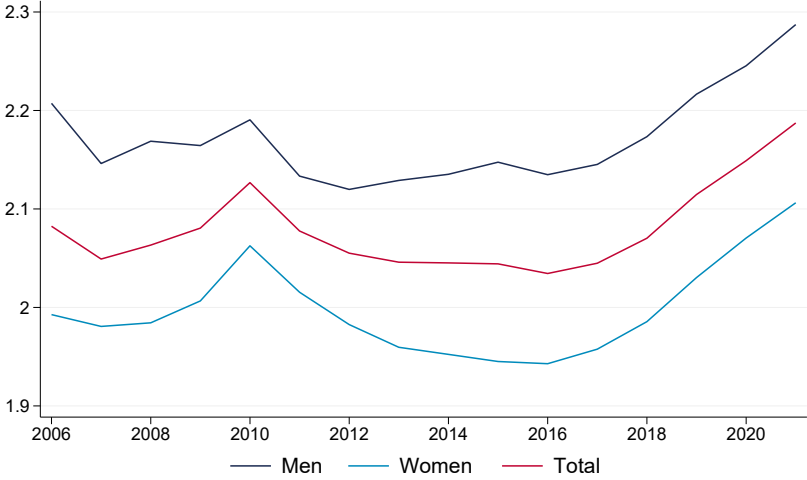
Notes: Source: Author's own calculation based on *Quadros de Pessoal*.

Figure 10: Average logarithm of real wage per hour (in euro) of employees with a bachelor's degree.



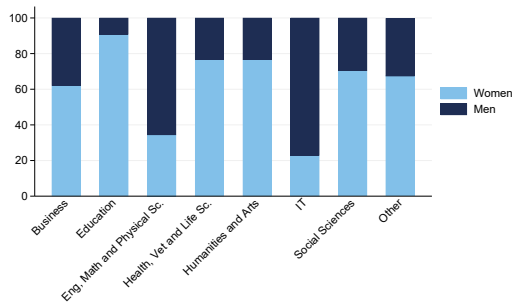
Notes: The chart depicts the average real wage per hour worked in each wave of QP (deflated using CPI, 2012 base year) *Source:* Author's own calculation based on *Quadros de Pessoal*.

Figure 11: Average logarithm of real wage per hour (in euro) of employees with a master's degree.

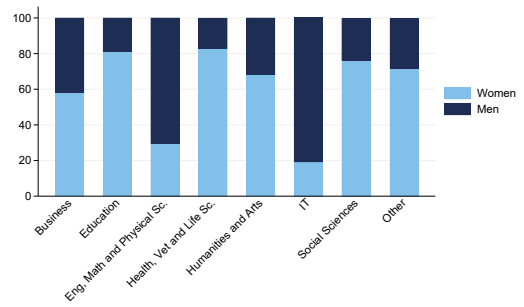


Notes: The chart depicts the average real wage per hour worked in each wave of QP (deflated using CPI, 2012 base year) *Source:* Author's own calculation based on *Quadros de Pessoal*.

Figure 12: Distribution of employees by field of study in bachelor's programs by gender.



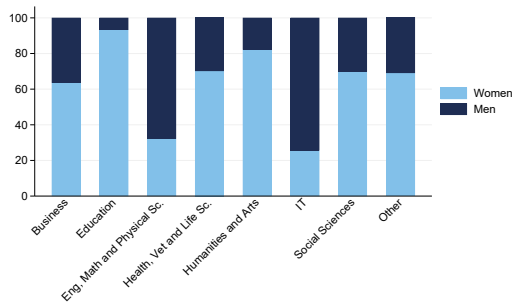
(a) 2006



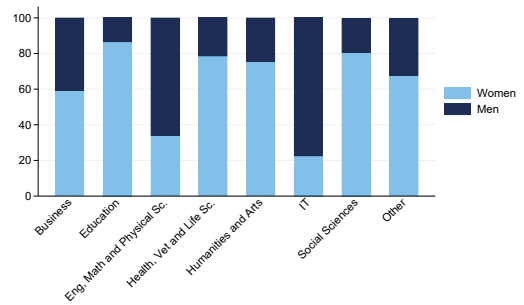
(b) 2021

Notes: Source: Author's own calculation based on *Quadros de Pessoal*.

Figure 13: Distribution of employees by field of study in master's programs by gender.



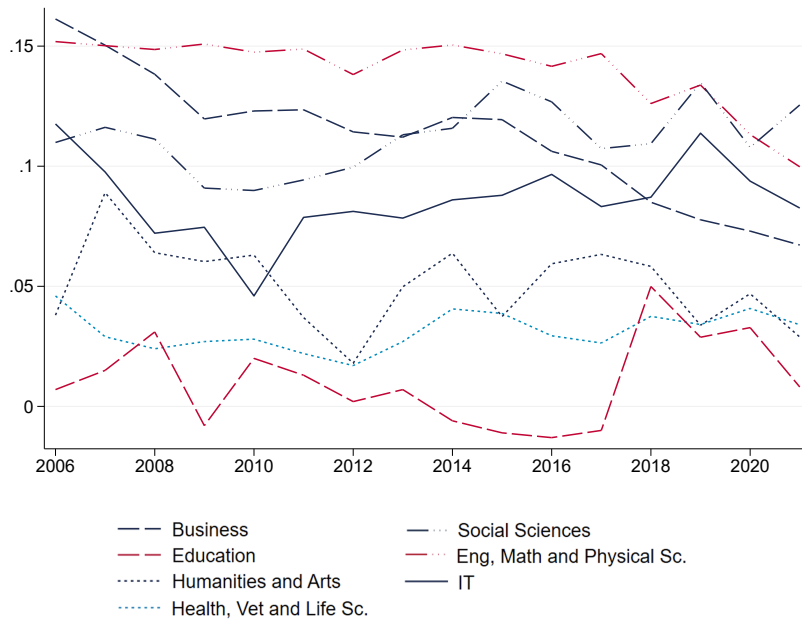
(a) 2006



(b) 2021

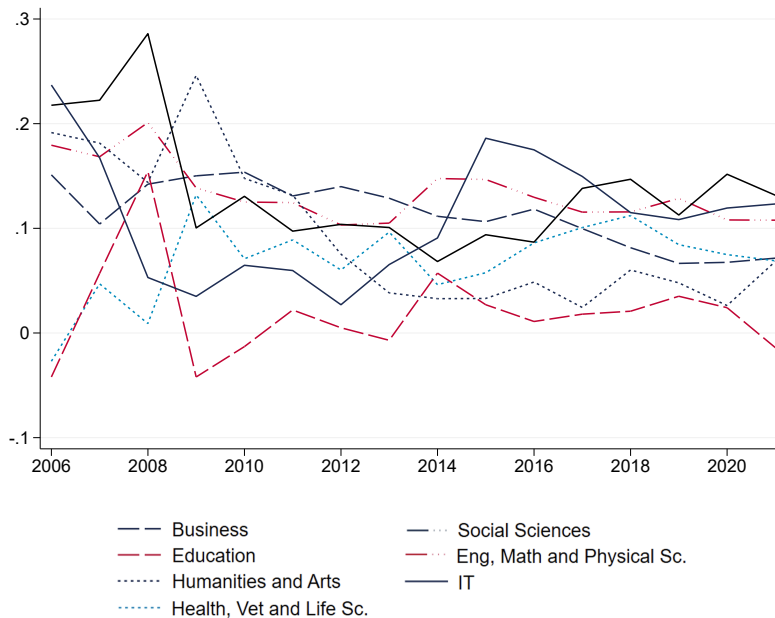
Notes: Source: Author's own calculation based on *Quadros de Pessoal*.

Figure 14: Estimated gender wage gap by field of study in bachelors' degrees.



Notes: The Figure displays the estimated wage gender gap by field of study in bachelors' programs. The gap is calculated by summing the gender dummy coefficient (the one from high school) and the interaction term coefficients for each field of study from Table 10. In general, all the interaction term coefficients are statistically significant. *Source:* Author's own calculation based on *Quadros de Pessoal*.

Figure 15: Estimated gender wage gap by field of study in masters' degrees.



Notes: The Figure displays the estimated wage gender gap by field of study in masters' programs. The gap is calculated by summing the gender dummy coefficient (the one from high school) and the interaction term coefficients for each field of study from Table 10. Nevertheless, not all coefficients of the interaction terms are statistically significant, including Engineering, Social Sciences and IT. *Source:* Author's own calculation based on *Quadros de Pessoal*.

Table 3: Estimates from a non-gender-specific OLS regression without and with additional controls, respectively. The baseline are individuals with only high school education.

	2006	2010	2013	2015	2017	2021
<i>Dep. Var.:</i>	<i>Log Hourly Real Income</i>					
Panel A: Without Controls						
Bachelors	0.481*** (0.00213)	0.430*** (0.00183)	0.376*** (0.00189)	0.340*** (0.00188)	0.306*** (0.00168)	0.319*** (0.00153)
Masters	0.441*** (0.00778)	0.528*** (0.00565)	0.532*** (0.00392)	0.526*** (0.00325)	0.473*** (0.00267)	0.484*** (0.00229)
Age	0.00533 (0.0219)	-0.0562*** (0.0195)	0.0211 (0.0199)	-0.0364* (0.0192)	-0.0264 (0.0170)	0.0309** (0.0154)
Age sqrd	0.000571 (0.000397)	0.00147*** (0.000353)	4.24e-05 (0.000360)	0.00107*** (0.000348)	0.000804*** (0.000309)	-0.000281 (0.000279)
Tenure	0.0633*** (0.00130)	0.0620*** (0.00114)	0.0755*** (0.00116)	0.0590*** (0.00115)	0.0459*** (0.00104)	0.0246*** (0.000955)
Tenure sqrd	-0.00484*** (0.000157)	-0.00512*** (0.000135)	-0.00597*** (0.000140)	-0.00422*** (0.000141)	-0.00345*** (0.000128)	-0.00188*** (0.000128)
Intercept	0.936*** (0.301)	1.946*** (0.268)	0.794*** (0.273)	1.631*** (0.263)	1.624*** (0.233)	1.027*** (0.211)
R-squared	0.248	0.264	0.263	0.242	0.223	0.233
Firm Size	No	No	No	No	No	No
Region controls	No	No	No	No	No	No
Industry controls	No	No	No	No	No	No
Panel B: With Controls						
Bachelors	0.449*** (0.00200)	0.403*** (0.00179)	0.363*** (0.00186)	0.328*** (0.00184)	0.299*** (0.00165)	0.288*** (0.00153)
Masters	0.456*** (0.00707)	0.508*** (0.00524)	0.495*** (0.00369)	0.483*** (0.00309)	0.434*** (0.00257)	0.428*** (0.00224)
Age	0.00190 (0.0198)	-0.0506*** (0.0180)	0.0175 (0.0184)	-0.0234 (0.0179)	-0.0356** (0.0160)	0.0308** (0.0144)
Age sqrd	0.000537 (0.000359)	0.00133*** (0.000326)	5.53e-05 (0.000334)	0.000796** (0.000324)	0.000949*** (0.000290)	-0.000298 (0.000262)
Tenure	0.0606*** (0.00118)	0.0546*** (0.00106)	0.0668*** (0.00109)	0.0550*** (0.00108)	0.0514*** (0.000983)	0.0261*** (0.000904)
Tenure sqrd	-0.00475*** (0.000142)	-0.00412*** (0.000125)	-0.00510*** (0.000131)	-0.00407*** (0.000132)	-0.00411*** (0.000120)	-0.00165*** (0.000121)
Intercept	0.884*** (0.273)	1.848*** (0.248)	1.032*** (0.254)	1.691*** (0.246)	1.975*** (0.220)	1.254*** (0.199)
R-squared	0.383	0.374	0.367	0.343	0.316	0.322
Firm Size	Yes	Yes	Yes	Yes	Yes	Yes
Region controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	189,782	190,139	168,287	175,135	203,434	242,539

Notes: This table presents the estimates from Equation 2 using a non-gender-specific OLS regression, therefore excluding the gender gap dummy from the equation. The baseline category is individuals with only high school education. Panel A reports results without additional controls, while Panel B includes controls for firm size, region and industry characteristics. Significance levels are represented by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on "Quadros de Pessoal".

Table 4: Estimates from an OLS regression with additional controls for women and men, respectively. The baseline are individuals with only high school education.

	2006	2010	2013	2015	2017	2021
<i>Dep. Var.:</i>	<i>Log Hourly Real Income</i>					
Panel A: Women						
Bachelors	0.477*** (0.00242)	0.432*** (0.00219)	0.388*** (0.00224)	0.349*** (0.00222)	0.310*** (0.00204)	0.301*** (0.00191)
Masters	0.473*** (0.00846)	0.528*** (0.00678)	0.498*** (0.00478)	0.476*** (0.00394)	0.425*** (0.00326)	0.423*** (0.00283)
Age	-0.00345 (0.0243)	-0.0412* (0.0220)	0.0144 (0.0225)	-0.00661 (0.0221)	-0.0295 (0.0201)	0.0309* (0.0186)
Age sqrd	0.000497 (0.000441)	0.00104*** (0.000400)	2.33e-05 (0.000408)	0.000407 (0.000400)	0.000740** (0.000366)	-0.000359 (0.000338)
Tenure	0.0607*** (0.00145)	0.0517*** (0.00130)	0.0657*** (0.00134)	0.0505*** (0.00133)	0.0461*** (0.00125)	0.0282*** (0.00118)
Tenure sqrd	-0.00461*** (0.000174)	-0.00378*** (0.000154)	-0.00490*** (0.000160)	-0.00361*** (0.000164)	-0.00372*** (0.000153)	-0.00238*** (0.000160)
Intercept	0.923*** (0.335)	1.605*** (0.305)	0.863*** (0.312)	1.310*** (0.305)	1.807*** (0.279)	1.205*** (0.257)
R-squared	0.433	0.434	0.427	0.390	0.351	0.361
Observations	104,259	106,289	93,947	94,997	107,368	123,760
Panel B: Men						
Bachelors	0.447*** (0.00321)	0.400*** (0.00291)	0.360*** (0.00309)	0.334*** (0.00303)	0.314*** (0.00267)	0.299*** (0.00243)
Masters	0.462*** (0.0115)	0.496*** (0.00780)	0.499*** (0.00552)	0.507*** (0.00472)	0.467*** (0.00396)	0.465*** (0.00347)
Age	0.00639 (0.0310)	-0.0477* (0.0284)	0.0154 (0.0294)	-0.0519* (0.0280)	-0.0354 (0.0245)	0.0323 (0.0216)
Age sqrd	0.000586 (0.000563)	0.00139*** (0.000515)	0.000182 (0.000533)	0.00139*** (0.000508)	0.00103* (0.000445)	-0.000266 (0.000392)
Tenure	0.0598*** (0.00186)	0.0572*** (0.00167)	0.0690*** (0.00173)	0.0594*** (0.00169)	0.0562*** (0.00150)	0.0256*** (0.00134)
Tenure sqrd	-0.00434*** (0.000225)	-0.00418*** (0.000197)	-0.00523*** (0.000208)	-0.00427*** (0.000206)	-0.00428*** (0.000184)	-0.00115*** (0.000177)
Intercept	0.798* (0.428)	1.783*** (0.392)	1.068*** (0.405)	2.069*** (0.385)	1.923*** (0.337)	1.207*** (0.297)
R-squared	0.363	0.347	0.335	0.326	0.310	0.317
Observations	85,523	83,850	74,340	80,138	96,066	118,779
Firm Size	Yes	Yes	Yes	Yes	Yes	Yes
Region controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimates from Equation 2 via OLS, where the baseline category are individuals with only high school education. Panel A reports the results from the regression for women while Panel B reports the results from the regression for men. Both regressions include controls for firm size, region and industry characteristics. Significance levels are represented by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on "Quadros de Pessoal".

Table 5: Estimates from an OLS regression with additional controls, where the baseline are individuals with a bachelor's degree.

	2006	2010	2013	2015	2017	2021
<i>Dep. Var.:</i>	<i>Log Hourly Real Income</i>					
Panel A						
Masters	-0.000359 (0.00757)	0.118*** (0.00549)	0.148*** (0.00397)	0.165*** (0.00339)	0.136*** (0.00289)	0.140*** (0.00255)
Age	-0.0849** (0.0356)	-0.130*** (0.0285)	0.0127 (0.0294)	-0.000762 (0.0287)	-0.0321 (0.0261)	0.0330 (0.0240)
Age sqrd	0.00223*** (0.000645)	0.00277*** (0.000516)	0.000113 (0.000531)	0.000416 (0.000521)	0.000932** (0.000474)	-0.000224 (0.000436)
Tenure	0.0846*** (0.00246)	0.0763*** (0.00197)	0.103*** (0.00193)	0.0775*** (0.00197)	0.0723*** (0.00182)	0.0343*** (0.00176)
Tenure sqrd	-0.00644*** (0.000347)	-0.00597*** (0.000281)	-0.00837*** (0.000264)	-0.00552*** (0.000280)	-0.00562*** (0.000260)	-0.00171*** (0.000276)
Intercept	2.360*** (0.492)	3.203*** (0.394)	1.216*** (0.406)	1.400*** (0.397)	1.950*** (0.361)	1.340*** (0.331)
R-squared	0.198	0.176	0.227	0.232	0.197	0.180
Observations	68,398	85,163	77,883	80,550	93,057	110,600
Panel B: Women						
Masters	-0.00876 (0.00929)	0.113*** (0.00733)	0.132*** (0.00519)	0.144*** (0.00435)	0.122*** (0.00363)	0.125*** (0.00317)
Age	-0.124*** (0.0424)	-0.109*** (0.0343)	0.00655 (0.0348)	0.0248 (0.0344)	-0.0176 (0.0314)	0.0649** (0.0289)
Age sqrd	0.00278*** (0.000769)	0.00225*** (0.000621)	0.000109 (0.000630)	-0.000158 (0.000623)	0.000539 (0.000571)	-0.000910* (0.000525)
Tenure	0.0844*** (0.00294)	0.0726*** (0.00239)	0.0990*** (0.00228)	0.0671*** (0.00235)	0.0631*** (0.00218)	0.0333*** (0.00211)
Tenure sqrd	-0.00627*** (0.000413)	-0.00518*** (0.000339)	-0.00758*** (0.000307)	-0.00417*** (0.000329)	-0.00454*** (0.000305)	-0.00199*** (0.000328)
Intercept	2.913*** (0.586)	2.892*** (0.474)	1.264*** (0.482)	1.049** (0.476)	1.712*** (0.436)	0.974** (0.400)
R-squared	0.199	0.192	0.250	0.237	0.194	0.184
Observations	41,724	53,134	48,793	49,148	56,041	65,427
Panel C: Men						
Masters	0.00918 (0.0122)	0.101*** (0.00812)	0.140*** (0.00602)	0.168*** (0.00524)	0.145*** (0.00455)	0.161*** (0.00410)
Age	-0.0199 (0.0602)	-0.143*** (0.0483)	0.0265 (0.0505)	-0.0543 (0.0484)	-0.0247 (0.0437)	0.0122 (0.0399)
Age sqrd	0.00122 (0.00109)	0.00315*** (0.000872)	-1.87e-05 (0.000913)	0.00146* (0.000877)	0.000906 (0.000791)	0.000273 (0.000723)
Tenure	0.0862*** (0.00413)	0.0857*** (0.00328)	0.113*** (0.00337)	0.0920*** (0.00337)	0.0845*** (0.00307)	0.0343*** (0.00293)
Tenure sqrd	-0.00638*** (0.000586)	-0.00733*** (0.000474)	-0.00943*** (0.000476)	-0.00656*** (0.000488)	-0.00638*** (0.000457)	-0.000620 (0.000471)
Intercept	1.471* (0.833)	3.356*** (0.667)	1.025 (0.697)	2.112*** (0.668)	1.816*** (0.602)	1.570*** (0.550)
R-squared	0.212	0.179	0.224	0.243	0.204	0.175
Observations	26,674	32,029	29,090	31,402	37,016	45,173
Firm Size	Yes	Yes	Yes	Yes	Yes	Yes
Region controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimates from Equation 2 using OLS, where the baseline category are individuals with a bachelor's degree. Panel A reports the results from a non-gender-specific OLS regression, while Panel B and C present the estimates from two separate OLS regressions, for women and men, respectively. These predictors, from all the panels, include additional controls for firm size, region and industry characteristics. Significance levels are represented by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on "Quadros de Pessoal".

Table 6: Estimates from an OLS regression including an interaction between degree level and field of study, without additional controls.

	2006	2010	2013	2015	2017	2021
<i>Dep. Var.:</i>	<i>Log Hourly Real Income</i>					
Bachelors						
Business	0.529*** (0.00370)	0.476*** (0.00345)	0.443*** (0.00364)	0.419*** (0.00370)	0.370*** (0.00346)	0.346*** (0.00337)
Health, Life Sciences and Vet	0.609*** (0.00521)	0.588*** (0.00328)	0.506*** (0.00303)	0.470*** (0.00316)	0.422*** (0.00297)	0.451*** (0.00291)
Education	0.432*** (0.00698)	0.365*** (0.00577)	0.314*** (0.00653)	0.252*** (0.00758)	0.189*** (0.00790)	0.133*** (0.00886)
Eng., Maths and Phy. Sciences	0.518*** (0.00406)	0.467*** (0.00341)	0.416*** (0.00393)	0.383*** (0.00398)	0.355*** (0.00360)	0.394*** (0.00358)
Humanities and Arts	0.323*** (0.00763)	0.305*** (0.00636)	0.274*** (0.00714)	0.237*** (0.00716)	0.208*** (0.00639)	0.188*** (0.00589)
Social Sciences	0.544*** (0.00498)	0.466*** (0.00457)	0.407*** (0.00537)	0.370*** (0.00612)	0.305*** (0.00595)	0.285*** (0.00602)
IT	0.608*** (0.00760)	0.500*** (0.00625)	0.466*** (0.00633)	0.460*** (0.00630)	0.459*** (0.00558)	0.504*** (0.00507)
Other	0.468*** (0.00484)	0.392*** (0.00422)	0.327*** (0.00475)	0.287*** (0.00482)	0.255*** (0.00444)	0.237*** (0.00441)
Masters						
Business	0.451*** (0.0160)	0.597*** (0.0147)	0.648*** (0.00920)	0.681*** (0.00723)	0.617*** (0.00584)	0.590*** (0.00516)
Health, Life Sciences and Vet	0.560*** (0.0269)	0.685*** (0.0166)	0.545*** (0.0113)	0.513*** (0.00868)	0.485*** (0.00687)	0.469*** (0.00602)
Education	0.334*** (0.0354)	0.368*** (0.0315)	0.356*** (0.0240)	0.266*** (0.0171)	0.228*** (0.0130)	0.257*** (0.0114)
Eng., Maths and Phy. Sciences	0.453*** (0.0178)	0.520*** (0.00941)	0.566*** (0.00623)	0.574*** (0.00518)	0.526*** (0.00428)	0.550*** (0.00367)
Humanities and Arts	0.311*** (0.0361)	0.340*** (0.0287)	0.367*** (0.0216)	0.311*** (0.0197)	0.260*** (0.0154)	0.279*** (0.0127)
Social Sciences	0.540*** (0.0236)	0.513*** (0.0193)	0.473*** (0.0139)	0.462*** (0.0120)	0.401*** (0.00997)	0.393*** (0.00909)
IT	0.537*** (0.0402)	0.555*** (0.0196)	0.619*** (0.0130)	0.633*** (0.0111)	0.661*** (0.00935)	0.716*** (0.00864)
Other	0.391*** (0.0208)	0.471*** (0.0163)	0.386*** (0.0130)	0.389*** (0.0105)	0.337*** (0.00873)	0.335*** (0.00758)
Age	0.0121 (0.0212)	-0.0538*** (0.0188)	0.0124 (0.0191)	-0.0386** (0.0185)	-0.0229 (0.0164)	0.0415*** (0.0148)
Age sqrd	0.000425 (0.000384)	0.00144*** (0.000341)	0.000203 (0.000347)	0.00110*** (0.000335)	0.000732** (0.000298)	-0.000463* (0.000269)
Sex (male = 1)	0.193*** (0.00195)	0.161*** (0.00176)	0.155*** (0.00181)	0.149*** (0.00175)	0.131*** (0.00155)	0.120*** (0.00140)
Tenure	0.0615*** (0.00126)	0.0573*** (0.00110)	0.0711*** (0.00112)	0.0550*** (0.00111)	0.0427*** (0.00101)	0.0223*** (0.000925)
Tenure sqrd	-0.0045*** (0.000152)	-0.0046*** (0.000131)	-0.0055*** (0.000135)	-0.0038*** (0.000136)	-0.0031*** (0.000124)	-0.0016*** (0.000124)
Intercept	0.766*** (0.291)	1.833*** (0.258)	0.840*** (0.263)	1.596*** (0.254)	1.516*** (0.225)	0.811*** (0.203)
R-squared	0.296	0.315	0.317	0.298	0.276	0.285
Observations	189,782	190,139	168,287	175,135	203,434	242,539
Firm Size	No	No	No	No	No	No
Region controls	No	No	No	No	No	No
Industry controls	No	No	No	No	No	No

Notes: This table presents the coefficients derived from Equation 3 via OLS to estimate the wage premium to education across different fields of study and degree levels, by using an interaction between the two. The omitted category is high school degree holders. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on "Quadros de Pessoal".

Table 7: Estimates from an OLS regression including an interaction between degree level and field of Study, with additional controls.

	2006	2010	2013	2015	2017	2021
<i>Dep. Var.:</i>	<i>Log Hourly Real Income</i>					
Bachelors						
Business	0.455*** (0.00343)	0.388*** (0.00331)	0.375*** (0.00352)	0.363*** (0.00358)	0.324*** (0.00336)	0.278*** (0.00328)
Health, Life Sciences and Vet	0.639*** (0.00504)	0.600*** (0.00356)	0.524*** (0.00337)	0.479*** (0.00342)	0.441*** (0.00322)	0.463*** (0.00320)
Education	0.474*** (0.00669)	0.376*** (0.00564)	0.336*** (0.00639)	0.270*** (0.00737)	0.215*** (0.00764)	0.159*** (0.00853)
Eng., Maths and Phy. Sciences	0.504*** (0.00375)	0.456*** (0.00322)	0.401*** (0.00373)	0.367*** (0.00379)	0.343*** (0.00345)	0.360*** (0.00343)
Humanities and Arts	0.294*** (0.00696)	0.269*** (0.00590)	0.247*** (0.00668)	0.215*** (0.00674)	0.187*** (0.00605)	0.147*** (0.00559)
Social Sciences	0.447*** (0.00461)	0.380*** (0.00431)	0.342*** (0.00508)	0.314*** (0.00580)	0.271*** (0.00566)	0.244*** (0.00572)
IT	0.551*** (0.00697)	0.485*** (0.00586)	0.470*** (0.00601)	0.455*** (0.00601)	0.440*** (0.00538)	0.436*** (0.00490)
Other	0.444*** (0.00445)	0.373*** (0.00394)	0.315*** (0.00447)	0.274*** (0.00456)	0.245*** (0.00422)	0.209*** (0.00421)
Masters						
Business	0.440*** (0.0146)	0.520*** (0.0136)	0.547*** (0.00864)	0.577*** (0.00687)	0.526*** (0.00561)	0.479*** (0.00497)
Health, Life Sciences and Vet	0.660*** (0.0244)	0.724*** (0.0154)	0.576*** (0.0105)	0.533*** (0.00818)	0.498*** (0.00654)	0.469*** (0.00575)
Education	0.427*** (0.0322)	0.395*** (0.0291)	0.376*** (0.0225)	0.273*** (0.0161)	0.254*** (0.0124)	0.254*** (0.0109)
Eng., Maths and Phy. Sciences	0.489*** (0.0162)	0.509*** (0.00871)	0.527*** (0.00586)	0.526*** (0.00494)	0.479*** (0.00413)	0.487*** (0.00355)
Humanities and Arts	0.348*** (0.0328)	0.331*** (0.0264)	0.352*** (0.0202)	0.304*** (0.0185)	0.232*** (0.0145)	0.226*** (0.0120)
Social Sciences	0.520*** (0.0215)	0.468*** (0.0178)	0.431*** (0.0130)	0.411*** (0.0113)	0.361*** (0.00944)	0.329*** (0.00862)
IT	0.488*** (0.0365)	0.536*** (0.0181)	0.611*** (0.0122)	0.608*** (0.0105)	0.619*** (0.00890)	0.629*** (0.00823)
Other	0.429*** (0.0188)	0.471*** (0.0151)	0.357*** (0.0121)	0.354*** (0.00985)	0.313*** (0.00827)	0.293*** (0.00719)
Age	0.0182 (0.0192)	-0.0549*** (0.0173)	0.00860 (0.0178)	-0.0301* (0.0173)	-0.0253 (0.0155)	0.0366*** (0.0140)
Age sqrd	0.000242 (0.000349)	0.00142*** (0.000314)	0.000224 (0.000323)	0.000907*** (0.000314)	0.000754*** (0.000282)	-0.000395 (0.000254)
Sex (male = 1)	0.164*** (0.00183)	0.136*** (0.00168)	0.122*** (0.00175)	0.120*** (0.00170)	0.103*** (0.00151)	0.0975*** (0.00137)
Tenure	0.0586*** (0.00115)	0.0509*** (0.00102)	0.0628*** (0.00106)	0.0516*** (0.00105)	0.0479*** (0.000955)	0.0234*** (0.000878)
Tenure sqrd	-0.0043*** (0.000138)	-0.0037*** (0.000121)	-0.0047*** (0.000127)	-0.0037*** (0.000128)	-0.0037*** (0.000117)	-0.0014*** (0.000118)
Intercept	0.564** (0.265)	1.808*** (0.239)	1.068*** (0.246)	1.701*** (0.238)	1.761*** (0.213)	1.095*** (0.193)
R-squared	0.420	0.417	0.408	0.384	0.355	0.363
Observations	189,782	190,139	168,287	175,135	203,434	242,539
Firm Size	Yes	Yes	Yes	Yes	Yes	Yes
Region controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the coefficients derived from Equation 3 via OLS to estimate the wage premium to education across different fields of study and degree levels, by using an interaction between the two. The omitted category is high school degree holders. This regression includes additional controls for firm size, region and industry characteristics. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on "Quadros de Pessoal".

Table 8: Estimates from an OLS regression with additional controls, where the baseline are individuals with only high school education.

	2006	2010	2013	2015	2017	2021
<i>Dep. Var.:</i>	<i>Log Hourly Real Income</i>					
With Controls						
Bachelors	0.463*** (0.00196)	0.416*** (0.00176)	0.375*** (0.00184)	0.342*** (0.00182)	0.312*** (0.00164)	0.301*** (0.00152)
Masters	0.467*** (0.00691)	0.511*** (0.00513)	0.498*** (0.00362)	0.491*** (0.00304)	0.445*** (0.00254)	0.442*** (0.00222)
Age	-0.00349 (0.0194)	-0.0514*** (0.0176)	0.0171 (0.0181)	-0.0259 (0.0176)	-0.0349** (0.0157)	0.0315** (0.0142)
Age sqrd	0.000617* (0.000351)	0.00133*** (0.000319)	5.02e-05 (0.000328)	0.000827*** (0.000319)	0.000924*** (0.000286)	-0.000316 (0.000259)
Sex (male = 1)	0.172*** (0.00182)	0.148*** (0.00168)	0.134*** (0.00174)	0.131*** (0.00170)	0.115*** (0.00151)	0.111*** (0.00137)
Tenure	0.0604*** (0.00116)	0.0543*** (0.00104)	0.0675*** (0.00107)	0.0547*** (0.00106)	0.0510*** (0.000969)	0.0265*** (0.000892)
Tenure sqrd	-0.00452*** (0.000139)	-0.00399*** (0.000123)	-0.00509*** (0.000128)	-0.00392*** (0.000130)	-0.00399*** (0.000119)	-0.00168*** (0.000120)
Intercept	0.867*** (0.267)	1.764*** (0.243)	0.941*** (0.250)	1.627*** (0.242)	1.879*** (0.217)	1.156*** (0.196)
R-squared	0.411	0.399	0.388	0.364	0.335	0.340
Observation	189,782	190,139	168,287	175,135	203,434	242,539
Firm Size	Yes	Yes	Yes	Yes	Yes	Yes
Region controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimates derived from Equation 2 via OLS, where the baseline category is individuals with high school education. The difference between this regression and the one presented in Table 3 (Panel B) is the inclusion of the gender dummy variable. Significance levels are represented by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on "Quadros de Pessoal".

Table 9: Estimates from an OLS regression including an interaction term between gender and level of education, with additional controls.

	2006	2010	2013	2015	2017	2021
<i>Dep. Var.:</i>	<i>Log Hourly Real Income</i>					
Bachelors	0.477*** (0.00252)	0.432*** (0.00226)	0.387*** (0.00235)	0.350*** (0.00235)	0.311*** (0.00214)	0.301*** (0.00200)
Masters	0.474*** (0.00905)	0.527*** (0.00722)	0.492*** (0.00510)	0.473*** (0.00420)	0.423*** (0.00344)	0.419*** (0.00297)
Gender (Male = 1)	0.182*** (0.00222)	0.164*** (0.00217)	0.145*** (0.00228)	0.135*** (0.00223)	0.110*** (0.00199)	0.106*** (0.00182)
Gender ×						
× Bachelors	-0.0312*** (0.00373)	-0.0371*** (0.00330)	-0.0297*** (0.00348)	-0.0193*** (0.00346)	0.00109 (0.00313)	-0.00174 (0.00287)
× Masters	-0.0142 (0.0139)	-0.0337*** (0.0102)	0.0113 (0.00708)	0.0371*** (0.00590)	0.0474*** (0.00491)	0.0487*** (0.00425)
Age	-0.00257 (0.0194)	-0.0512*** (0.0176)	0.0165 (0.0181)	-0.0259 (0.0176)	-0.0332** (0.0157)	0.0316** (0.0142)
Age sqrd	0.000601* (0.000351)	0.00133*** (0.000319)	6.22e-05 (0.000328)	0.000828*** (0.000319)	0.000892*** (0.000286)	-0.000319 (0.000259)
Tenure	0.0604*** (0.00116)	0.0541*** (0.00104)	0.0673*** (0.00107)	0.0544*** (0.00106)	0.0509*** (0.000969)	0.0265*** (0.000892)
Tenure sqrd	-0.00451*** (0.000139)	-0.00396*** (0.000123)	-0.00507*** (0.000128)	-0.00389*** (0.000130)	-0.00398*** (0.000119)	-0.00168*** (0.000120)
Intercept	0.847*** (0.267)	1.751*** (0.243)	0.942*** (0.250)	1.627*** (0.242)	1.860*** (0.217)	1.159*** (0.196)
R-squared	0.411	0.399	0.389	0.365	0.335	0.340
Observations	189,782	190,139	168,287	175,135	203,434	242,539
Firm Size	Yes	Yes	Yes	Yes	Yes	Yes
Region controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimates derived from Equation 2 via OLS, where the baseline category is individuals with high school education. In this regression was included an interaction term between gender and level of education to analyse how gender influences the wage premium associated with each degree level. Significance levels are represented by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on "Quadros de Pessoal".

Table 10: Estimates from an OLS regression including an interaction term between gender and level of education, controlling for fields of study and with additional controls.

	2006	2010	2013	2015	2017	2021
<i>Dep. Var.:</i>	<i>Log Hourly Real Income</i>					
Bachelors	0.361*** (0.00462)	0.333*** (0.00349)	0.277*** (0.00344)	0.260*** (0.00321)	0.246*** (0.00280)	0.255*** (0.00245)
Masters	0.438*** (0.0173)	0.446*** (0.0147)	0.402*** (0.00933)	0.396*** (0.00763)	0.335*** (0.00621)	0.392*** (0.00481)
Sex (Male = 1)	0.179*** (0.00221) (0.00222)	0.157*** (0.00215) (0.00217)	0.137*** (0.00225) (0.00228)	0.129*** (0.00221) (0.00223)	0.105*** (0.00197) (0.00199)	0.100*** (0.00180) (0.00182)
Gender ×						
× Bachelors	-0.0483*** (0.00387)	-0.0526*** (0.00341)	-0.0372*** (0.00361)	-0.0263*** (0.00360)	-0.00647** (0.00324)	-0.00939*** (0.00295)
× Masters	-0.0177 (0.0147)	-0.0305*** (0.0110)	-0.0273*** (0.00776)	-0.00493 (0.00642)	0.00368 (0.00524)	0.00533 (0.00446)
Bachelors						
Business	0.114*** (0.00527)	0.0779*** (0.00430)	0.114*** (0.00438)	0.114*** (0.00424)	0.0808*** (0.00386)	0.0276*** (0.00359)
Health, Life Sciences and Vet	0.293*** (0.00645)	0.283*** (0.00449)	0.258*** (0.00428)	0.226*** (0.00414)	0.197*** (0.00378)	0.210*** (0.00361)
Education	0.123*** (0.00781)	0.0556*** (0.00624)	0.0677*** (0.00688)	0.0154** (0.00772)	-0.0298*** (0.00788)	-0.0934*** (0.00867)
Eng., Maths and Phy. Sciences	0.173*** (0.00557)	0.156*** (0.00433)	0.149*** (0.00467)	0.124*** (0.00455)	0.101*** (0.00406)	0.111*** (0.00382)
Humanities and Arts	-0.0513*** (0.00801)	-0.0450*** (0.00648)	-0.0161** (0.00715)	-0.0355*** (0.00710)	-0.0568*** (0.00634)	-0.104*** (0.00578)
Social Sciences	0.103*** (0.00608)	0.0647*** (0.00508)	0.0779*** (0.00569)	0.0622*** (0.00622)	0.0267*** (0.00597)	-0.00796 (0.00591)
IT	0.224*** (0.00811)	0.189*** (0.00655)	0.219*** (0.00663)	0.214*** (0.00651)	0.198*** (0.00578)	0.189*** (0.00514)
Other	0.101*** (0.00597)	0.0599*** (0.00478)	0.0522*** (0.00515)	0.0233*** (0.00508)	0.000767 (0.00463)	-0.0422*** (0.00445)
Masters						
Business	0.0103 (0.0214)	0.0886*** (0.0194)	0.158*** (0.0122)	0.184*** (0.00981)	0.190*** (0.00795)	0.0852*** (0.00650)
Health, Life Sciences and Vet	0.231*** (0.0291)	0.289*** (0.0208)	0.183*** (0.0137)	0.140*** (0.0108)	0.162*** (0.00867)	0.0764*** (0.00715)
Education	-0.00334 (0.0363)	-0.0402 (0.0323)	-0.0180 (0.0241)	-0.119*** (0.0176)	-0.0807*** (0.0137)	-0.138*** (0.0117)
Eng., Maths and Phy. Sciences	0.0606*** (0.0226)	0.0815*** (0.0167)	0.142*** (0.0108)	0.131*** (0.00884)	0.142*** (0.00717)	0.0912*** (0.00564)
Humanities and Arts	-0.0816** (0.0366)	-0.101*** (0.0298)	-0.0395* (0.0219)	-0.0889*** (0.0197)	-0.104*** (0.0156)	-0.166*** (0.0127)
Social Sciences	0.0907*** (0.0267)	0.0346 (0.0227)	0.0385** (0.0157)	0.0182 (0.0133)	0.0261** (0.0110)	-0.0626*** (0.00960)
IT	0.0594 (0.0398)	0.108*** (0.0232)	0.227*** (0.0154)	0.213*** (0.0129)	0.281*** (0.0108)	0.233*** (0.00937)
Other	-0.000390 (0.0246)	0.0403** (0.0205)	-0.0331** (0.0149)	-0.0388*** (0.0121)	-0.0231** (0.0100)	-0.100*** (0.00832)
Intercept	0.539** (0.265)	1.795*** (0.239)	1.051*** (0.246)	1.681*** (0.238)	1.757*** (0.213)	1.093*** (0.193)
R-squared	0.421	0.418	0.408	0.384	0.355	0.363
Observations	189,782	190,139	168,287	175,135	203,434	242,539
Firm Size	Yes	Yes	Yes	Yes	Yes	Yes
Region controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimates derived from Equation 2 via OLS, where the baseline category is individuals with high school education. In this regression was included an interaction term between gender and level of education to analyse how gender influences the wage premium associated with each degree level. Additionally, it was controlled for fields of study to examine whether differences in fields of study contribute to the gender gap. Significance levels are represented by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on "Quadros de Pessoal".

Table 11: Estimates from an OLS regression including an interaction term between gender and level and field of education, with additional controls.

	2006	2010	2013	2015	2017	2021
<i>Dep. Var.:</i>	<i>Log Hourly Real Income</i>					
Gender (Male = 1)	0.179*** (0.00221)	0.157*** (0.00215)	0.137*** (0.00225)	0.129*** (0.00221)	0.105*** (0.00197)	0.100*** (0.00180)
Gender ×						
Bachelors						
× Business	-0.0177*** (0.00685)	-0.0340*** (0.00648)	-0.0249*** (0.00692)	-0.00960 (0.00707)	-0.00446 (0.00664)	-0.0328*** (0.00645)
× Health, Life Sciences and Vet	-0.133*** (0.0110)	-0.129*** (0.00714)	-0.110*** (0.00685)	-0.0903*** (0.00735)	-0.0786*** (0.00708)	-0.0660*** (0.00702)
× Education	-0.172*** (0.0216)	-0.137*** (0.0181)	-0.130*** (0.0213)	-0.140*** (0.0240)	-0.115*** (0.0218)	-0.0919*** (0.0214)
× Eng., Maths and Phy. Sciences	-0.0271*** (0.00762)	-0.00951 (0.00656)	0.0114 (0.00786)	0.0178** (0.00807)	0.0419*** (0.00734)	-0.000233 (0.00733)
× Humanities and Arts	-0.141*** (0.0162)	-0.0940*** (0.0133)	-0.0872*** (0.0146)	-0.0916*** (0.0145)	-0.0417*** (0.0128)	-0.0711*** (0.0119)
× Social Sciences	-0.0691*** (0.00980)	-0.0671*** (0.00972)	-0.0239** (0.0118)	0.00646 (0.0134)	0.00234 (0.0132)	0.0255* (0.0133)
× IT	-0.0614*** (0.0163)	-0.111*** (0.0146)	-0.0586*** (0.0150)	-0.0411*** (0.0152)	-0.0218 (0.0134)	-0.0174 (0.0120)
× Other	-0.0482*** (0.00929)	-0.0512*** (0.00840)	-0.0757*** (0.00977)	-0.0529*** (0.00995)	-0.0520*** (0.00904)	-0.0477*** (0.00916)
Masters						
× Business	-0.0279 (0.0302)	-0.00334 (0.0274)	-0.00823 (0.0172)	-0.0226* (0.0137)	-0.00525 (0.0112)	-0.0285*** (0.00991)
× Health, Life Sciences and Vet	-0.206*** (0.0533)	-0.0861** (0.0372)	-0.0406 (0.0260)	-0.0714*** (0.0195)	-0.00428 (0.0154)	-0.0310** (0.0137)
× Education	-0.221* (0.129)	-0.170** (0.0853)	-0.144** (0.0706)	-0.102** (0.0479)	-0.0870** (0.0390)	-0.114*** (0.0314)
× Eng., Maths and Phy. Sciences	0.000425 (0.0346)	-0.0319* (0.0194)	-0.0320** (0.0130)	0.0177* (0.0107)	0.0105 (0.00858)	0.00780 (0.00728)
× Humanities and Arts	0.0125 (0.0858)	-0.00931 (0.0563)	-0.0987** (0.0440)	-0.0960** (0.0419)	-0.0806** (0.0319)	-0.0316 (0.0279)
× Social Sciences	0.0386 (0.0468)	-0.0264 (0.0437)	-0.0362 (0.0333)	-0.0351 (0.0286)	0.0332 (0.0248)	0.0316 (0.0217)
× IT	0.0579 (0.0833)	-0.0923** (0.0469)	-0.0716** (0.0351)	0.0571* (0.0312)	0.0446* (0.0243)	0.0233 (0.0195)
× Other	-0.0139 (0.0406)	0.0317 (0.0303)	-0.0217 (0.0248)	-0.0300 (0.0203)	-0.0351** (0.0171)	-0.0253* (0.0153)
Intercept	0.522** (0.265)	1.782*** (0.239)	1.076*** (0.245)	1.684*** (0.238)	1.755*** (0.213)	1.090*** (0.193)
R-squared	0.421	0.419	0.409	0.385	0.356	0.364
Observations	189,782	190,139	168,287	175,135	203,434	242,539
Firm Size	Yes	Yes	Yes	Yes	Yes	Yes
Region controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimates derived from Equation 2 via OLS, where the baseline category is individuals with high school education. In this regression was included an interaction term between gender and level and field of education to isolate the impact of field choices on the gender wage gap. While not presented in the table, the regression also included coefficients for the level of education and field of study, and all of these coefficients were statistically significant. Significance levels are represented by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on "Quadros de Pessoal".