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THE WAGE RETURNS TO HIGHER EDUCATION BY FIELD OF STUDY AND IMPACT ON THE DEMAND FOR THOSE FIELDS IN PORTUGAL

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Resumo

Esta dissertação aperfeiçoa a compreensão das dinâmicas complexas entre o mercado de trabalho e as decisões de estudo em Portugal, estimando os prémios salariais associados a várias áreas de estudo e explorando como esses prémios influenciam a procura educacional. Este estudo investiga os fatores que influenciam a escolha de cursos de ensino superior, com um foco particular no impacto dos prémios salariais na tomada de decisão. O estudo utiliza regressões salariais Mincerianas para estimar os prémios salariais, com base em dados dos 'Quadros de Pessoal'. Além disso, avalia uma medida indireta da procura por áreas de estudo através das notas médias dos últimos classificados no processo de seleção nacional, utilizando dados da DGES. Os resultados revelam variações salariais significativas entre diferentes áreas e indicam que prémios salariais mais altos estão associados a uma maior procura. Apesar de algumas limitações dos dados, os resultados oferecem insights valiosos sobre como os incentivos económicos afetam as escolhas no ensino superior. Os resultados indicam que os campos de estudo com prémios salariais mais elevados tendem a ser mais atrativos, sugerindo que os estudantes são influenciados pela perspetiva de maiores ganhos futuros ao selecionarem os seus cursos de ensino superior. Isso demonstra uma clara atenção às condições do mercado de trabalho, com foco nos potenciais retornos económicos. Contudo, de forma surpreendente, a taxa de desemprego não se revela um fator determinante nas suas escolhas.

Códigos-JEL: I21, I26, J24, J31

Palavras-chave: Retorno à educação; prémio salarial; capital humano; ensino superior; tomada de decisão em educação; seleção do curso.

Abstract

This dissertation enhances the understanding of the intricate dynamics between the labour market and study decisions in Portugal by estimating wage premiums associated with various fields of study and exploring how these premiums influence educational demand. It investigates the factors influencing the selection of higher education courses, with a particular focus on the impact of wage premiums on decision-making. The study employs Mincerian wage regressions to estimate wage premiums using data from 'Quadros de Pessoal'. Additionally, it assesses an indirect measure of study field demand through the average grades of the last admitted individuals in the national selection process, using data from DGES. The findings reveal significant wage variations across different fields and indicate that higher wage premiums are associated with increased demand for study fields. Despite some data limitations, the results provide valuable insights into how economic incentives affect higher education choices. The results indicate that fields of study with higher wage premiums tend to be more attractive, suggesting that students are influenced by the prospect of greater future earnings when selecting their higher education courses. This demonstrates clear attention to labor market conditions, with a focus on potential economic returns. However, surprisingly, the unemployment rate does not prove to be a determining factor in their choices.

JEL-codes: I21, I26, J24, J31

Key-words: Returns to education; wage premium; human capital; higher education; decision-making in education; course selection.

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Chapter 1. Introduction

There has been a growing trend of higher education graduates in Portugal in recent decades. There is a clear objective of improving the qualifications of the Portuguese, as it is assumed that education plays a crucial role as a driver of individual prosperity and as a catalyst for broader societal progress (Alves et al., 2010).

So, education should have social returns but also private returns. Becker's analysis of Human Capital assumes that more education leads to higher productivity and, consequently, a higher wage. Becker argues that individuals make decisions about investing in education based on an assessment of their age-earnings profile (Becker, 1962, 1993). In contrast, Spence put forward the idea of education as a signalling device. According to Spence's signalling theory, education might appear to be productive but does not really influence the productive efficiency. Employers use educational qualifications as a screening tool for workers, making it beneficial for individuals with high abilities to pursue advanced education, as the signal attached to it pays off (Spence, 1973). Therefore, in both Spence's signalling theory and Becker's human capital theory, the analysis of future wage benefits plays a crucial role in making decisions about individual investment in education.

Thus, if an individual's decision regarding whether to invest further in education depends on financial characteristics, then the decision on what type of education to invest in should also depend on these characteristics, as it will also affect the age-earnings profile.

Therefore, it would be interesting to find out whether students really consider the impact on age-earnings profile when choosing a higher education course.

There is literature that addresses the choice of a higher education course, where income prospects are considered as a decisive factor in the decision. To the best of my knowledge, the literature on Portugal is constrained not only by the number of existing studies but also by the nature of its methodology, predominantly relying on small sample case studies. For instance, a study conducted with a sample of students from courses in the Business Sciences Area at the Escola Superior de Tecnologia e Gestão do Instituto Politécnico de Portalegre concluded that finding a well-paid job is cited as one of the main reasons why the sample entered higher education (José, 2005). Another example can be given about a study with a sample of students from Lisbon and Setúbal where it was concluded that job prospects or career progression are one of the main reasons for choosing the current course. Although little mentioned, the professional opportunities of the degree and the base wage in the area for recent graduates were also mentioned as reasons for choosing the course (Patrício, 2020).

Thus, the evolution of the wage premium could, in theory, influence the choice of a higher education course. Therefore, this dissertation probes whether individuals, when choosing higher education areas, factor in the potential impact on their age-earnings profile.

This research is primarily positioned within the field of Labour Economics, contributing to the field by exploring the relationship between the decision to invest in education and the expected return. This research also aims to contribute to the extension of the literature on the process of choosing a higher education course in Portugal. Furthermore, through the simultaneous estimation of the wage premium by study field and the assessment of its impact on the demand for higher education study fields, this dissertation seeks to provide a new perspective to the literature by offering a more quantitative analysis, not focused only on interviews with reduced samples.

This dissertation is organized into seven main chapters, beginning with Chapter 1, which serves as the introduction. Chapter 2 provides a thorough literature review, exploring Becker's Human Capital Theory, Spencer's Signalling Theory, the application of the Mincer equation to estimate wage premiums, as well as the factors that influence the choice of a higher education course and institution. Chapter 3 focuses on the context of higher education in Portugal, examining the qualifications of the Portuguese population and the structure of the Portuguese Higher Education System. Chapter 4 looks into the data and statistics, offering an in-depth analysis of the 'Quadros de Pessoal' and the data provided by DGES regarding the General Access Regime. In Chapter 5, the methodology employed in this research is outlined, focusing on the analysis of wage premiums by study field and the demand for study fields. Chapter 6 presents the results of the study, followed by a discussion of the findings. Finally, Chapter 7 concludes the dissertation with a summary of the key insights and implications of the research.

Chapter 2. Literature review

2.1 Becker's Human Capital Theory

Gary Stanley Becker's work on the topic of "human capital" started in the 1960s when the use of this term was still criticized. Becker (1962) defined investment in human capital as any activity that affects real income in the future by integrating resources into people. Individuals can invest in their own human capital, and this decision can be evaluated using economic methods that are often employed to analyse financial investments with a forward-looking perspective. (Weiss, 2015).

According to Becker (1993), the two most crucial investments in human capital are education and training. Becker's studies showed that attending high school and college in the US significantly increases one's income, even after deducting the direct and indirect expenses of education and accounting for the superior ability and better backgrounds of those with higher education. Becker (1993) also states that on-the-job training plays a crucial role in the significant rise in earnings that occurs as workers gain more experience in their jobs. A key element of Becker's theory is that human capital investments tend to respond rationally to benefits and costs. Similarly to investments in physical capital, wealth-maximizing individuals only invest in human capital when the expected return from that investment is higher than the market interest rates (Fleischhauer, 2007).

Becker's analysis of human capital states that education increases earnings, but also productivity, mostly by supplying knowledge, skills, and a method of analysing issues. Becker (1993) recognizes an alternative view that says that schooling does not improve the productivity much but denies that view saying that this credentialism exists, but it does not account for the majority of the positive correlation between education and earnings.

Human capital theory has gained popularity in public policy and it has become an accepted metaphor for the relationship between education, work, productivity and earnings (Marginson, 2019). However, this theory has also been faced with criticism. Despite acknowledging some valid concerns, Tan (2014) concludes that it remains a robust theory. Importantly, he says that critics have yet to propose a compelling alternative model for guiding educational policies.

2.2 Spencer's Signalling Theory

Spence (1973) provided a recognized alternative to the human capital theory: the signalling theory. It distinguishes itself from the human capital theory by suggesting that educational achievements may serve as a signalling device, even if education per se does not enhance productivity. Despite the differences, both models try to explain the positive relation between education and wages. In both models, economic agents behave in similar ways: a) people choose to go to school to maximize their lifetime resources, and b) businesses hire people as long as their pay are commensurate with their production (Rinne & Zhao, 2010).

The key element of the signalling theory is that a significant part of an employee's ability cannot be observed directly by the employer, so it must be signalled through education (Frazis, 2002). More education is linked to a better income, not because it increases productivity but because it attests that the worker is suitable for the job. Workers with higher education levels are not a random sample, they tend to have characteristics that are appealing to the firms. Workers anticipate the way firms hire when they are making their education decisions, so, high-ability individuals will still choose to pursue a higher education because they will still benefit from it. As a result, education can 'sort' workers based on unobservable attributes (Brown & Sessions, 2004).

Empirical findings indicate that education raises people's wages significantly. However, there are two possible reasons for this: (1) the human capital theory, which views education as an investment that increases productivity, or (2) the screening/signalling theory, which views education as a sign of one's innate abilities (Fleischhauer, 2007).

Several authors have empirically compared both theories, yielding distinct results about which of the explanations should be given primacy. Arteaga (2018) used evidence from a reform at a Columbian university and concluded that human capital theory plays an important role and rejected a pure signalling model. Rohling (1986) performed an application of the Wilds Test on data from a Canadian survey of people who graduated from community colleges and universities in 1976 and with that, provided support for the human capital theory and disregarded the role of screening. The results presented in Rohling's study contradict the results of Miller and Volker (1984) that also performed an application of the Wilds Test but for Australian micro data. Miller and Volker study provides support for the screening/signalling theory.

Huntington-Klein (2021) argued that these theories are not mutually exclusive, listing multiple empirical studies that showed that both human capital and signalling explain a portion of the returns to education. This emphasizes that these theories are valuable theoretical tools, but while they are essential for generating hypotheses, they face limitations in providing clear guidance for real-world scenarios. As a result, they are deemed subpar for understanding education returns in the real world (Huntington-Klein, 2021).

2.3 Mincer equation to estimate the wage premium

Mincer (1974) proposed a human capital earnings function influenced by the human capital theory. The human capital earnings function has become a fundamental tool in labour economics, many studies consider the Mincer equation as a baseline in their research, employing it as a foundational framework (Björklund & Kjellström, 2002).

The standard Mincer equation (see equation 1 in the methodology section) is a widely used model to estimate the wage premium, it relates the logarithm of hourly earnings to years of schooling, years of work experience, and the square of years of work experience.

As listed by Chiswick (1997) and Lemieux (2006), there are several reasons for the popularity of the Mincer equation. Firstly, its foundation in a formal model of human capital investment contributes to its credibility and theoretical underpinning, which provides economic meanings for its coefficients. Second, given the positive skewness of wages and the growing inequality linked to higher levels of education, the equation reduces heteroskedasticity and moves the residuals distribution closer to normal by modelling the natural logarithm of earnings. Furthermore, since income, years of education, and post-school experience are data frequently easier to get than individual schooling expenditures, the Mincer equation seems to be an effective use of the data already available. Its adaptability is noteworthy since it makes it simple to include extra factors that are suited to the particular goals of the investigation. Also, the Mincer equation is a good tool for evaluating the effect of human capital investments on wages across various geographical and temporal dimensions since it makes cross-context comparisons easier. Finally, the equation's simplicity, coupled with its ability to capture complex relationships, has contributed to its widespread use.

Decades after the formulation of the standard Mincer Equation, it is noteworthy that many studies still tend to estimate regressions closely aligned with the Mincer equation, highlighting its ongoing relevance. To exemplify, recent research studies, like Araújo and Carneiro (2023), Andini (2023), Bollinger and Tasseva (2023), and Khan et al. (2023) have continued to employ and build upon the foundational Mincer equation in their analyses.

Even though the Mincer equation has been widely used and influential, it has some limitations and critiques. Although Mincer (1974) explored various functional forms for the earnings equation, the most commonly used is a straightforward linear specification for years of education. However, this approach may be inaccurate, as Lemieux (2006) points out the presence of 'credential' effects suggests the return on a year of schooling might be higher at certain educational milestones compared to other years. However, one of advantages of the Mincer equation is its flexibility, so, the variable ‘years of schooling’ can be replaced with dummy variables to represent each level of education.

Another limitation, as said by Patrinos (2016), is the assumption that returns to experience are the same at all levels of education because real-world experience effects can vary. The ‘experience’ factor includes on-the-job learning and institutional factors, like firms adjusting pay to discourage shirking. This complexity makes it challenging to precisely capture the influence of experience on earnings. Moreover, as stated by Lemieux (2006), the Mincer equation may either overestimate or underestimate the impact of experience and education on earnings for certain demographic groups. Lemieux (2006) presents a solution for this limitation, based on refining the standard Mincer equation, by incorporating higher-order polynomials of potential experience into the basic model, allowing for greater flexibility in capturing the relationship between experience and earnings, particularly for demographic groups such as young workers.

Lemieux (2006) further raises a concern regarding the apparent decrease in the suitability of the standard Mincer human capital earnings function for data analysis during the 1980s and 1990s when compared to the 1960s and 1970s. Nonetheless, the author attributes this observation primarily to the disparities in the relative supply and demand of educated labour during those years, rather than inherent flaws within the model itself.

Patrinos (2016) highlights another limitation of the Mincer equation: it fails to fully account for broader social rates of return associated with education investments. While private rates of return are useful, policy decisions often require consideration of social benefits. However, data limitations and the need for more sophisticated estimation techniques hinder the integration of these social benefits into the Mincer equation.

Aside from these limitations, the Mincer equation remains a simple and rather accurate approach of modelling the relationship between wages, education, and experience (Björklund & Kjellström, 2002; Lemieux, 2006; Patrinos, 2016).

2.4 Factors influencing the choice of a higher education course and institution

The choice of a higher education course is frequently a challenging decision for young individuals, as it is made early in life when personalities, preferences, and skills are evolving, and there is often insufficient knowledge about the labour market (Feld & Alves, 2022). The factors influencing the choice of a higher education course and institution can be broad and complex, involving a mix of personal, social, economic, and academic considerations.

The issue has sparked the interest of numerous researchers worldwide, with studies such as Sugahara et al. (2008) providing insights for Australia, Bait-Almal (2012) for Libya, Sabir et al. (2013) for Pakistan, Mishra et al. (2017) for Oman, Aggarwal and Sharma (2018) for India, Callender and Melis (2022) for England, Sadjail et al. (2022) for the Philippines, and Feld and Alves (2022) for Brazil. Despite several studies have addressed this issue directly or indirectly, the literature does not provide a consistent, comprehensive set of choice factors (Simões & Soares, 2010). The highlighted factors depend on the specific context of the study; therefore, this investigation will delve into the literature review and findings of various authors regarding the Portuguese case.

It is important to contextualize the literature review carried out by different authors on the topic. Patrício (2020) presents a table summarizing the factors influencing the choice of course and higher education institution listed in the literature. In order to facilitate the analysis of the factors, they were organized into 4 categories: factors linked to education, such as academic quality, reputation, and diversity of courses and programs; factors linked to the family and friends network, such as costs and financial viability, and recommendation from peers; personal factors, such as personal and professional development, career progression, gender, and probability of recruitment and entry into the job market; and geographic factors, such as location of the institution and proximity to home. Patrício (2020) categorized factors based on how often authors mentioned them, aiming for a comprehensive understanding of their relative importance in course selection. It was concluded that factors related to education are most influential, followed by those related to family networks and friends, personal factors, and geographic factors, in that order.

In their research, Simões and Soares (2010) delineated the crucial choice factors for a higher education institution, drawing from relevant literature and based on their relevance. These factors include academic reputation, costs, degree diversity, proximity to home and location, job prospects, facilities, social network influence, potential degree marketability, program availability, and the quality of education and teaching.

Raposo and Alves (2007) outlines a diverse array of factors mentioned in the literature that influence student choice in selecting a higher education institution. These factors can be categorized into three main groups: influence of others, such as influence from friends or family recommendations; personal and individual factors, such as social life or safety concerns; and institutional characteristics and perceptions about value and costs, such as academic reputation, quality of faculty and degrees, availability of degree programs, financial aid, job prospects, proximity to home, facilities, and accommodation options.

Having reviewed the existing literature regarding the influential factors, we will now proceed to examine the specific empirical findings of selected studies regarding the Portuguese context.

In studies employing research methodologies involving questionnaires with small sample sizes, especially those targeting specific geographical areas, it is imperative to interpret findings with caution. For example, José (2005) conducted a study with a sample size of only 116 students enrolled in courses within the Business Sciences Area at the Escola Superior de Tecnologia e Gestão do Instituto Politécnico de Portalegre. The study analysed students' main motivations for pursuing higher education. Results showed that about 36% aimed to enter their desired profession, 31% sought well-paying jobs, and 18% pursued further studies for intellectual growth. Besides, this study identified key factors influencing course selection: counselling, career prospects, and field of study. These factors were categorized into two clusters: Cluster 1, the predominant one, primarily driven by career prospects, where factors such as job availability and course quality exerted the most influence; and Cluster 2, characterized by atypical preferences and lesser prominence, where family influence played a role. Notably, only the second cluster cited family influence as a decisive factor, underscoring the significance of job prospects as the primary motivational driver for course selection. Another study with a similar methodological constraint is by Patrício (2020), in this study there is a methodological limitation due to the qualitative study being based on only 20 interviews.

In the study conducted by Tavares and Ferreira (2012), 11.467 students entering Portuguese higher education, from public universities, public polytechnics, and the private sector, completed a questionnaire regarding their motivations for pursuing higher education and selecting a specific institution. Students were asked the most important reason why they chose to attend higher education. The most common response, at 41.4%, was to prepare for a good career, followed by obtaining a degree at 20.1%. Other reasons included wanting to have more control over their life (12.5%), aiming for a well-paying job (8.4%), enjoying learning (8.1%), and wanting a good job (7.6%). Some students also mentioned factors like meeting family expectations, leaving home, inability to find a job, avoiding work, making new friends, and staying close to existing friends. The significance of these factors varied across institution types, with polytechnic students prioritizing reasons related to good jobs and salaries more than others. The decision to pursue higher education was also examined through a gender perspective. Male and female students share similar top reasons for pursuing higher education, such as career preparation and obtaining a degree. However, females also prioritize personal growth reasons, while males focus more on high-paying job opportunities. The study also examined whether the reasons attracting students to higher education vary based on their field of study. Notably, there are differences across all study areas regarding the most important reasons for attending higher education. While "preparing for a career" remained the top reason overall, "enjoying studying and learning" emerged as the second most important in Humanities, Secretariat, and Translation. In contrast, fields like Economy, Management, and Accountancy placed a higher emphasis on "wanting a high-paying job." These findings underscore the complex interplay of factors influencing students' decisions regarding higher education, highlighting the importance of considering institution type, gender, and field of study when analysing student motivations.

Considering the significant differences uncovered by Tavares and Ferreira (2012) across various fields of study, particularly in the importance attributed to career prospects and salaries, it is reasonable to anticipate that in this research, these disparities will be reflected on the influence of wage premiums associated with each field of study on the demand for that particular area of study.

Chapter 3. Higher Education in Portugal

3.1 Qualifications of the Portuguese population

The educational policy in Portugal emphasizes the mandatory level of schooling as a crucial factor influencing the retention of young individuals in education and delaying their entry into the job market. Over the past decades, there has been a gradual increase in this requirement, as evidenced by Sá et al. (2014). Mandatory schooling ceases either upon obtaining the diploma from a secondary education course or, irrespective of obtaining a diploma from any level of education, when the student turns 18 during the academic year. This was solidified in 2009 with the enactment of Law 85/2009, aligning Portugal's educational standards with those of the OECD.

Over the last few decades there has been a notable improvement in the qualifications of Portuguese individuals. For example, the illiteracy rate stood at 33.1% in 1960, witnessing a significant reduction to merely 3.1% by 2021 (Statistics Portugal, 2009) . Table 1, sourced from Pordata (2024), delineates the distribution of the Portuguese populace according to their highest attained level of education.

Table 1-Resident population aged between 16 and 89 years old by highest completed level of education (%)

Year	Educational attainment (%)					
	No education level (ISCED 0)	Basic Education			Secondary school (ISCED 3)	Higher education (ISCED 5 to 8)
		1st cycle (ISCED 1)	2nd cycle (ISCED 1)	3rd cycle (ISCED 2)		
2000	18,0	33,3	16,6	14,4	11,2	6,5
2005	13,6	31,1	15,7	16,7	13,5	9,4
2010	10,6	28,8	14,0	19,4	15,4	11,8
2015	8,1	23,6	10,6	19,9	20,3	17,5
2020	5,3	20,9	9,5	19,4	24,0	20,9
2021	4,7	20,3	9,2	19,4	24,7	21,7

Source: PORDATA

Table 1 highlights the significant changes in the levels of education achieved by the population, reflecting a notable improvement in qualifications. In 2000, 18% of the population had no formal education. This figure steadily decreased over the years, reaching 4.7% in 2021. This dramatic decline indicates a successful effort in reducing illiteracy and ensuring that more individuals have at least some level of formal education. Besides that, the proportion of the population completing secondary education (ISCED 3) rose significantly from 11.2% in 2000 to 24.7% in 2021. However, the most remarkable growth is observed in higher education attainment (ISCED 5 to 8), which increased from 6.5% in 2000 to 21.7% in 2021. This indicates a strong shift towards advanced educational qualifications and reflects broader access to higher education institutions and programs.

3.2 The Portuguese Higher Education System

The Portuguese educational system is structured under the Basic Law of the Educational System and includes three levels: primary, secondary, and higher education (DGES, 2024).

Portuguese higher education is organized into a binary system that includes both university education and polytechnic education, offered by public and private institutions. In Portugal, the university and polytechnic subsystems are mainly differentiated by their approach to research and development. University education prioritizes research promotion and knowledge creation, aiming to provide rigorous scientific and cultural preparation alongside technical training. In contrast, polytechnic education emphasizes applied research and development, concentrating on practical problem-solving and the application of knowledge (DGES, 2024).

Most higher education institutions in Portugal are situated in the densely populated coastal regions. Polytechnics, however, were established as part of a policy to promote local development, leading to a more balanced distribution across the country. Despite this effort, there remains some concentration along the coastal areas (Cardoso et al., 2008).

Portuguese higher education institutions have autonomy in scientific, pedagogical, cultural, and disciplinary domains. This includes setting entry conditions, designing study programs, establishing evaluation criteria, managing academic regulations, and determining timelines for administrative processes (DGES, 2024).

Enrolment in the first cycle in the Portuguese public higher education operates under a numerus clausus system where institutions set annual quotas. Applicants through the General Access Regime must complete secondary education and pass national exams, with specifics (number, subjects, minimum grades, weighting schemes) determined by each institution. Grades from the years of secondary school make up at least 50% of the admission criteria, with exams contributing at least 35%. Admission through the General Access Regime generally occurs in two phases: the first in July/August and the second in August/September, that uses vacancies remaining after the first phase to accommodate the unsuccessful applicants and those wishing to change their choices (Cardoso et al., 2008). In addition to the general regime, there are special competitions tailored for applicants with specific qualifications, thereby enabling new groups to access higher education (CRUP, 2024). In the 1st and 2nd phase the vacancies fixed for each course in each higher education institution are distributed among a general contingent and priority contingents. There is also a 3rd phase of the national competition with little vacancies, usually takes place in October, where the places allocated for each course in each higher education institution are distributed among a single contingent.

In 2005, reforms to the Basic Law of the Educational System were initiated to align with the Bologna Process, incorporating the European Credit Transfer System (ECTS) for study cycles, mobility, and diploma supplements (Eurydice, 2024). The Bologna Process requires European countries to develop several key objectives, such as promoting the European dimension in higher education, establishing a credit system like the European Credit Transfer System (ECTS) to facilitate student mobility, and overcoming barriers to the free movement of students and staff. It also aims to promote European cooperation in quality assurance through comparable criteria and methodologies, adopt a system of easily readable and comparable degrees (David & Abreu, 2017).

The Bologna Process takes its name from the Bologna Declaration, which was signed in 1999 in Bologna, Italy, by higher education ministers from 29 European countries, including Portugal. This declaration marked a significant commitment to harmonizing and reforming higher education systems across Europe to promote mobility, enhance academic quality, and increase international competitiveness. The Bologna Process aims to harmonize higher education systems across Europe. Participating countries pledged to adopt a three-cycle system encompassing bachelor's, master's, and doctoral studies. They also committed to mutual recognition of qualifications and study periods abroad, as well as implementing quality assurance mechanisms to strengthen the relevance and quality of education.

This system was initiated in 2006 and became fully operational in Portugal in the academic year of 2009/2010 (DGES, 2024). Since then, the Bologna Process has significantly

reshaped the Portuguese higher education system. There has been a noticeable increase in the percentage of the population with higher educational qualifications, rising from 9.4% in 2005 to 21.7% in 2021. These statistics are a direct result of the implementation of the Bologna Declaration, which restructured higher education into three study cycles – Bachelor's, Master's, and Doctorate – that are more concise and adaptable (Gouveia, 2019).
The first cycle typically lasts three years, while the second cycle usually takes one and a half to two years. In special cases, a combined degree known as an integrated master can be offered, which lasts for five to six years (Cardoso et al., 2008). This framework maintains previous degree titles but introduces shorter durations for bachelor's degrees compared to pre-Bologna systems.

David and Abreu (2017) research offers empirical evidence regarding Portuguese higher education institutions' engagement in the Bologna Process. It highlights an increase in higher education graduates aligned with EU trends, substantial growth in doctoral programs (third cycle), and the emergence of numerous highly specialized courses following the implementation of the Bologna Process.

Chapter 4. Data and statistics

4.1. Quadros de Pessoal

4.1.1. Data from Quadros de Pessoal

To calculate the wage premium by study field, we will use matched employer-employee data of the database Quadros de Pessoal. Quadros de Pessoal (QP) is a database that combines data from private sector employers and workers in Portugal and is collected by the Ministry of Labor, Solidarity and Social Security. The data contained in QP is based on a mandatory response questionnaire conducted annually. It encompasses almost all Portuguese employees, excluding public administrations and domestic workers. In QP, we can obtain information regarding workers, enabling an analysis of wage returns to education in the Portuguese private sector. This database contains individual-level data including worker identification number, nationality, gender, age, date of employment, tenure in the company, job category, employment status, contract type, contract duration, educational attainment level, profession, base wage, regular payments, working hours, along with data pertaining to the respective employing companies.

The data used in the analysis refers to the period from 2010 to 2021. For the purposes of this study, a limited set of variables was selected, new variables were generated, and some observations excluded. To prevent reporting errors that might impact the results, correction procedures were employed to address any potential issues within the raw dataset. The initial data processing step involved removing duplicate records, excluding individuals with an unlikely worker identification number, and maintaining only one observation per worker per year. Following, observations regarding individuals under 17 years old or over 68 years old were excluded. Additionally, individuals with educational levels below secondary education or unspecified educational levels were removed. Furthermore, individuals with PhDs were also eliminated due to their limited representation in the private sector, as reported by Almeida et al. (2017). Observations of individuals working part-time, with a weekly normal working period of fewer than 30 hours and monthly paid normal hours less than 120 hours, were also eliminated. The sample was further refined to Portuguese employed workers with complete base remuneration. Finally, observations with a base wage equal to zero or not reported were excluded.

In the QP dataset, individual educational attainment is represented as a categorical variable indicating the highest level of education completed. In terms of study area, the QP categorizes workers' training areas based on the CNAEF (National Classification of Education and Training Areas). However, in 2017, the Portuguese Superior Statistics Council opted to adopt the Portuguese version of ISCED 2013 (International Standard Classification of Education) to replace the CNAEF in all statistical operations necessitating a classification of education and training areas. As a result, in this analysis distinct variables are generated to allow analysis according to both the CNAEF and ISCED.

In respect to wages, total wages are defined as the sum of the base wage and other regular payments. Hourly wages are adjusted for normal working hours, and real wages are calculated using the Consumer Price Index for each respective year, with 2012 serving as the base year.

Hence, the final sample presents a total of 11.673.365 observations spanning from 2010 to 2021.

4.1.2. Descriptive statistics of the data from Quadros de Pessoal

The variables of interest are described in detail in Table 15 in Annex A.

The age distribution within the sample reveals a diverse age range. Specifically, 27.76% of individuals are between 17 and 30 years old, indicating a significant representation of younger adults, including recent graduates and early-career professionals. The largest age group, comprising 59.37% of the sample, falls between 31 and 49 years old, including mid-career professionals who are likely well-established in their respective fields. Lastly, 12.87% of individuals are aged between 50 and 67, representing a smaller segment of late-career professionals approaching retirement.

The distribution of observations per year from 2010 to 2021 is shown in Table 2. The data reveals a relatively well-distributed pattern of observations, however with a steady increase over the years.

Table 2-Number of observations per year

Year of reference	Frequency	Percentage
2010	804729	6,89
2011	826418	7,08
2012	803481	6,88
2013	824196	7,06

2014	863486	7,4
2015	921307	7,89
2016	979324	8,39
2017	1043712	8,94
2018	1112083	9,53
2019	1154250	9,89
2020	1143856	9,8
2021	1196523	10,25
Total	11673365	100

Source: Quadros de Pessoal

Regarding educational level of the final sample, there is a predominant representation of those with secondary or non-tertiary post-secondary education (57.64%), followed by individuals holding bachelor's degrees (38.15%), and a less represented cohort of individuals with master's degrees (4.22%). The gender distribution within each educational level of the sample is also relatively balanced, although there is a higher proportion of women with bachelor's degrees. Among those with secondary education, 51.82% are men and 48.18% are women. Among those with bachelor's degrees, 43.16% are men and 56.84% are women. And for individuals with master's degrees, 48.93% are men and 51.07% are women.

In addition to educational level, the distribution by field of study is also a crucial aspect for understanding the composition of the sample. Table 3 and Table 4 present the distribution of individuals with higher education across various fields of study, categorized according to the CNAEF (National Classification of Education and Training Areas) classification and the ISCED (International Standard Classification of Education) classification, respectively.

Table 3-Distribution of Observations of Individuals with Higher Education by CNAEF Study Field

CNAEF study field	CNAEF study field code (2 digits)	Frequency	Percentage

Teacher training and education sciences	14	194900	3,94
Arts	21	70734	1,43
Humanities	22	136444	2,76
Social and behavioural sciences	31	335571	6,79
Information and journalism	32	79981	1,62
Business sciences	34	938054	18,97
Law	38	110171	2,23
Life sciences	42	73015	1,48
Physical sciences	44	45990	0,93
Mathematics and statistics	46	54317	1,1
Computer science	48	236265	4,78
Engineering and related techniques	52	822530	16,63
Transforming industries	54	15509	0,31
Architecture and construction	58	93474	1,89
Agriculture, forestry and fisheries	62	44380	0,9
Veterinary sciences	64	22161	0,45
Health	72	549457	11,11
Social services	76	89881	1,82
Personal services	81	29821	0,6
Transport services	84	6372	0,13
Environmental protection	85	17989	0,36
Security services	86	6953	0,14
Unknown or unspecified	99	971447	19,64

Source: Quadros de Pessoal

The distribution in Table 3 highlights the prevalence of 'Business Sciences', 'Engineering and Related Techniques', and 'Health' as major fields of study among individuals with higher education in the sample. In the other hand, fields such as 'Transport Services', 'Security Services', and 'Transforming Industries' represent the smallest portion of the sample. Additionally, a high proportion of individuals fall into the 'Unknown or Unspecified' category.

Table 4- Distribution of Observations of Individuals with Higher Education by ISCED Study Field

ISCED study field	ISCED study field code (2 digits)	Fre-quency	Per-centage
Education	01	194900	3,94
Arts and humanities	02	207178	4,19
Social sciences, journalism and information	03	415552	8,4
Business, administration and law	04	1048225	21,2
Natural sciences, mathematics and statistics	05	173322	3,5
Information and Communication Technologies (ICTs)	06	236265	4,78
Engineering, manufacturing and construction	07	949502	19,2
Agriculture, forestry, fisheries and veterinary	08	66541	1,35
Health and welfare	09	639338	12,93
Services	10	43146	0,87
Field unknown	99	971447	19,64

Source: Quadros de Pessoal

The distribution in Table 4 once again highlights the significant representation of fields such as 'Business, administration and law', 'Engineering, manufacturing and construction' and 'Health and welfare'. Similarly to the CNAEF classification, the 'Services' sector demonstrates a relatively minimal representation. However, due to its broader categorization, ISCED showcases a more balanced distribution, minimizing discrepancies among categories. While CNAEF provides a more detailed breakdown, offering deeper insights into educational trends and workforce composition of the sample, ISCED classification presents more balanced categories without the risk of overly restrictive classifications with limited representation. The detailed field descriptions of CNAEF study fields and ISCED study fields are presented in the Table 16 and Table 17 in Annex A.

The final sample is relatively balanced in terms of gender, with 48.4% of the observations representing men and 51.6% representing women. However, Table 5 and Table 6 show that gender proportions vary significantly across different fields of study. Some fields are predominantly female-dominated, others are male-dominated, and some are relatively balanced.

Table 5- Gender Distribution Across CNAEF Study Fields

CNAEF study field	**CNAEF study field code (2 digits)**	**Male (%)**	**Female (%)**
Teacher training and education sciences	14	11,67	88,33
Arts	21	40,58	59,42
Humanities	22	22,87	77,13
Social and behavioural sciences	31	29,22	70,78
Information and journalism	32	32,43	67,57
Business sciences	34	42,8	57,2
Law	38	34,21	65,79
Life sciences	42	29,12	70,88
Physical sciences	44	43,94	56,06
Mathematics and statistics	46	38,28	61,72
Computer science	48	79,71	20,29
Engineering and related techniques	52	75,70	24,30
Transforming industries	54	49,56	50,44
Architecture and construction	58	60,1	39,9
Agriculture, forestry and fisheries	62	55,43	44,57
Veterinary sciences	64	30,22	69,78
Health	72	22,52	77,48
Social services	76	8,48	91,52
Personal services	81	30,42	69,58
Transport services	84	74,78	25,22
Environmental protection	85	35,65	64,35

Security services	86	51,24	48,76
Unknown or unspecified	99	40,5	59,5

Source: Quadros de Pessoal

The gender distribution across CNAEF study fields, as shown in Table 5, reveals significant variations. Fields such as 'Teacher training and education sciences', 'Humanities', 'Social and behavioural sciences', 'Life sciences', 'Health' and 'Social services', are female dominated. On the contrary, 'Computer science', 'Engineering and related techniques', and 'Transport services' are male dominated fields. Also, some fields, like 'Transforming industries' and 'Security services' display a rather balanced gender representation.

Table 6-Gender Distribution Across ISCED Study Fields

ISCED study field	ISCED study field code (2 digits)	Male (%)	Female (%)
Education	01	11,67	88,33
Arts and humanities	02	28,92	71,08
Social sciences, journalism and information	03	29,84	70,16
Business, administration and law	04	41,9	58,1
Natural sciences, mathematics and statistics	05	35,92	64,08
Information and Communication Technologies (ICTs)	06	79,71	20,29
Engineering, manufacturing and construction	07	72,98	27,02
Agriculture, forestry, fisheries and veterinary	08	47,03	52,97
Health and welfare	09	20,54	79,46
Services	10	40,33	59,67
Field unknown	99	40,5	59,5

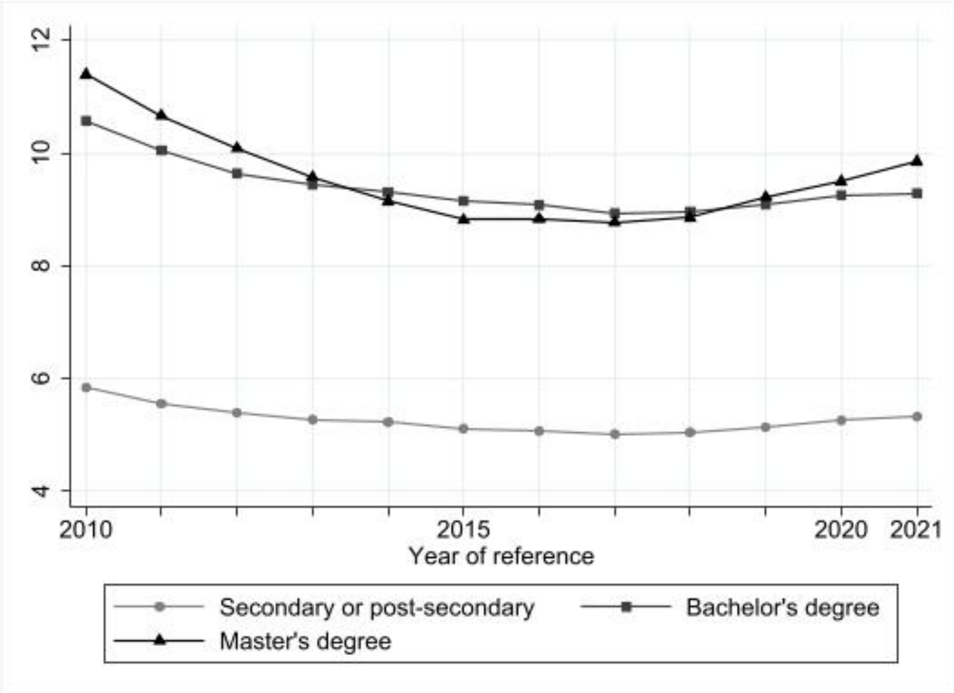
Source: Quadros de Pessoal

Similarly, the gender distribution across ISCED study fields, as presented in Table 6, shows diverse trends. Fields like 'Education', 'Arts and humanities', 'Social sciences, journalism and information' and 'Health and welfare' are female dominated. On the other hand, 'Information and Communication Technologies (ICTs)' and 'Engineering, manufacturing, and construction' are male dominated. Fields such as 'Agriculture, forestry, fisheries, and veterinary' and 'Services' show a more balanced gender distribution. The ISCED study fields, being less detailed, result in the loss of certain nuances. For example, according to the CNAEF study fields, 'Veterinary Sciences' is female dominated, while the broader ISCED category 'Agriculture, Forestry, Fisheries, and Veterinary' appears relatively balanced in terms of gender. Similarly, 'Transport Services', which is male dominated according to the CNAEF classification, falls under the broader ISCED category 'Services', which is relatively balanced but leans towards a higher female representation. These examples illustrate how the aggregation can conceal specific gender distributions observed in the more detailed CNAEF study fields.

The gender distribution across CNAEF study fields and ISCED study fields highlights the gender-specific trends and preferences within each area of study, already studied within the literature. These distributions suggest that gender may influence an individual's decision when choosing their field of study, reflecting extensive cultural, societal and economic factors. For example, Tavares and Ferreira (2012) found that while both males and females share similar top reasons for pursuing higher education, females also prioritize personal growth, whereas males are more focused on high-paying job opportunities. These different priorities influence their decisions regarding the choice of study field, so it is expected that for women, prioritizing personal growth may lead them to consider fields that offer opportunities for self-development and fulfilment, such as humanities, education, or social services. On the other hand, men, whose focus is on well-paying job opportunities, may be more inclined to pursue fields like engineering or computer science which may offer higher wages.

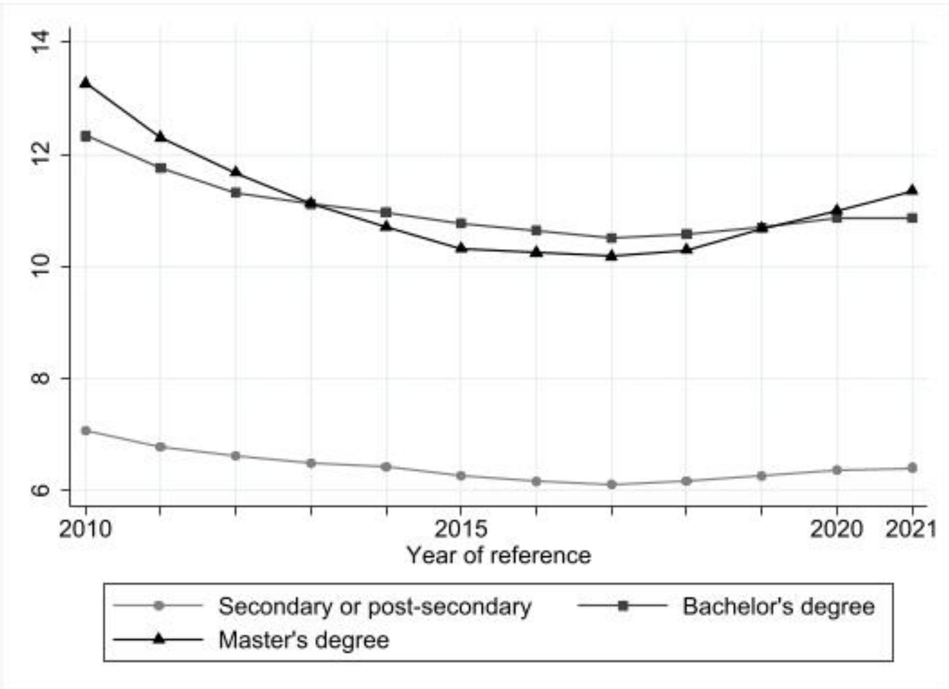
Turning to the economic outcomes associated with these study field choices, it's essential to consider how wages vary across different study fields but also different educational levels. Figure 1 and Figure 2 present the real hourly base wage per education level and the real hourly total wage per education level.

Figure 1-Real hourly base wage per education level, in euros



Source: Quadros de Pessoal

Figure 2-Real hourly total wage per educational level, in euros

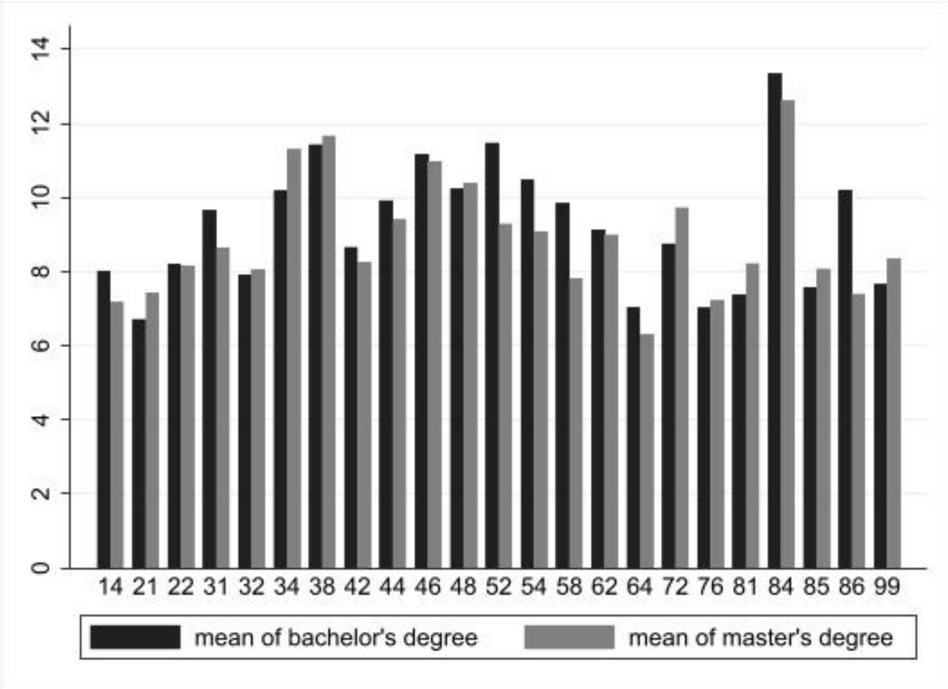


Source: Quadros de Pessoal

Figure 1 and Figure 2 show that the individuals with secondary or post-secondary education consistently have the lowest hourly wages across the years. From 2010 to 2017, there was a slight decrease in their wages, followed by a slight increase from 2017 onwards. Despite this, their wages remain significantly lower compared to those with higher education degrees. Those with a bachelor's degree earn higher wages than individuals with only secondary or post-secondary education. Their wages exhibit a slight decline from 2010, reaching a low in 2015, and then show a gradual increase towards 2021. Similar to bachelor's degree holders, the master's degree holders' wages decline from 2010, stabilize around 2015, and then rise again towards 2021. Strangely, from 2014 to 2017, individuals holding a bachelor's degree earned more than those with a master's degree. This anomaly is attributed to the lack of control for age or experience and for the fact that many of the master's degree holders during this period were post-Bologna master's graduates, meaning they were younger and had less experience, thus earning less in their early years of employment. So, the data indicates that higher educational qualifications generally lead to higher wages, reflecting the premium placed on advanced skills and knowledge in the labour market.

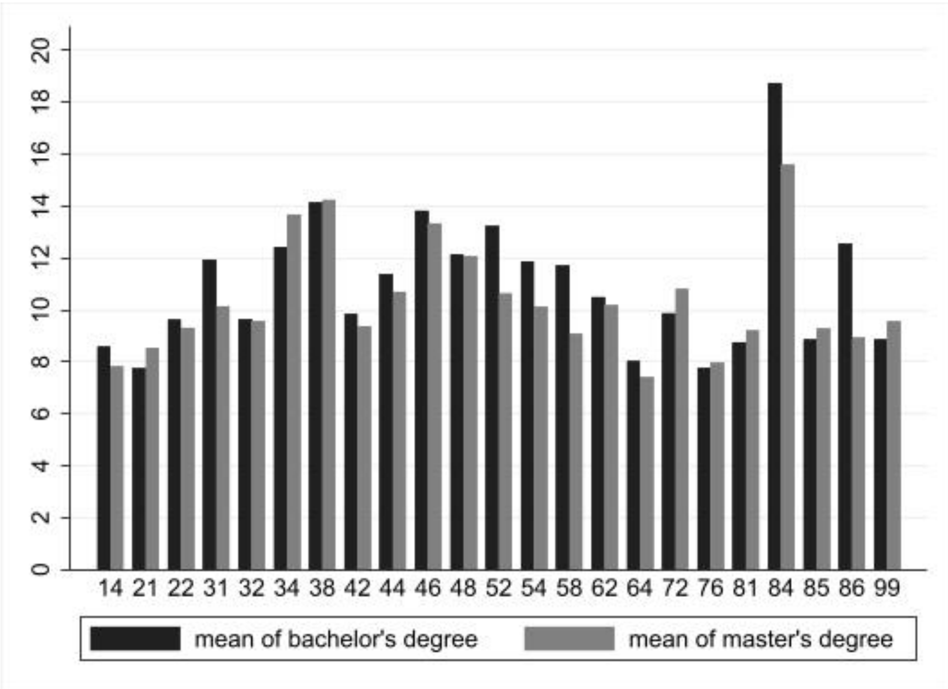
Following the discussion of general wage trends associated with different levels of education, the subsequent analysis focuses on wages according to specific fields of study. Figure 3 and Figure 4 show the real hourly base wage per CNAEF study area and the real hourly total wage per CNAEF study.

Figure 3-Real hourly base wage per CNAEF study area, in euros



Source: Quadros de Pessoal

Figure 4- Real hourly total wage per CNAEF study area, in euros

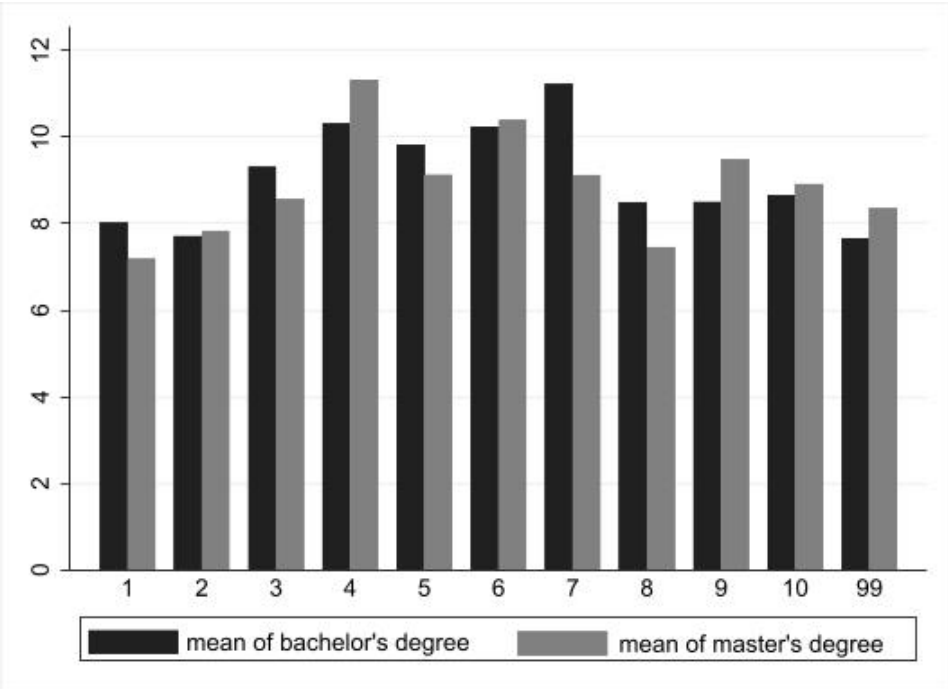


Source: Quadros de Pessoal

The data from the figures above show that the wages vary significantly between study fields. Some study fields have low average base wages: '14-Teacher training and education services', '21-Arts', '64-Veterinary sciences', '76-Social Services' and '81-Personal Services', with real hourly base wages inferior to 7,5 euros. Not surprisingly, the fields with lower wages are female dominated. Conversely, some fields show significantly higher average base wages: '34-Business sciences', '38-Law', '46-Mathematics and statistics', '48-Computer science' and '84-Transport Services', with real hourly base wages exceeding 10 euros for both bachelor's degree holders and master's degree holders. The wages of the study field 'Transport services' really stand up with base wages around 13 euros, highlighting the value of knowledge and skills in this sector. Interestingly, 'Transport Services' is the field with the fewest graduates in the sample and heavily male-dominated.

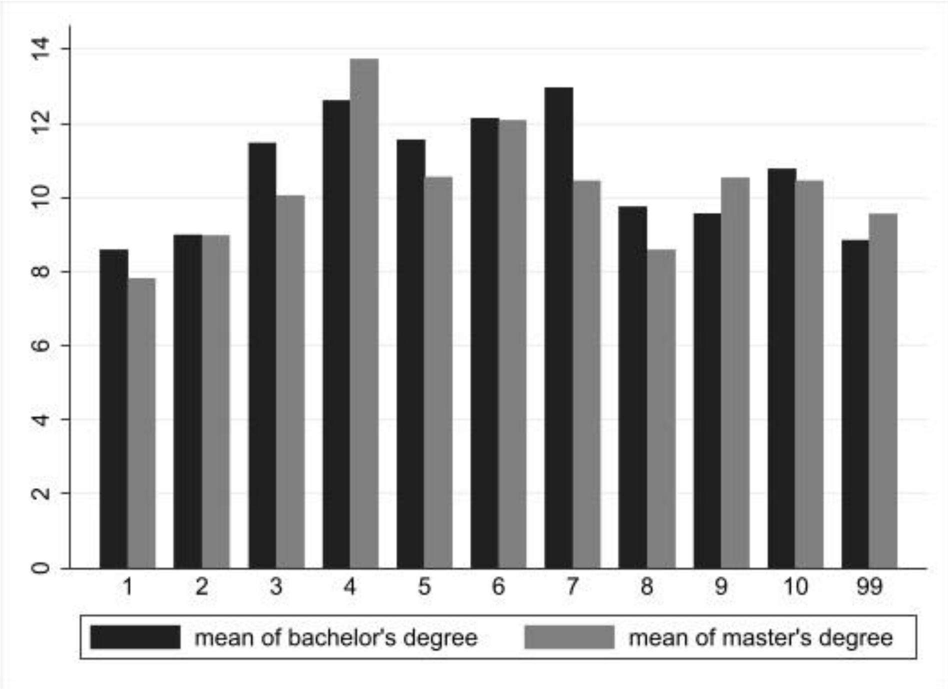
Figure 5 and Figure 6 show the real hourly base wage per ISCED study field and the real hourly total wage per ISCED study field.

Figure 5- Real hourly base wage per ISCED study field, in euros



Source: Quadros de Pessoal

Figure 6- Real hourly total wage per ISCED study, in euros



Source: Quadros de Pessoal

Figures above show that, once again, ISCED study fields, being less detailed, result in the loss of certain nuances. There is no longer such a substantial variation in salaries between areas of study. However, the fields with lower wages are '1-Education', '2-Arts and Humanities' and '8-Agriculture, forestry, fisheries and veterinary', female dominated fields. On the other hand, the higher paying fields are '4-Business, administration and law', '6-Information and Communication Technologies (ICTs)' and '7-Engineering, manufacturing and construction' with base wages above 10 euros.

4.2. DGES

4.2.1. Data from DGES regarding the General Access Regime: Public Higher Education National Access Selection

The Directorate General for Higher Education (DGES) makes available, every year, a document with the classifications of those last placed in the general regime of each course at public universities and public polytechnics.

This dissertation uses the DGES data to estimate the demand by study field. Although the demand by study field is not directly quantifiable as a numerical value, it can be indirectly estimated by calculating the average grade of the last classified individuals through the national selection process for higher education courses within each specific study field. This average grade can then serve as a proxy for estimating the demand for that study field. Therefore, to fulfil that purpose, there is going to be used data from the period of 2015 to 2021 and only from the 1st phase of the national access selection, as it is considered that the first phase is enough to highlight the preferences of that year. In this study, data is used solely from continental Portugal, excluding observations from the Azores and Madeira due to the unique geographical and socioeconomic factors of those regions.

In the document made available by DGES, there is information about each establishment and course, the degree of the course, the initial vacancies, the number of individuals placed, the number of vacancies left for 2nd phase and the average grade of the last classified individuals of each course. For this study, new variables were created, including the study field, average grade per study field, total vacancies per study field, total vacancies remaining for the second phase per study field, unemployment propensity per study field, proportion of women per study field, average wage per study field, and wage premium per study field. While the variables about the establishment, the course, the degree of the course, the initial vacancies, the number of individuals placed, the number of vacancies left and the year are already defined in the original document made available by DGES, the other variables are extracted from other sources.

The variable of study field is a correspondence between the course and the respective study field and was made with the help of DGES Course Index by Education/Training Area. In terms of the variable of study field, the database Quadros de Pessoal categorizes workers' training areas based on the CNAEF (National Classification of Education and Training Areas) (2 digits). Since the ISCED study fields (2 digits) are less detailed and result in the loss of certain nuances, the study field in this database is also defined based on CNAEF (2 digits).

Some adjustments were made to the grades for each course. The original variable, representing the grade of the last classified for each course doesn't have a value for courses that, in that year, didn't had any candidates placed. So, in these cases, the grade was assumed to be 95 as an applicant with a grade of 95 would be able to enter that course if they applied, as 95 is the minimum grade required for most courses. Then, based on this variable, was created a new variable 'grade_mean' that represents the average grade per study field per year.

The variables of total vacancies per study field and total vacancies remaining for the second phase per study field are created based on the original variables of initial vacancies per course and number of vacancies left for 2nd phase per course.

The data for the variable of unemployment propensity per study field was extracted from the database Brighter Future and is the unemployment rate of recent graduates per study field.

Additionally, a variable was created to represent the proportion of women compared to men in each study field, using data from Quadros de Pessoal to calculate this proportion.

The variables of average wage per study field and wage premium per study field were also calculated using data from Quadros de Pessoal. The wage premium variable is the coefficient of the 'higher_educ' variable from a series of regressions conducted for each study field and each year.

4.2.2. Descriptive statistics from the data from DGES regarding the General Access Regime

The variables of interest are described in detail in Table 18 of Annex A.

The dataset contains 7,119 observations from 2015 to 2021, each categorized into one of the 22 distinct study areas, as indicated by the 'cnaef_codes_study_area' variable.

Table 7 provides a detailed frequency distribution of courses across various study fields from 2015 to 2021.

Table 7-Number of higher education courses per year per CNAEF study fields

		Year							
Study Field	**CNAEF study field**	2015	2016	2017	2018	2019	2020	2021	**Total**
14	Teacher training and education sciences	31	31	29	29	29	29	29	207
21	Arts	78	79	78	79	80	79	79	552
22	Humanities	65	66	68	68	68	68	69	472
31	Social and behavioural sciences	65	66	66	66	65	65	65	458
32	Information and journalism	21	21	21	22	22	22	22	151

34	Business sciences	147	146	149	149	148	147	147	1,033
38	Law	21	22	21	22	22	22	22	152
42	Life sciences	35	34	34	33	33	33	32	234
44	Physical sciences	29	30	31	31	32	32	31	216
46	Mathematics and statistics	12	13	14	15	16	16	16	102
48	Computer science	27	27	28	27	27	28	30	194
52	Engineering and related techniques	158	164	161	166	167	171	173	1,16
54	Transforming industries	22	22	23	20	21	22	23	153
58	Architecture and construction	41	40	40	38	36	36	36	267
62	Agriculture, forestry and fisheries	25	26	26	26	24	24	24	175
64	Veterinary sciences	9	9	9	9	9	10	10	65
72	Health	97	98	100	102	101	101	101	700
76	Social services	31	31	29	28	28	29	29	205
81	Personal services	64	66	66	67	65	63	64	455
84	Transport services	3	3	3	3	3	3	3	21
85	Environmental protection	17	18	18	19	18	18	18	126
86	Security	3	3	3	3	3	3	3	21

	services								
Total		1,001	1,015	1,017	1,022	1,017	1,021	1,026	7,119

Source: DGES

Table 7 illustrates a considerable disparity in the total number of courses available across various study fields. For instance, study field 34-Business Sciences stands out with between 146 and 149 courses per year, significantly higher than other fields. This large number suggests that this field either has a broad curriculum, high student demand, and/or extensive institutional resources dedicated to it. By contrast, study field 84-Transport Services and study field 86-Security Services, have the lowest numbers, with only 3 courses per year each, this indicates that they are niche fields.

Continuing from the analysis of the number of courses, it is essential to examine the number of vacancies available across these study fields to understand the capacity and demand. Table 8 presents the total number of vacancies by study field and year.

Table 8-Number of vacancies per year per CNAEF study fields

	Year							
CNAEF study field	2015	2016	2017	2018	2019	2020	2021	**Total**
14 Teacher training and education sciences	1194	1219	1147	1137	1114	1258	1239	8308
21 Arts	3137	3140	3123	3117	3162	3387	3344	22410
22 Humanities	2690	2718	2769	2695	2734	3010	3029	19645
31 Social and behavioural sciences	3797	3856	3854	3770	3746	4120	4047	27190
32 Information and journalism	1012	1009	1006	1020	1036	1123	1114	7320
34 Business sciences	7092	7033	7088	7098	7047	8107	7681	51146
38 Law	1919	1899	1896	1892	1885	2027	1950	13468

42 Life sciences	1893	1864	1846	1801	1802	1958	1886	13050
44 Physical sciences	875	913	965	989	1024	1171	1145	7082
46 Mathematics and statistics	441	484	517	540	570	662	660	3874
48 Computer science	1009	982	1066	1104	1193	1365	1380	8099
52 Engineering and related techniques	8966	9002	9042	9253	9431	10539	10616	66849
54 Transforming industries	639	604	610	525	513	618	617	4126
58 Architecture and construction	2033	1932	1880	1741	1675	1837	1817	12915
62 Agriculture, forestry and fisheries	795	816	819	831	740	777	798	5576
64 Veterinary sciences	494	499	509	509	515	572	581	3679
72 Health	6642	6703	6750	6754	6696	7005	6963	47513
76 Social services	1112	1112	1065	1050	1046	1160	1144	7689
81 Personal services	2740	2834	2843	2916	2917	3148	3095	20493
84 Transport services	83	83	87	87	87	89	101	617
85Environmental protection	616	578	570	575	529	630	582	4080
86 Security services	65	60	50	70	70	87	72	474
Total	49244	49340	49502	49474	49532	54650	53861	355603

Source: DGES

So, the data reveals an overall growing number of vacancies, where the year 2020 saw the highest number of vacancies at 54,650. In 2020, the number of vacancies in higher education saw a substantial increase, marking a 10% rise from the previous year. This boost, aimed at accommodating the rise in candidates, included approximately 400 additional spots in highly sought-after programs with top-achieving students. The increase reflects government policy adjustments in response to the unprecedented rise in applicants and underscores a broader effort to expand higher education access. This increase indicates growing confidence among young people and their families in the value of higher education. Moreover, it signifies a significant step towards widening the social base for higher education recruitment and advancing the progressive qualification of the Portuguese population (DGES, 2020). Most fields exhibit a relatively consistent number of vacancies each year, with slight increases or decreases. Study field 52-Engineering and related techniques, had the highest number of vacancies and study field 34-Business Sciences not only has a high number of courses but also shows a substantial number of vacancies, reflecting the importance and popularity of these fields. In the other hand, study fields such as 84-Transport Services and 86-Security Services, which have the lowest number of courses, also show a limited number of vacancies.

Following the review of course availability and vacancy statistics, it is important to analyse the average grade of the last classified individuals for different study fields. This assessment provides further insight into the academic competitiveness of each study field. Table 9 presents the average entry grades of the last classified individuals of the 1st phase of the general access regime for each study field from 2015 to 2021.

Table 9-Average entry grades of the last classified individuals of the first phase of the general access regime per year per CNAEF study fields

	Year							
CNAEF study field	2015	2016	2017	2018	2019	2020	2021	**Mean**
14 Teacher training and education sciences	113,14	113,48	115,24	113,15	116,73	123,22	127,70	117,52
21 Arts	126,97	128,52	130,49	132,13	132,12	138,90	144,63	133,39

22 Humanities	122,05	125,10	127,95	127,94	130,53	139,22	143,49	130,90
31 Social and behavioural sciences	133,84	133,95	137,65	136,36	140,82	148,88	151,70	140,46
32 Information and journalism	133,99	134,37	137,27	134,39	136,37	142,07	147,08	137,93
34- Business sciences	121,91	122,44	127,92	125,90	129,54	135,68	138,00	128,77
38 Law	131,15	131,22	136,54	135,56	139,16	147,06	151,72	138,92
42 Life sciences	131,54	128,97	129,98	129,17	128,50	141,67	153,62	134,78
44 Physical sciences	123,03	126,77	129,29	132,00	134,48	139,77	141,39	132,39
46 Mathematics and statistics	130,74	136,50	144,22	141,53	144,91	150,01	144,80	141,82
48 Computer science	117,45	117,77	121,19	120,27	123,37	129,38	125,65	122,15
52Engineering and related techniques	124,31	127,10	130,71	129,06	129,58	135,83	135,22	130,26
54 Transforming industries	116,25	118,30	121,20	117,36	117,20	124,10	119,57	119,14
58Architecture and	112,19	113,36	113,30	114,17	118,16	124,01	133,11	118,33

construction								
62Agriculture, forestry and fisheries	118,11	110,19	110,42	111,30	113,53	119,25	117,93	114,39
64 Veterinary sciences	131,20	132,96	136,78	135,46	134,96	144,54	155,91	138,83
72 Health	134,53	129,78	131,89	131,20	130,60	146,81	155,69	137,21
76 Social services	113,03	112,44	113,58	114,52	117,80	122,39	130,34	117,73
81Personal services	119,13	117,64	120,97	118,42	120,36	128,81	130,57	122,27
84Transport services	131,00	129,73	133,47	130,57	133,87	144,00	139,00	134,52
85Environmental protection	112,61	110,67	113,79	115,22	113,96	119,53	120,67	115,21
86Security services	103,40	102,33	111,60	111,83	109,60	112,70	117,83	109,90
Mean	122,80	122,89	126,16	125,34	127,10	134,45	137,53	128,04

Source: DGES

The data reveals significant variations across different fields, reflecting changes in academic standards and competitive dynamics. The data reveals that Mathematics and Statistics (Field 46), Social and Behavioural Sciences (Field 31), Veterinary Sciences (Field 64), Information and Journalism (Field 32), and Health (Field 72) are among the fields with the highest average entry grades. These high averages suggest that these fields are highly academically competitive, attracting students with strong academic backgrounds. On the other hand, Agriculture, Forestry, and Fisheries (Field 62) and Security Services (Field 86) have the lowest average entry grades. There was an overall trend of rise in the average entry grades, however, in 2020 and 2021 the grades increased substantially. The COVID-19 pandemic significantly affected the education sector, leading to adjustments such as allowing students to take national exams only in subjects essential for higher education admissions. This measure, that continued into 2021, resulted in a noticeable rise in average entry grades for university courses. In 2020, average grades for 12th-grade exams increased compared to 2019, with some subjects showing a rise of over three points. Although average grades fell slightly in 2021 compared to 2020, they remained higher than pre-pandemic levels. The pandemic's impact, coupled with a tough job market, led to a surge in applicants for higher education, with a 22% increase from 2019 to 2020 and a further 2.3% rise from 2020 to 2021 (Fundação José Neves, 2022a). Despite this, the number of available places and enrolled students decreased slightly in 2021. This heightened competition, alongside fewer spots, contributed to the increase in entry grades. So, this trend reflects not only the increased demand for higher education but also the adjustments made to accommodate students during the pandemic.

The significant increase in average entry grades, particularly in 2020 and 2021, highlights the competitive nature of certain study fields. To further illustrate this, Table 10 shows the distribution of courses with entry grades above 170 across various study fields.

Table 10- Distribution of Courses with Average Entry Grades Above 170 by Study Field

CNAEF study field	Study field code (2 digits)	Frequency	Percentage
Teacher training and education sciences	14	0	0
Arts	21	8	4.04
Humanities	22	9	4.55
Social and behavioural sciences	31	6	3.03
Information and journalism	32	2	1.01
Business sciences	34	6	3.03
Law	38	4	2.02
Life sciences	42	5	2.53
Physical sciences	44	11	5.56
Mathematics and statistics	46	11	5.56
Computer science	48	0	0
Engineering and related techniques	52	66	33.33

Transforming industries	54	0	0
Architecture and construction	58	6	3.03
Agriculture, forestry and fisheries	62	0	0
Veterinary sciences	64	4	2.02
Health	72	60	30.30
Social services	76	0	0
Personal services	81	0	0
Transport services	84	0	0
Environmental protection	85	0	0
Security services	86	0	0
	Total	198	100.00

Source: DGES

The table reveals an evident concentration of high average entry grades in certain study fields. Specifically, Engineering and Related Techniques (Field 52) and Health (Field 72) are the most competitive, with 66 and 60 courses respectively having average entry grades above 170. These fields together represent over 60% of all courses with such high entry grades, underscoring their popularity and the strong academic performance required for admission.

Other notable fields include Mathematics and Statistics (Field 46) and Life Sciences (Field 44), each contributing 11 courses, further indicating high competitiveness in these areas.

In contrast, study fields like Agriculture, Forestry, and Fisheries (Field 62) and Security Services (Field 86) have no high-grade courses, reflecting different academic demands and student interest.

In conclusion, the descriptive statistics of the General Access Regime from 2015 to 2021 reveal significant disparities in the availability of courses and competitiveness across different study fields. The increase in the number of vacancies in response to the COVID-19 pandemic, along with the rise in entry grades, highlights the dynamic nature and pressures within the higher education system. Fields such as Engineering and Health are particularly competitive, reflecting high demand and the perceived importance of these areas. The trends analysed indicate the need for ongoing adjustments in educational policies to balance the supply of vacancies and meet the preferences and needs of students.

Chapter 5. Methodology

5.1. Wage premium by study field

A common approach to estimate wage premiums is to use the Mincer earnings function (Mincer, 1974), a widely recognized framework in labour economics:

Equation 5.1

$$\boldsymbol{\log w = \beta s + \delta_1 exp + \delta_2 exp^2 + \varepsilon}$$

Being w the wage rate, s the years of schooling, exp the years of work experience, and exp2 a quadratic on experience that captures the concavity of the age-earnings profile.

This dissertation follows a common approach relying on Mincerian wage regressions like the one in Equation 5.1. The Mincer equation may be biased due to measurement errors in educational levels and omitted individual characteristics like ability that affect wages. These biases can lead to overestimation of returns. However, this is not a major problem for this study because, similar to Campos and Reis (2018), the goal of this study is to describe the education returns from 2010 to 2021, not to assess causal relationships. And given that the unobserved factors which might bias the results are likely to remain constant over time, they influence only the magnitude of the returns, not their evolution, so, that is why there is no use of instrumental variables or control function methods.

The data is drawn from 'Quadros de Pessoal', which is a database that combines data from employers and workers in the private sector in Portugal. The data used is from 2010 onwards.

Because 'Quadros de Pessoal' doesn't provide information about a workers experience, age will be used as proxy for experience, as used by Campos and Reis (2018). Also, in 'Quadros de Pessoal' individual educational level is represented as a categorical variable indicating the highest level of education completed.

So, in this dissertation is going to be considered a wage regression like Equation 5.2 controlling for age, age square, tenure, tenure square and a set of dummy variables that assume the value 1 depending on the completion of, respectively, high school, a bachelor's degree or a master's degree, where the base category is completion of high school education. Workers with PhDs are excluded due to their minimal representation in the private sector.

Equation 5.2

$$\boldsymbol{log\ w_{i,k} = \propto_k + \sum_{j=2}^{3} \beta_j E_{j,i} + \delta_{1,k} age_{i,k} + \delta_{2,k} age_{i,k}{}^2 + \delta_{3,k} tenure_{i,k} + \delta_{4,k} tenure_{i,k}{}^2 + \varepsilon_{i,k}}$$

Where: ***wi,k*** is the real hourly base wage of the worker. ***Ej***, j $=\{1,2,3\}$ are indicator variables that equal one for individuals reporting completion of each of the following levels of education: (1) high school; (2) bachelor's degree; and (3) master's degree (the first category is omitted in the regressions). ***agei,k*** is the worker's age. ***tenurei,k*** is the years in the current company. And ***εi,k*** the error term capturing unobserved factors.

Equation 5.2 is going to be run to first estimated to calculate the wage premium by educational level. Then, Equation 5.3 is going to be estimated to calculate the wage premium of bachelor's degree and master's degree by CNAEF study field.

Equation 5.3

$$\boldsymbol{log\ w_{i,k} = \propto_k + \sum_{j=2}^{3} \beta_j E_{j,i} + \sum_{q=2}^{22} \beta_q S_{q,i} + \varphi_{1,k} age_{i,k} + \varphi_{2,k} age_{i,k}{}^2 + \varphi_{3,k} tenure_{i,k} + \varphi_{4,k} tenure_{i,k}{}^2 + \varepsilon_{i,k}}$$

Where: ***wi,k*** is the real hourly base wage of a worker. ***Ej***, j $=\{1,2,3\}$ are indicator variables that equal one for individuals reporting completion of each of the following levels of education: (1) high school; (2) bachelor's degree; and (3) master's degree (the first category is omitted in the regressions). ***Sq***, q $=\{1,2,\ldots,22\}$ are indicator variables that equal one for individuals holding a degree in each of the following study fields: (1) Teacher Training and Education Sciences; (2) Arts; (3) Humanities; (4) Social and Behavioural Sciences; (5) Information and Journalism; (6) Business Sciences; (7) Law; (8) Life Sciences; (9) Physical Sciences; (10) Mathematics and Statistics; (11) Computer Science; (12) Engineering and Related Techniques; (13) Transforming Industries; (14) Architecture and Construction; (15) Agriculture, Forestry, and Fisheries; (16) Veterinary Sciences; (17) Health; (18) Social Services; (19) Personal Services; (20) Transport Services; (21)Environmental Protection and (22) Security Services (the first category is omitted in the regressions). ***agei,k*** is the worker's age. ***tenurei,k*** is the years in the current company. And ***εi,k*** the error term capturing unobserved factors.

In the regressions based on Equation 5.2 and Equation 5.3, we apply robust standard errors to address potential heteroscedasticity. Additionally, we employ clustering of standard errors by the worker identification number to address the correlation of errors across multiple observations of the same worker. In longitudinal data, where multiple wage observations are available for the same individual across different time periods, errors may be correlated within individuals. If this intra-worker correlation is not accounted for, it can lead to biased standard errors, and consequently, misleading statistical inference. By clustering the standard errors at the worker level, we allow the model to account for the fact that multiple observations from the same individual are likely to share similar unobserved characteristics, such as innate ability or motivation, that could influence wages. This clustering approach corrects for the potential correlation of errors within each worker's observations, leading to more accurate and reliable standard errors.

After estimating Equation 5.3, additional regressions will be performed for each study field and for each year to estimate the wage premium over time. This leads to Equation 5.4, which estimates the wage premium for each CNAEF study field for each year. The values of the coefficients for higher education will be then employed in the analysis of demand by study field. The regressions based on Equation 5.4 are run separately for each year of the analysis and for each study field.

Equation 5.4

$$\log w_{i,k} = \propto_k + \beta_d H_{d,i} + \varphi_{1,k} age_{i,k} + \varphi_{2,k} {age_{i,k}}^2 + \varphi_{3,k} tenure_{i,k} + \varphi_{4,k} {tenure_{i,k}}^2 + \varepsilon_{i,k}$$

Where: ***wi,k*** is the real hourly base wage of a worker. ***Hd,i*** is an indicator variable representing the completion of a bachelor's degree and/or a master's degree. ***agei,k*** is the worker's age. ***tenurei,k*** is the years in the current company. And ***εi,k*** the error term capturing unobserved factors.

5.2. Demand by study field

The demand by study field is not directly quantifiable as a numerical value. However, it is possible to estimate it indirectly by calculating the average grade of the last classified individuals through the national selection process for higher education courses within each specific study field. This average grade can then be used as a proxy for estimating the demand for that study field, under the assumption that higher average grades reflect greater competition and, consequently, higher demand.

Several factors influence the average grade in a study field, but they do not necessarily correlate directly with demand. For example, the number of available vacancies in a specific course at a university, the number of leftover vacancies from previous years, and the national average exam scores for that year reflect the overall academic performance rather than demand. Conversely, factors such as the wage premium associated with the study field in previous years or the unemployment rate within that field are likely to influence demand. Additionally, the proportion of women in a study field may also impact demand, as gender has been shown to influence study decisions.

In this dissertation, to estimate the impact of wage premiums on the demand for study fields it's estimated a series of wage regressions based on Equation 5.5. Equation 5.5 models the mean grade as a function of the specified predictors, adjusting for the impact of year fixed effects.

Equation 5.5

$$\begin{aligned} G_{i,t} = \propto &+ \beta 1\ wage\_premium\_5years_{i,t} + \beta 2\ unemployment\_last\_year_{i,t} \\ &+ \beta 3\ women\_proportion_{i,t} + \beta 4\ vacancies\_total_{i,t} \\ &+ \beta 5\ leftovers\_total_{i,t} + \sum_{j=1}^{6} \gamma_j\ year_j + \varepsilon_{i,t} \end{aligned}$$

Being: ***Gi,k*** is the average grade of the last classified individuals in higher education courses of study field i, it is calculated by averaging the grades of the last classified individuals of all courses or participants within that study field i for a year. ***wage_premium_5years*** indicates the wage premium associated with a specific study field over the previous five years. ***unemployment_last_year*** represents the unemployment rate of recent graduates of a specific study field in the previous year. ***women_proportion*** measures the percentage of women relative to men currently working who graduated from study field i. ***vacancies_total*** represents the total number of vacancies in courses in a specific study field in a year. ***leftovers_total*** represents the total number of vacancies that remain unfilled, it could be used to capture how excessive supply impact the dependent variable. ***Year*** are dummy variables representing different years in the dataset (2015 to 2021), each dummy variable equals 1 if the observation belongs to that specific year and 0 otherwise. Year fixed effects control for time-specific factors that may influence the dependent variable, such as overall academic performance that year or in the cases of 2020 and 2021 the impact of the Covid-19 adjustments. And ***εi,t*** is the error term capturing unobserved factors.

The model, based on Equation 5.5, will allow to assess the impact of wage premiums on the demand for fields of study. By employing this approach, we aim to better understand how wage premiums influence the attractiveness and demand for study fields over time. However, we are unable to determine the specific influence of wage premiums on each individual field of study due to insufficient data for a more detailed analysis. While the model offers insights into the overall impact on demand across study fields, it does not allow us to isolate the effect for each specific field because of these data limitations.

Chapter 6. Results and discussion

6.1. Wage premium by study field

In this section, we present the results of the wage regressions analysis conducted to estimate the wage premiums associated with different levels of educational attainment and different fields of study.

Firstly, the regression analysis, based on Equation 5.2, was conducted to estimate the wage premiums associated with completing a bachelor's degree and a master's degree, while controlling for age, age squared, tenure, and tenure squared but not controlling for the different study fields. In this regression, coefficients βj, $j = \{2,3\}$, represent the wage increase associated with completing schooling level j, compared to individuals who have only completed high school (education level j =1, the omitted category). Table 11presents detailed results.

Table 11-Wage regression-OLS-based on Equation 5.2

Bachelor's degree	0.5142*** (0.0007)
Master's degree	0.6522*** (0.0016)
Age	0.0213*** (0.0002)
Age square	-0.0001*** (0.0000)
Tenure	0.0251*** (0.0001)
Tenure square	-0.0003*** (0.0000)
Constant	0.7465*** (0.0041)
Observations	11672874
F-statistic	> 99999.00
Prob > F	0.0000
R-Squared	0.3996
Root MSE	0.4337
* p<0.10, ** p<0.05, *** p<0.01	

Note: Coefficients obtained from OLS regressions with robust standard errors clustered by worker, using specification (2) pooling data for men and women, from 2010 to 2021. Standard errors in parentheses.

Source: Author's calculations based on Quadros de Pessoal. Results obtained using the STATASE 17 program.

Analysing these results, we find that education is a decisive factor in an individual's wage. Individuals with a bachelor's degree earn approximately 51.42% more per hour than those with only a high school education, while those with a master's degree earn about 65.22% more. Each additional year of age is associated with a 2.13% increase in hourly wages, but the negative coefficient for age squared (-0.0001) indicates diminishing returns, though the effect is minimal. Similarly, each additional year of tenure at the current job increases hourly wages by 2.51%, but the negative coefficient for tenure squared (-0.0003) suggests a slight reduction in this effect over time.

Building upon the previous analysis, we extend the regression model to account for the impact of different fields of study on wage premiums. Using Equation 5.3, we include controls for various study fields to better understand how educational attainment affects wages across different areas of specialization. Equation 5.3 introduces indicator variables for 22 specific study fields, allowing us to estimate how the wage premium associated with a bachelor's or master's degree varies depending on the field of study. This approach provides a more nuanced view of how the value of education is perceived in different sectors. In this regression, coefficients βj, j = $\{2,3\}$, also represent the wage increase associated with completing schooling level j, compared to individuals who have only completed high school (education level j =1, the omitted category). Also, coefficients βq, q = $\{1,\ldots,22\}$ represent the wage increase associated with each study field, omitting CNAEF study field=99 "Unknown or Unspecified". Table 12 presents the detailed results.

Table 12-Wage regression-OLS-based on Equation 5.3- controlling for study field

Bachelor's degree	0.3868*** (0.0013)
Master's degree	0.4964*** (0.0019)
Age	0.0220*** (0.0002)
Age square	-0.0001*** (0.0000)
Tenure	0.0241*** (0.0001)
Tenure square	-0.0002*** (0.0000)
Study Field=14	-0.0141*** (0.0024)
Study Field=21	-0.0855*** (0.0040)
Study Field=22	-0.0387*** (0.0033)
Study Field=31	0.1074*** (0.0025)

Study Field=32	0.0071 (0.0044)
Study Field=34	0.1660*** (0.0019)
Study Field=38	0.2109*** (0.0047)
Study Field=42	0.0957*** (0.0045)
Study Field=44	0.1548*** (0.0062)
Study Field=46	0.2661*** (0.0057)
Study Field=48	0.3022*** (0.0026)
Study Field=52	0.2790*** (0.0019)
Study Field=54	0.1605*** (0.0110)
Study Field=58	0.0910*** (0.0045)
Study Field=62	0.0332*** (0.0066)
Study Field=64	-0.0641*** (0.0074)
Study Field=72	0.1902*** (0.0018)
Study Field=76	-0.0578*** (0.0030)
Study Field=81	-0.0735*** (0.0065)
Study Field=84	0.3671*** (0.0163)
Study Field=85	0.0194** (0.0082)
Study Field=86	0.0951*** (0.0170)
Constant	0.7381*** (0.0040)
Observations	11672874
F-statistic	45607.24
Prob > F	0.0000
R-Squared	0.4174
Root MSE	0.4272
* p<0.10, ** p<0.05, *** p<0.01	

Note: Coefficients obtained from OLS regressions with robust standard errors clustered by worker, using specification (3) pooling data for men and women, from 2010 to 2021. Standard errors in parentheses.

Source: Author's calculations based on Quadros de Pessoal. Results obtained using the STATASE 17 program.

The results indicate that the wage premiums associated with education remain substantial when controlling for study field. Specifically, individuals with a bachelor's degree earn approximately 38.68% more per hour than those with only high school education, while those with a master's degree earn about 49.64% more. The age and tenure factors also have similar coefficients as before.

When controlling for study fields, significant differences emerge in the wage premiums across various fields. 34-Business Sciences, 38-Law, 44- Physical sciences, 46-Mathematics and Statistics, 48-Computer Science, 52- Engineering and related techniques, 54- Transforming industries, 72- Health and 84-Transport Services are associated with the highest positive wage premiums, reflecting substantial earnings advantages over other fields, having a degree in these fields is associated with an increase of more than 15% in hourly wages.

While fields like 31- Social and behavioral sciences, 42- Life sciences, 58- Architecture and construction, 62- Agriculture, forestry and fisheries, 85- Environmental protection and 86- Security services also show positive coefficients, though not as high.

Other fields such as 14- Teacher training and education sciences, 21- Arts, 22- Humanities, 64- Veterinary sciences, 76- Social services and 81- Personal services have negative coefficients, meaning that individuals with a degree in these fields earn less per hour than those with degrees in other areas of study.

However, study field 32-Information and Journalism did not show statistically significant coefficients. This suggests that there isn't strong evidence to confirm that this field has a consistent impact on wages.

An interesting pattern emerges when examining the wage premiums across different study fields, particularly in relation to gender composition. Curiously, the fields with negative coefficients are all female dominated, as we can see in Table 5. Among the fields with the highest wage premiums, five out of nine are female dominated. This suggests that certain fields where women are prevalent still offer substantial wage premiums. Equally, among the fields with positive but lower wage premiums, three out of six are also female dominated. This contrast highlights the complex nature of gender dynamics in the labour market.

The analysis reveals another notable pattern, this time concerning the relationship between wage premiums and the average entry grades required for different fields of study. Among the nine fields with high wage premiums, seven have above-average entry grades, as we can see in Table 9. This suggests that fields offering higher wages may require stronger academic qualifications for admission. In opposition, among the six fields with low but positive wage premiums, only two have above-average entry grades. Additionally, three of the six fields with negative wage premiums also require above-average entry grades. This indicates that high entry grades do not necessarily lead to higher wages. Overall, while higher entry grades are often associated with higher wages in certain fields, this is not a universal rule, highlighting the complex relationship between entry requirements, field of study, and wage outcomes.

Following this analysis of wage premiums by study field, we further examined how these premiums have evolved over time by applying Equation 5.4. This approach allows us to assess annual variations in wage premiums for each CNAEF study field, offering insights into the temporal dynamics of wage premiums associated with higher education. To analyse the evolution of wage premiums associated with higher education across different fields of study over time, we performed separate annual regressions for each field of study, as specified by Equation 5.4. Given the extensive number of regressions conducted (264 in total), we will only reference the coefficients for higher education to summarize the key trends observed. Table 13 below shows the higher education coefficients by field of study and year.

The coefficients for higher education show varying trends across different fields of study and over time. Analysing these coefficients shows a general decline in the average coefficient from 0.5445 in 2010 to 0.4625 in 2021, suggesting a reduction in the average value associated with higher education over these years. Even if we don't consider the years of 2020 and 2021 (to eliminate the impact of COVID-19), almost all study fields showed a general decrease in their coefficients. The reduction in the coefficients can be linked to broader wage trends. Between 2011 and 2019, wage increases were more substantial for less qualified workers due to higher minimum wages and changes in collective bargaining, with a 5% increase for those with basic education. In contrast, wages for workers with secondary and higher education decreased by 3% and 11%, respectively (Fundação José Neves, 2022b). It is also essential to recognize that these coefficients are derived from regressions where the dependent variable is the logarithm of the real hourly base wage. The adjustment for inflation accounts for changes in the cost of living, thus providing a more accurate representation of the real value of higher education across the years.

Examining specific fields, most fields experienced a decline in their coefficients between 2010 and 2021. A notable exception to this general trend is study field 48-Computer Science. Contrary to most fields, Computer Science saw a slight increase in its coefficient, rising from 0,7129 in 2010 to 0,7187 in 2021. This positive trend suggests that the value of education in this field is perceived to be growing, highlighting its increasing relevance and demand in the labour market.

The most substantial decline was in study field 58-Architecture and Construction, with a reduction of 35.31% in its coefficient, falling from 0.6256 in 2010 to 0.4047 in 2021. This decrease parallels the overall contraction in the construction sector, where the total turnover had a 19.7% decrease over the 2010-2020 period (European Construction Sector Observatory, 2020). This suggest that the challenges facing Field 58-Archicteture and Construction, are indicative of wider sectoral issues, including decreased demand and shifts in the economic landscape affecting construction and architecture. Field 76-Social services also saw an enormous decrease, with a reduction of almost 30% in its coefficient, falling from 0.4135 in 2010 to 0.2906 in 2021. The decline in the field of social work can be attributed to structural changes in the welfare state, austerity measures, and economic constraints following the financial crisis of 2008, which led to reduced public funding and job opportunities in the social sector (Hespanha, 2018). These factors, compounded by the ongoing professional challenges within social work, such as low pay, high job demands, and limited career progression, have collectively contributed to the decreasing appeal of this field during the specified period.

Overall, the results presented in Table 11, Table 12 and Table 13 indicate that, while higher education still provides a wage premium, its value has declined over time. Additionally, field-specific variations show that some areas, like Architecture and Construction, as well as Social Services, have experienced more significant declines, reflecting sector-specific challenges. The analysis also highlights the impact of gender composition, with many fields showing lower or negative premiums being female dominated, however, gender dynamics play a role in wage outcomes but are not the sole factor. Furthermore, high entry grades do not always correlate with higher wages, indicating that the relationship between academic requirements and wage outcomes is complex.

Table 13-Summary Table of Higher Education Coefficients by Field of Study and Year

Field	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Mean
14	0,4312	0,4367	0,4343	0,4317	0,4075	0,3978	0,3825	0,3663	0,3614	0,3536	0,3578	0,3536	0,3929
21	0,3551	0,3603	0,3327	0,3295	0,3082	0,3114	0,3028	0,2883	0,2779	0,2814	0,2880	0,2906	0,3105
22	0,3911	0,3869	0,3836	0,3895	0,3718	0,3660	0,3661	0,3598	0,3537	0,3517	0,3442	0,3301	0,3662
31	0,5756	0,5641	0,5492	0,5385	0,5268	0,5189	0,5067	0,4960	0,4772	0,4702	0,4702	0,4626	0,5130
32	0,4352	0,4331	0,4224	0,4220	0,4071	0,4156	0,4111	0,4032	0,3822	0,3765	0,3748	0,3754	0,4049
34	0,5991	0,6022	0,5902	0,5865	0,5750	0,5744	0,5664	0,5585	0,5527	0,5552	0,5502	0,5439	0,5712
38	0,6437	0,6400	0,6338	0,6274	0,6168	0,6149	0,6115	0,6088	0,6036	0,6124	0,5970	0,5944	0,6170
42	0,5848	0,5690	0,5540	0,5455	0,5240	0,5053	0,4917	0,4760	0,4665	0,4530	0,4611	0,4490	0,5067
44	0,6190	0,6168	0,5997	0,5824	0,5699	0,5745	0,5506	0,5506	0,5346	0,5300	0,5148	0,5016	0,5621
46	0,6996	0,7017	0,6963	0,6842	0,6702	0,6650	0,6746	0,6629	0,6555	0,6574	0,6718	0,6586	0,6748
48	0,7129	0,7063	0,6951	0,6974	0,6770	0,6861	0,6935	0,6840	0,6946	0,7007	0,7081	0,7187	0,6979
52	0,7122	0,7086	0,7058	0,7047	0,6926	0,6920	0,6819	0,6734	0,6680	0,6733	0,6717	0,6694	0,6878
54	0,6019	0,6077	0,5787	0,5686	0,5617	0,5843	0,5741	0,5655	0,5570	0,5343	0,5601	0,5388	0,5694
58	0,6256	0,6133	0,5858	0,5587	0,5359	0,4910	0,4694	0,4482	0,4212	0,4144	0,4086	0,4047	0,4981
62	0,4536	0,4638	0,4552	0,4521	0,4520	0,4374	0,4309	0,4359	0,4295	0,4295	0,4310	0,4222	0,4411
64	0,4140	0,3890	0,3669	0,3399	0,3396	0,3350	0,3376	0,3098	0,2995	0,2973	0,3038	0,3170	0,3374
72	0,6423	0,6244	0,6040	0,5967	0,5892	0,5901	0,5923	0,5627	0,5795	0,5713	0,5606	0,5466	0,5883
76	0,4135	0,4023	0,3867	0,3719	0,3491	0,3484	0,3465	0,3300	0,3134	0,2937	0,2973	0,2906	0,3453

81	0,3529	0,3390	0,3269	0,3158	0,3121	0,3166	0,3146	0,3131	0,3142	0,3098	0,3188	0,3069	0,3201
84	0,8160	0,8228	0,8131	0,8124	0,8113	0,7944	0,8048	0,7853	0,7328	0,7520	0,7439	0,6675	0,7797
85	0,4838	0,4941	0,4679	0,4572	0,4254	0,4278	0,4139	0,4027	0,3885	0,3940	0,4073	0,3934	0,4297
86	0,4150	0,3984	0,4005	0,6716	0,6327	0,5966	0,5514	0,5077	0,5564	0,5622	0,3363	0,3385	0,4973
Mean	0,5445	0,5400	0,5265	0,5311	0,5162	0,5111	0,5034	0,4904	0,4827	0,4806	0,4717	0,4625	0,5051

Note: Coefficients obtained from OLS regressions, using specification (4) pooling data for men and women, from 2010 to 2021. All coefficients shown are significant at 1% level.

Source: Author's calculations based on Quadros de Pessoal. Results obtained using the STATASE 17 program.

6.2. Demand by study field

In this section, we present the results of the regression analysis exploring the relationship between demand by field of study and their associated wage premiums.

The regression analysis, based on Equation 5.5, was conducted to assess the impact of wage premiums on the demand for fields of study. Due to the constraints of the dataset, which includes 22 study fields observed only over 7 years, the total number of observations is limited to 154. This relatively small sample size imposes significant constraints on the robustness and generalizability of our findings. Due to this, we cannot assess the impact of wage premiums on each individual field of study. Although this model sheds light on the general effect on demand across various fields, it does not enable us to separate the impact for each specific field due to these data constraints.

The regression analysis examined the influence of various factors on the average grades of the last classified individuals in higher education courses, serving as a proxy for demand by study field. The model used Equation 5.5 to explore how wage premiums, unemployment rates, gender proportions, initial vacancies and leftover vacancies affect the average grade, adjusting for year-specific effects.

The results of the regression are presented in Table 14 below.

Table 14- Study field demand regression-OLS-based on Equation 5.5

wage_premium_5years	15.3169** (7.5918)
unemployment_last_year	-0.3850 (0.2696)
women_proportion	0.0292 (0.0590)
vacancies_total	0.0030*** (0.0005)
leftovers_total	-0.0179*** (0.0030)
2016	-0.8936 (2.4659)
2017	0.4742 (2.5628)
2018	0.2509 (2.6386)
2019	0.8520 (2.9494)
2020	7.0503** (2.9953)
2021	11.2251*** (2.8023)
Constant	116.7026*** (8.0983)
Observations	154

F-Statistic	14.5
Prob > F	0.0000
R-Squared	0.5291
Root MSE	8.1084
* p<0.10, ** p<0.05, *** p<0.01	

Note: Coefficients obtained from OLS regression, using specification (5) pooling data for men and women, from 2015 to 2021.

Source: Author's calculations based on DGES data from the General Access Regime, Quadros de Pessoal and Brighter Future. Results obtained using the STATASE 17 program.

The results reveal several important findings.

Firstly, and most importantly, this regression shows a positive coefficient of 15.3169 of the wage premiums over five years, significant at the 5% level. This suggests that for every 0.1 increase in the wage premium (equivalent to a 10-percentage point increase), the average grade of the last classified individuals in a study field increases by approximately 1.53 points. So, the wage premiums over five years demonstrate a statistically significant positive impact on average grades, indicating that higher wage premiums correlate with increased demand for a particular field. This suggests that fields offering more desirable wage prospects tend to attract higher-performing students, enhancing the overall competitiveness within those fields.

The positive and significant impact of wage premiums on the demand for study fields, as evidenced by the regression analysis, corroborates the literature's claims that economic factors, particularly future earning potential, are central to students' choices in higher education. This relationship highlights the critical role of wage expectations in influencing educational decisions, supporting the broader understanding that students prioritize fields with better career prospects and higher wages. As highlighted in Section 2.4, career prospects and the potential for well-paying jobs are consistently identified as key motivators for students when selecting their field of study. The findings from this regression analysis provide empirical support for these motivations.

While the regression analysis provides valuable insights into the overall impact of wage premiums on the demand for study fields, it is unfortunate that the data limitations prevent a more detailed exploration of how these wage premiums might differently influence demand across various fields of study. The literature highlights significant differences in how students prioritize factors like career prospects and salaries when selecting a course, with fields such as Economics, Management, and Accountancy placing a stronger emphasis on high-paying job opportunities (Tavares and Ferreira, 2012). Based on these findings, it would be reasonable to expect that wage premiums might have a more pronounced impact on demand in these fields, resulting in higher coefficients in the regression analysis. Conversely, areas such as Humanities, Secretariat, and Translation, where students prioritize personal interest and enjoyment of learning over wage prospects, might show a lower sensitivity to wage premiums, potentially leading to lower coefficients. However, due to the constraints of the dataset, we are unable to conduct a nuanced analysis that could capture these expected differences. This limitation is particularly regrettable, as a more granular analysis would have allowed us to better understand the field-specific dynamics and how wage expectations shape educational choices in different areas. The absence of sufficient data prevents us from fully leveraging the insights provided by the literature, leaving a gap in our understanding of how wage premiums might variably influence the demand for different study fields.

In contrast to the significant impact of wage premiums, other factors such as the previous year's unemployment rate do not show a statistically significant effect on demand. Specifically, while the unemployment rate has a negative coefficient, it does not provide a reliable prediction for demand. Students clearly pay attention to labour market conditions, focusing on potential economic returns, as demonstrated by the significant and positive coefficient of the wage premium. However, surprisingly, the unemployment rate does not appear to be a relevant factor in their choices. This discrepancy highlights a critical insight into student decision-making: students seem to prioritize potential wage outcomes over employment rates when selecting their fields of study. This finding implies that students are more motivated by the promise of higher salaries than by concerns about job security or market saturation.

Besides, the proportion of women in a study field is also not statistically significant. This indicates that the gender composition of a field may not have a significant impact on the demand for a field. Specifically, the analysis aimed to explore whether fields that are predominantly female or male attract students differently. The lack of statistical significance suggests that students' choices are not influenced by the gender balance within a field.

On the contrary, the total number of vacancies in a study field has a positive coefficient of 0.0030, significant at the 1% level. This result suggests that an increase in the number of available spots is associated with a very slight increase in the average grade. Conversely, the number of leftover vacancies has a negative coefficient of -0.0179, also significant at the 1% level. This indicates that fields with more unfilled positions are associated with a decrease in the average grade by about 1.79 points per leftover vacancy, reflecting lower demand.

However, it is important to consider the possibility of reverse causality in this relationship. While the data suggest that an increase in vacancies is associated with higher average grades, it is conceivable that this effect could be due to high-performing students influencing the allocation of more vacancies. In other words, it might be that higher average grades lead to an increase in the number of available spots, rather than the other way around. Administrative regulations and institutional practices, such as those outlined in Dispatch No. 6343-C/2020 (Ministério da Ciência Tecnologia e Ensino Superior, 2020) , do adjust the number of vacancies based on demand. The Ministry of Science, Technology, and Higher Education issues guidelines and vacancy limits for university admissions each academic year to optimize the alignment between supply and demand. For instance, the Dispatch No. 6343-C/2020 outlines directives for setting vacancies for the national admission process and local access competitions for the 2020-2021 academic year. This regulatory framework helps to clarify the positive coefficient observed in the relationship between the number of vacancies and grades. Administrative regulations and institutional practices adjust the number of available spots based on demand. This suggests that increasing vacancies in response to higher demand generally attracts more competitive students. The regulations impose restrictions on the number of available vacancies based on demand and unemployment rates. For example, Article 12 stipulates that cycles of study with insufficient enrolment in the previous three academic years cannot open new vacancies. Additionally, Article 13 restricts the increase in vacancies for programs experiencing higher unemployment rates compared to both the institution and the specific field of education. Also, the Dispatch No. 6343-C/2020 highlights the importance of programs in digital skills, data science, and Medicine. Unlike other programs, these fields may increase their number of vacancies relative to previous academic years, reflecting their critical role and higher demand. Administrative regulations aim to better rationalize the supply of academic programs and meet demand effectively. By adjusting the number of vacancies based on demand, these guidelines help to ensure that higher education institutions align their offerings with market needs. This mechanism supports the notion that administrative adjustments, such as increasing vacancies in response to higher demand, contribute to improved student quality and better alignment between educational supply and labour market needs.

Lastly, the significant and positive effects for 2020 and 2021 suggest an increase in grades, likely influenced by adjustments during the COVID-19 pandemic. As we seen before in Section 4.2.2, the COVID-19 pandemic significantly affected the education sector, leading to several adjustments that resulted in a visible rise in average entry grades for university courses.

In summary, the analysis indicates that wage premiums and vacancy dynamics play expressive roles in influencing the demand for study fields, as reflected in the average grades of the last admitted students.

However, the analysis is constrained by the small sample size of 154 observations across 22 study fields over 7 years, which limits the robustness and generalizability of the findings. Further research with more comprehensive data would be necessary to confirm these results and provide more detailed insights into the impact on individual study fields.

Chapter 7. Conclusions

This dissertation has explored two central objectives: estimating wage premiums associated with various fields of study and understanding how these premiums influence educational demand.

The analysis presented in Section 6.1 demonstrates that higher educational attainment significantly impacts wage premiums. Individuals with a bachelor's degree earn approximately 51.42% more per hour compared to those with only a high school diploma, while those with a master's degree about 65.22% more. When controlling for study fields, wage premiums vary significantly. Fields such as Business Sciences, Law, Physical sciences, Mathematics and Statistics, Computer Science, Engineering and related techniques, Transforming industries, Health and Transport Services show the highest wage premiums. Conversely, fields like Teacher training and education sciences, Arts, Humanities, Veterinary sciences, Social services and Personal services exhibit lower wage premiums, indicating lesser financial returns compared to other areas. The temporal analysis reveals a general decline in wage premiums across most fields from 2010 to 2021. This trend aligns with general wage dynamics, where wage growth for less qualified workers has outpaced that for higher education graduates. Notably, Computer Science avoided this trend, showing a slight increase in wage premiums, underscoring the growing value of education in this sector. On the other hand, fields such as Architecture and Construction and Social Services have experienced more significant declines, reflecting sector-specific challenges.

The second objective, analysing how wage premiums affect demand, demonstrates a clear relationship between higher wage premiums and increased demand for study fields. The analysis presented in Section 6.2 provides empirical evidence that wage premiums have a significant positive effect on demand, with a coefficient of 15.3169 (significant at the 5% level). Specifically, for every 0.1 unit increase in the wage premium (equivalent to a 10-percentage point increase), the average grade of the last classified individuals in a study field increases by approximately 1.532 points. This suggests that students are highly responsive to potential economic returns when selecting their fields of study. This finding aligns with the hypothesis that students are motivated by potential future earnings, leading to increased competitiveness for fields with higher wage prospects. The regression also highlights the relation between the number of vacancies and demand. An increase in the number of vacancies is positively associated (coefficient of 0.0030) with higher average grades and, consequently, demand. Conversely, the presence of leftover vacancies negatively (coefficient of -0.0179) impacts average grades, reflecting reduced demand. These findings underscore the importance of aligning educational supply with market needs and suggest that administrative adjustments to vacancy numbers are related to an attempt to align demand and supply. The study found that previous year's unemployment rates and the proportion of women in a study field do not have a statistically significant impact on demand. The lack of significance for the unemployment rate suggests that students are less concerned with job security or market saturation and more focused on potential wage outcomes. The lack of statistical significance for the women proportion indicates that students' choices are not influenced by the gender balance within a field. On the other hand, the COVID-19 pandemic had a significant impact on the higher education landscape, as evidenced by the notable increase in average entry grades in 2020 and 2021. This period of disruption led to adjustments that affected student performance and entry requirements.

The first part of this study benefited from a large dataset, Quadros de Pessoal, which enabled the calculation of wage premiums at the field level. However, this dataset's structure limited the analysis to broad fields of study rather than specific courses. This limitation has notable implications for the study. Fields of study involve a diverse range of individual courses, each with distinct characteristics and motivations influencing student choices. For example, within the broader field of Social and Behavioural Sciences, courses in Economics and Psychology may offer different wage premiums and have varying entry requirements. These differences are not captured by the aggregated field-level data used in this study. As a result, the analysis may not fully reflect the specific economic benefits associated with individual courses within this field. The inability to calculate wage premiums at the course level restricts the analysis further. Detailed data on specific courses would have allowed for more nuanced regressions on the second part of this study that could incorporate variables such as necessary entry exams or the location of educational institutions. According to the literature, these factors significantly influence student decisions and educational outcomes but are obscured when analysing data aggregated at the field level.

The second part of this study, while based on a sample of 154 observations across 22 study fields over seven years, provides valuable insights despite its size. It offers a foundational perspective on the nuanced impacts of wage premiums on demand. While the sample size presents opportunities for more extensive exploration, it sets the stage for future research to build upon these findings with larger datasets and more detailed analyses.

In conclusion, this dissertation successfully calculates wage premiums across various fields of study and demonstrates their significant impact on demand. High wage premiums are associated with increased demand, reinforcing the role of economic incentives in shaping educational choices. Vacancy dynamics also play a crucial role, highlighting the importance of aligning educational supply with market needs. The impact of the COVID-19 pandemic further underscores the need for adaptive policies in higher education.

Despite data limitations, the findings contribute to a deeper understanding of how economic factors influence higher education demand, providing a foundation for future research and policy development.

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Appendices

Annex A

Table 15-Description of variables of interest

Variable	Description
year	Reference year
worker_num	Worker identification number
female	Dummy variable for worker gender: 1 if female, 0 if male
age	Worker age
tenure	Tenure: years of experience in the current company
ctpro	Professional category
stpro	Situation in the profession
type_contract	Type of contract
reg_dur	Work duration regime
ctrem	Remuneration control
base_wage	Base wage paid (in euros)
reg_benefits	Regular benefits
base_wage_level	Monthly base wage scale
cpi	Consumer price index for Portugal between 2010 and 2021 (base year: 2012)
r_base_wage	Real monthly base wage (in euros)
r_h_base_wage	Real hourly base wage (in euros)
log_rbwageh	Logarithm of real hourly base wage
r_total_wage	Real monthly total wage (in euros)
r_h_total_wage	Real hourly total wage (in euros), being total wage the base wage plus the regular benefits
log_rtwageh	Logarithm of real hourly total wage
normal_weekly_hours	Normal weekly working period
normal_paid_monthly_hours	Normal paid monthly hours
suplem_paid_monthly_hours	Additional paid monthly hours
habil1	Educational qualifications (1 digit)
habil2	Educational qualifications (2 digits)
habil	Educational qualifications
nqua1	Qualification level
Educational level:	Dummy variables for highest educational level completed by the worker

secondary_postsec	Secondary education and non-tertiary post-secondary education level IV
bachelor	Bachelor's degree
masters	Master's degree
higher_educ	Dummy variable that equals 1 if a person has either a bachelor's or a master's degree
cnaef_codes_study_area	Study area code according to CNAEF (2 digits)
cnaef_study_area	Study area according to CNAEF
isced_codes_study_area	Study area code according to ISCED (2 digits)
isced_study_area	Study area according to ISCED

Source: Quadros de Pessoal

Table 16- Detailed field descriptions of CNAEF study fields

Major Groups	Fields of Study	Areas of Education and Training
0. General Programs	*01. Basic Programs*	010. Basic Programs
	08. Literacy	080. Literacy
	09. Personal Development	090. Personal Development
1. Education	*14. Teacher Training and Education Sciences*	140. Teacher Training and Education Sciences (*)
		142. Educational Sciences
		143. Early Childhood Educator Training
		144. Primary and Secondary Education Teacher Training (1st and 2nd cycles)
		145. Specific Subject Teacher Training
		146. Vocational and Technical Teacher Training
		149. Teacher Training and Educational Sciences — programs not classified elsewhere
2. Arts and Humanities	*21. Arts*	210. Arts (*)
		211. Fine Arts
		212. Performing Arts
		213. Audio-visual and Media Production
		214. Design
		215. Craft
		219. Arts — programs not classified elsewhere
	22. Humanities	220. Humanities (*)

		221. Religion and Theology 222. Foreign Languages and Literatures 223. Mother Tongue and Literature 225. History and Archaeology 226. Philosophy and Ethics 229. Humanities — programs not classified elsewhere
3. Social Sciences, Business, and Law	*31. Social and Behavioural Sciences*	310. Social and Behavioural Sciences (*) 311. Psychology 312. Sociology and Other Studies 313. Political Science and Citizenship 314. Economics 319. Social and Behavioural Sciences — programs not classified elsewhere
	32. Information and Journalism	320. Information and Journalism (*) 321. Journalism and Reporting 322. Library, Archive, and Documentation (LAD) 329. Information and Journalism — programs not classified elsewhere
	34. Business Sciences	340. Business Sciences (*) 341. Trade 342. Marketing and Advertising 343. Finance, Banking, and Insurance 344. Accounting and Taxation 345. Management and Administration 346. Secretariat and Administrative Work 347. Organization/Company Framework 349. Business Sciences — programs not classified elsewhere
	38. Law	380. Law
4. Science, Mathematics, and Computing	*42. Life Sciences*	420. Life Sciences (*) 421. Biology and Biochemistry 422. Environmental Sciences 429. Life Sciences — programs not classified elsewhere
	44. Physical Sciences	440. Physical Sciences (*) 441. Physics 442. Chemistry 443. Earth Sciences 449. Physical Sciences — programs not classified elsewhere

	46. Mathematics and Statistics	460. Mathematics and Statistics (*) 461. Mathematics 462. Statistics 469. Mathematics and Statistics — programs not classified elsewhere
	48. Computer science	480. Computing (*) 481. Computer Science 482. User-Oriented Computing 489. Computing — programs not classified elsewhere
5. Engineering, Manufacturing, and Construction	*52. Engineering and Related Techniques*	520. Engineering and Related Techniques (*) 521. Metallurgy and Metalworking 522. Electricity and Energy 523. Electronics and Automation 524. Chemical Process Technology 525. Vehicle Construction and Repair 529. Engineering and Related Techniques — programs not classified elsewhere
	54. Transforming Industries	540. Transforming Industries (*) 541. Food Industries 542. Textile, Clothing, Footwear, and Leather Industries 543. Materials (wood, cork, paper, plastic, glass, and other industries) 544. Extractive Industries 549. Transforming Industries — programs not classified elsewhere
	58. Architecture and Construction	580. Architecture and Construction (*) 581. Architecture and Urban Planning 582. Civil Engineering and Construction 589. Architecture and Construction — programs not classified elsewhere
6. Agriculture	*62. Agriculture, Forestry, and Fisheries*	620. Agriculture, Forestry, and Fisheries (*) 621. Agricultural and Animal Production 622. Floriculture and Gardening 623. Forestry and Hunting 624. Fisheries 629. Agriculture, Forestry, and Fisheries — programs not classified elsewhere

	64. Veterinary Sciences	640. Veterinary Sciences
7. Health and Social Protection	*72. Health*	720. Health (*) 721. Medicine 723. Nursing 724. Dental Sciences 725. Diagnostic and Therapeutic Technologies 726. Therapy and Rehabilitation 727. Pharmaceutical Sciences 729. Health — programs not classified elsewhere
	76. Social Services	760. Social Services (*) 761. Child and Youth Care Services 762. Social Work and Counselling 769. Social Services — programs not classified elsewhere
8. Services	*81. Personal Services*	810. Personal Services (*) 811. Hospitality and Catering 812. Tourism and Leisure 813. Sports 814. Domestic Services 815. Beauty Care 819. Personal Services — programs not classified elsewhere
	84. Transport Services	840. Transport Services
	85. Environmental Protection	850. Environmental Protection (*) 851. Environmental Protection Technology 852. Natural Environments and Wildlife 853. Public Health Services 859. Environmental Protection — programs not classified elsewhere
	86. Security Services	860. Security Services (*) 861. Protection of Persons and Property 862. Occupational Health and Safety 863. Military Security 869. Security Services — programs not classified elsewhere
9. Unknown or Unspecified	*99. Unknown or Unspecified*	999. Unknown or unspecified

Note: (*) Transversal programs, in which the "0" should be used in the third position.

Source: Ordinance No. 256/2005, of March 16 (Ministério das Actividades Económicas e do Trabalho, 2005)

Table 17- Detailed field descriptions of ISCED study fields

Broad Field	Narrow Field	Detailed Field
00 Generic programmes and qualifications	000 Generic programmes and qualifications not further defined	0000 Generic programmes and qualifications not further defined
	001 Basic programmes and qualifications	0011 Basic programmes and qualifications
	002 Literacy and numeracy	0021 Literacy and numeracy
	003 Personal skills and development	0031 Personal skills and development
	009 Generic programmes and qualifications not elsewhere classified	0099 Generic programmes and qualifications not elsewhere classified
01 Education	011 Education	0110 Education not further defined
		0111 Education science
		0112 Training for pre-school teachers
		0113 Teacher training without subject specialisation
		0114 Teacher training with subject specialisation
		0119 Education not elsewhere classified
	018 Inter-disciplinary programmes and qualifications involving education	0188 Inter-disciplinary programmes and qualifications involving education
02 Arts and humanities	020 Arts and humanities not further defined	0200 Arts and humanities not further defined
	021 Arts	0210 Arts not further defined
		0211 Audio-visual techniques and media production
		0212 Fashion, interior and industrial design
		0213 Fine arts
		0214 Handicrafts
		0215 Music and performing arts
		0219 Arts not elsewhere classified
	022 Humanities (except languages)	0220 Humanities (except languages) not further defined
		0221 Religion and theology
		0222 History and archaeology

		0223 Philosophy and ethics 0229 Humanities (except languages) not elsewhere classified
	023 Languages	0230 Languages not further defined
		0231 Language acquisition
		0232 Literature and linguistics 0239 Languages not elsewhere classified
	028 Inter-disciplinary programmes and qualifications involving arts and humanities	0288 Inter-disciplinary programmes and qualifications involving arts and humanities
	029 Arts and humanities not elsewhere classified	0299 Arts and humanities not elsewhere classified
03 Social sciences, journalism and information	030 Social sciences, journalism and information not further defined	0300 Social sciences, journalism and information not further defined
	031 Social and behavioural sciences	0310 Social and behavioural sciences not further defined
		0311 Economics
		0312 Political sciences and civics
		0313 Psychology
		0314 Sociology and cultural studies 0319 Social and behavioural sciences not elsewhere classified
	032 Journalism and information	0320 Journalism and information not further defined
		0321 Journalism and reporting 0322 Library, information and archival studies 0329 Journalism and information not elsewhere classified
	038 Inter-disciplinary programmes and qualifications involving social sciences, journalism and information	0388 Inter-disciplinary programmes and qualifications involving social sciences, journalism and information
	039 Social sciences, journalism and information not elsewhere classified	0399 Social sciences, journalism and information not elsewhere classified
04 Business, administration and law	040 Business, administration and law not further defined	0400 Business, administration and law not further defined
	041 Business and administration	0410 Business and administration not further defined
		0411 Accounting and taxation 0412 Finance, banking and insurance 0413 Management and administration

		0414 Marketing and advertising 0415 Secretarial and office work 0416 Wholesale and retail sales 0417 Work skills 0419 Business and administration not elsewhere classified
	042 Law	0421 Law
	048 Inter-disciplinary programmes and qualifications involving business, administration and law	0488 Inter-disciplinary programmes and qualifications involving business, administration and law
	049 Business, administration and law not elsewhere classified	0499 Business, administration and law not elsewhere classified
05 Natural sciences, mathematics and statistics	050 Natural sciences, mathematics and statistics not further defined	0500 Natural sciences, mathematics and statistics not further defined
	051 Biological and related sciences	0510 Biological and related sciences not further defined 0511 Biology 0512 Biochemistry 0519 Biological and related sciences not elsewhere classified
	052 Environment	0520 Environment not further defined 0521 Environmental sciences 0522 Natural environments and wildlife 0529 Environment not elsewhere classified
	053 Physical sciences	0530 Physical sciences not further defined 0531 Chemistry 0532 Earth sciences 0533 Physics 0539 Physical sciences not elsewhere classified
	054 Mathematics and statistics	0540 Mathematics and statistics not further defined 0541 Mathematics 0542 Statistics
	058 Inter-disciplinary programmes and qualifications involving natural sciences, mathematics and statistics	0588 Inter-disciplinary programmes and qualifications involving natural sciences, mathematics and statistics
	059 Natural sciences, mathematics and statistics not elsewhere classified	0599 Natural sciences, mathematics and statistics not elsewhere classified

06 Information and Communication Technologies (ICTs)	061 Information and Communication Technologies (ICTs)	0610 Information and Communication Technologies (ICTs) not further defined
		0611 Computer use
		0612 Database and network design and administration
		0613 Software and applications development and analysis
		0619 Information and Communication Technologies (ICTs) not elsewhere classified
	068 Inter-disciplinary programmes and qualifications involving Information and Communication Technologies (ICTs)	0688 Inter-disciplinary programmes and qualifications involving Information and Communication Technologies (ICTs)
07 Engineering, manufacturing and construction	070 Engineering, manufacturing and construction not further defined	0700 Engineering, manufacturing and construction not further defined
	071 Engineering and engineering trades	0710 Engineering and engineering trades not further defined
		0711 Chemical engineering and processes
		0712 Environmental protection technology
		0713 Electricity and energy
		0714 Electronics and automation
		0715 Mechanics and metal trades
		0716 Motor vehicles, ships and aircraft
		0719 Engineering and engineering trades not elsewhere classified
	072 Manufacturing and processing	0720 Manufacturing and processing not further defined
		0721 Food processing
		0722 Materials (glass, paper, plastic and wood)
		0723 Textiles (clothes, footwear and leather)
		0724 Mining and extraction
		0729 Manufacturing and processing not elsewhere classified
	073 Architecture and construction	0730 Architecture and construction not further defined
		0731 Architecture and town planning
		0732 Building and civil engineering

	078 Inter-disciplinary programmes and qualifications involving engineering, manufacturing and construction 079 Engineering, manufacturing and construction not elsewhere classified	0788 Inter-disciplinary programmes and qualifications involving engineering, manufacturing and construction 0799 Engineering, manufacturing and construction not elsewhere classified
08 Agriculture, forestry, fisheries and veterinary	080 Agriculture, forestry, fisheries and veterinary not further defined	0800 Agriculture, forestry, fisheries and veterinary not further defined
	081 Agriculture	0810 Agriculture not further defined 0811 Crop and livestock production 0812 Horticulture 0819 Agriculture not elsewhere classified
	082 Forestry	0821 Forestry
	083 Fisheries	0831 Fisheries
	084 Veterinary	0841 Veterinary
	088 Inter-disciplinary programmes and qualifications involving agriculture, forestry, fisheries and veterinary	0888 Inter-disciplinary programmes and qualifications involving agriculture, forestry, fisheries and veterinary
	089 Agriculture, forestry, fisheries and veterinary not elsewhere classified	0899 Agriculture, forestry, fisheries and veterinary not elsewhere classified
09 Health and welfare	090 Health and welfare not further defined	0900 Health and welfare not further defined
	091 Health	0910 Health not further defined 0911 Dental studies 0912 Medicine 0913 Nursing and midwifery 0914 Medical diagnostic and treatment technology 0915 Therapy and rehabilitation 0916 Pharmacy 0917 Traditional and complementary medicine and therapy 0919 Health not elsewhere classified
	092 Welfare	0920 Welfare not further defined 0921 Care of the elderly and of disabled adults 0922 Childcare and youth services 0923 Social work and counselling 0929 Welfare not elsewhere classified

	098 Inter-disciplinary programmes and qualifications involving health and welfare 099 Health and welfare not elsewhere classified	0988 Inter-disciplinary programmes and qualifications involving health and welfare 0999 Health and welfare not elsewhere classified
10 Services	100 Services not further defined 101 Personal services 102 Hygiene and occupational health services 103 Security services 104 Transport services 108 Inter-disciplinary programmes and qualifications involving services 109 Services not elsewhere classified	1000 Services not further defined 1010 Personal services not further defined 1011 Domestic services 1012 Hair and beauty services 1013 Hotel, restaurants and catering 1014 Sports 1015 Travel, tourism and leisure 1019 Personal services not elsewhere classified 1020 Hygiene and occupational health services not further defined 1021 Community sanitation 1022 Occupational health and safety 1029 Hygiene and occupational health services not elsewhere classified 1030 Security services not further defined 1031 Military and defence 1032 Protection of persons and property 1039 Security services not elsewhere classified 1041 Transport services 1088 Inter-disciplinary programmes and qualifications involving services 1099 Services not elsewhere classified
99 Field unknown	999 Field unknown	9999 Field unknown

Source:(UNESCO Institute for Statistics, 2015)

Table 18-Description of variables of interest-second part

Variable	Description
vacancies	Initial vacancies of each course

placed	Students placed in each course
grade	Grade of the last classified student of each course
leftovers	Number of vacancies left for 2nd phase of each course
year	Reference year
studyfield	Field of study field of each course (CNAEF classification)
cnaef_codes_study_area	Study area code according to CNAEF (2 digits)
grade_mean	Average grade per study field
vacancies_total	Total vacancies per study field
leftovers_total	Total vacancies left for 2nd phase per study field
unemployment_propensity	Unemployment rate of recent graduates per study field
average_wage	Average wage per study field
women_proportion	Proportion of women compared to men in each study field
wage_premium	Wage premium of higher education in each study field
wage_premium_5years	Wage premium of higher education in each study field in the last 5 years
unemployment_last_year	Unemployment rate of recent graduates per study field in the previous year

Source: DGES data from the General Access Regime, Quadros de Pessoal and Brighter Future

(DGES-Direção Geral do Ensino Superior, n.d.) (Fundação Belmiro de Azevedo, 2024) (GEP - Gabinete de Estratégia e Planeamento, n.d.)