Universidade de Aveiro
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BRUNO VILHENA PIRES

A PERSISTÊNCIA DOS DESAJUSTAMENTOS EDUCAÇÃO-TRABALHO NA TRANSIÇÃO PARA O EMPREGO: UM ESTUDO A NÍVEL UNIVERSITÁRIO

THE PERSISTENCE OF MISMATCHES IN THE TRANSITION TO EMPLOYMENT: A UNIVERSITY-LEVEL STUDY

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Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Economia, realizada sob a orientação científica do Doutor Hugo Casal Figueiredo, Professor Auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro, e coorientação da Doutora Joana Maria Costa Martins das Dores, Professora Auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro.

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Para a minha irmã.

To my sister.

o júri

presidente

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palavras-chave Sobrequalificação, Subqualificação, Desajustamentos educacionais, Transições escola-trabalho, Salários

resumo

Estudos recentes sugerem que, embora os desajustamentos educação-trabalho diminuam ao longo dos anos iniciais de carreira dos diplomados, estes conseguem deixar um efeito de cicatriz que diminui a probabilidade desses mesmos diplomados virem a conseguir encontrar uma correspondência adequada no futuro, o que resulta em penalizações salariais duradouras. Estes estudos mostram também que esses efeitos são reforçados quando os desajustamentos educacionais e de competências são combinados.

Esta dissertação utiliza um inquérito a nível universitário de acompanhamento de *alumni* para medir a magnitude e persistência desses efeitos de desencontro nos rendimentos e nas carreiras dos recém-diplomados. Fazemos uso da natureza detalhada e institucional do conjunto de dados obtido, nomeadamente, a existência de dois momentos de recolha de dados desfasados no tempo, para controlar a importância relativa de efeitos individuais observáveis e não observáveis associados quer às características de formação dos diplomados, quer à natureza dos empregos que estes desempenham.

As análises desenvolvidas revelam que a existência de desajustamentos educação-trabalho são frequentes (atingindo mais de dois terços dos diplomados mesmo três anos depois da conclusão do curso) e que provocam um efeito negativo ao nível dos retornos salariais dos diplomados do ensino superior. Mostram também que esses efeitos persistem em larga medida durante os primeiros anos no mercado de trabalho. Revelam ainda importantes efeitos de interação entre a obtenção do segundo ciclo de Ensino Superior (mestrados) e essa condição de desajustamento. Essa interação resulta em prémios significativos para mestres (face aos licenciados) mas, ainda assim, não isenta diplomados de segundo ciclo das penalizações decorrentes desse tipo de desencontros (embora menores do que no caso de licenciados em situações de desajustamento). Os resultados desta investigação parecem confirmar a importância das características da estrutura produtiva da Economia Portuguesa no condicionamento dos salários atribuídos aos diplomados do ensino superior.

keywords

Overskilling, Underskilling, Educational mismatch, School-to-work transitions, Wages

abstract

A series of recent studies suggest that, while education-job mismatches decrease throughout graduates’ initial career years, they leave a scarring effect lowering the likelihood of finding an adequate match in the future and resulting in lasting earnings penalties. Such research also shows that such effects are reinforced when education and skill mismatches are combined.

This dissertation uses a university-level follow up alumni survey to account for the persistence effects of such job-education mismatches in graduates’ earnings and careers during their initial transition to employment. We make use of the detailed and institutional nature of the dataset, namely the collection of data in two different points in time, in order to control for both observed and unobserved individual determinants of earnings.

The analyses reveal that the existence of education-job mismatches has a negative effect on graduates’ wage returns, effects that persist to a large extent during the first years in the labour market. They also reveal important interaction effects between attaining a Master’s degree and the probability of mismatch. This interaction results in significant earnings premiums for postgraduates (vis-à-vis first-degree graduates) but does not exempt them from the earnings penalties associated with different types of mismatch (although lower than those of mismatched first-degree graduates). Our research results seem to confirm the importance of demand-side factors (associated with the specific characteristics of the Portuguese productive structure) in conditioning graduates’ earnings trajectories.

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List of Abbreviations and Acronyms

DGEEC – Direção-Geral de Estatísticas da Educação e Ciência

Eq. – Equation

GDP – Gross Domestic Product

HE – Higher Education

HILDA – Household, Income and Labour Dynamics in Australia

i.e. – *id est* – that is

INE – Instituto Nacional de Estatística

N. º – Number

OECD – Organisation for Economic Co-operation and Development

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1. Introduction

Several studies conducted over the last few years show clear evidence that many newly graduated individuals enter the labour market in situations of mismatch (Battu, Belfield and Sloane, 1999; Carroll and Tani, 2013; Dolton and Vignoles, 2000). This is a situation defined as the discrepancy between the skills and competences of recent graduates and those required by the jobs they perform. This raises relevant questions because, although some theories on this subject suggest that this is only a transitory phenomenon, namely until a job is found that suits the qualifications of recent graduates to those required for employment, others confirm the negative, widespread, and persistent effects over time of such a situation at the beginning of the career (Arulampalam, 2001). Among other problems, this issue suggests an underutilisation of the skills acquired by recent graduates in Higher Education Institutions in the labour market, which may reveal costs for society as a whole (McGuinness, 2006). Thus, the question of the effects of educational mismatches on employment, and the phenomenon of overskilling and underskilling, in particular, is still an open question in the scientific literature that seeks to gauge the potential effects of accepting a job for which one has additional skills at the beginning of the career, and the effects of persistence in this situation over time.

This dissertation uses data from a university-level survey of recent graduates from the University of Aveiro, Portugal, which were collected in two waves, in an initial survey in 2012 (referring to students graduated in the previous triennia), and in a follow up survey in 2015. The use of data from this survey, carried out at the university level, proved advantageous for several reasons. The existence of data from graduates from different scientific areas is combined with the coverage of a wide range of the characteristics of the graduates' career paths. These include employer characteristics (such as the size of the company, sector of activity, location), detailed information about education paths (educational performance, cycle of studies) as well as information of labour market experience and an assessment of the degree of mismatch between individual skills and job-required competences. Graduates also provide information on whether the job matches their field of study. On the other hand, it should be noted that the use of data at the level of a single university can bring with it problems in securing representativeness to the national level. Still, it allows us to obtain relevant data and infer about the ecosystem of the *alumni* of the University of Aveiro whose employment destination span widely across Portugal.

Portugal is also a good case study on the main theme of this dissertation. In recent decades, Portugal has experienced a very significant increase in the number of students enrolled in Higher Education, and a general increase in the educational level of its population, although it remains below the European Union average in terms of the level of qualifications of its inhabitants (Figueiredo, Teixeira and Rubery, 2013). Despite this increase, Portuguese labour legislation is also characterized by its great rigidity, creating barriers and costs to companies´ adjustment processes of the labour market (Martins, 2009), among other significant barriers. In addition to this, being a factor even more relevant to this study, the data used in this dissertation was recorded, in the first wave, during a period of strong economic and financial crisis in the country and, in the second wave, already during a period of sustained economic recovery. This may provide an interesting benchmark on the role of education-job mismatches in conditioning recovery from financial crises that usually scar graduates' employment prospects.

The contribution of this dissertation is then to query the determinants of being in an education-job mismatch situation and to measure and quantify the effects of the persistence of a state of match/mismatch on graduates' wage returns.

This dissertation is organised as follows: chapter 2 reviews traditional theories and explanations for the existence of the phenomena of overskilling and underskilling, contrasting these explanations with the most recent results in scientific literature. The chapter also makes a contextualization of the reality of the Portuguese labour market regarding the evolution of overall educational levels and higher education attainment in particular. Chapter 3 explains the construction of the sample used in this study, its collection method and the selection and modelling of variables, as well as the analyses of their attrition. This explanation carries over to Chapter 4 where the methodological approach used in our calculations is explained. Chapter 5 presents and discuss the results obtained and the robustness analyses carried out. Finally, chapter 6 presents the main conclusions, limitations and public policy recommendations as well as suggestions for future work.

2. Literature Review

The focus of this dissertation is on the transition of graduates from Higher Education into the labour market and the persistent effects that, over time, overskilling and other education-job mismatches can have on Higher Education graduates' earnings trajectories and on what are the determinants of being in such a situation, and how they act through time. We start by defining what overskilling is, the different concepts that are related to it, how it can be measured and how it is going to be treated in this work.

2.1. What do we mean by overskilling and why does it matter?

A situation of overskilling occurs when a worker considers that his qualifications and skills are not being fully used in their job (Mavromaras, Mahuteau, Sloane and Wei, 2013). This situation ends up reflecting a mismatch between the worker and their job and an under-utilisation of skills in the labour market. Throughout the existent literature about the matter of overeducation, it is common to find the concepts of overeducation, overskilling and overqualification used interchangeably as terms that approach the same or a similar phenomenon. And, as though as, generally speaking, the latter two – overskilling and overqualification – can be used under the umbrella of the first one – overeducation –, strictly speaking, they do not mean the same thing.

As pointed out by Capsada-Munsech (2017), "overeducation is conceptualized as an excess of educational skills gained in formal education, whereas overqualification sticks to education credentials" (p. 4), while "overskilling refers to the situation in which workers possess more skills than the ones required to perform the job tasks" (p. 4). In practical terms, this can lead to a situation in which a worker may be overeducated and not overskilled. In this sense, Mavromaras and McGuinness (2012) expose that overeducation is more prone to measurement error in that "it compares educational attainment taken to be a proxy for individual human capital, with job entry qualifications taken to be a proxy for skill job content" (p. 619), failing to effectively encompass the issues of workers' innate abilities, the capacity of a worker to learn skills on the job, and that the requirements for entry into employment can be a form of "credentialism"

(p. 619). In this sense, the concept of overskilling overcomes these constraints by asking workers directly for their skills level and whether or not they feel those are adjusted to the requirements of the jobs they occupy. As such, for the sake of consistency, and due to the nature of our dataset, we will prefer the use of overskilling in this dissertation, unless when referring to specific literature.

The most common and most studied implications of being overskilled are lower wages as a result of wage penalties, and lower wage growth when compared to adequately matched workers (Büchel and Mertens, 2004; Korpi and Tåhlin, 2009), as well as lower productivity and less job satisfaction (Allen and van der Velden, 2001; Mavromaras, McGuinness, O'Leary, Sloane and Wei, 2013), with results showing that overskilling even results in cognitive decline for workers that experience it, although not for underskilled workers, according with de Grip, Bosma, Willems and van Broxtel (2008). According to McCormick (1990), this phenomenon may also act as strong negative signal to employers, and a bad entry in the labour market can have long lasting effects in careers, with being in a mismatched position in the first job increasing significantly the probability of remaining in such a position in the next jobs, by six to nine times more (Robert, 2014). Despite these negative implications of accepting a non-optimal entry in the labour market, many recent graduates still risk in accepting jobs for which they are overeducated. This may be justified as recent-graduates, and other job seekers, try to escape the scarring effects of being unemployed (Arulampalam, 2001), or that they find it to be a learning experience that will provide the shortest path and the skills to a perfectly matched job.

As such, the debate on the issue of overskilling and education-job mismatches has remained relevant over the years and it is important to deepen it in order to better discover its effects on workers and, like this dissertation, the effects of its persistence over time.

2.2. Theoretical approaches to overskilling

In the existing literature, there are some theoretical approaches that have been consistently used throughout the years to drive the research on overeducation. These approaches, as pointed out by McGuinness (2006), have been the main existing interpretations on – and of – the labour market and authors have steadily worked on the overeducation phenomenon trying to frame it within them, and not by developing a single framework dedicated to the overeducation phenomenon, or by trying to find out which of the theories is best suited to describe this issue. As stated by Sloane (2003), this debate over overeducation has instead contributed to expand the human capital framework by focusing on job characteristics and workers' preferences. As such, the empirical literature on the subject of overskilling and on education-job mismatches has not been conclusive on the effects, persistent or not, that they have on workers across the time.

Table 1 – Main features of overeducation theories.

Theoretical approach and author(s)	Nature of the phenomenon	Main characteristics	Cause of the mismatch
Human capital theory, Becker, 1964	Temporary	Overeducation is a temporary phenomenon in the beginning of careers, that is adjusted once the skills of the worker and the needs of the company are met through job searching.	Imperfect information. Supply side.
Job competition model, Thurow, 1975	Persistent	The educational level required to perform a job forms a hierarchy which is matched according to the educational level of workers. This leads to an incentive to invest in education as high skilled jobs are to be performed by high skilled workers. Overeducation occurs and can be persistent if workers' education levels are above job requirements.	Mismatch between workers' educational level and job requirements. Demand and supply side.
Career mobility theory, Sicherman and Galor, 1990	Temporary or persistent	Workers become overeducated because they fail to clearly signal their educational levels to firms. To leave this state a worker must achieve a level of personal capacity where they can clearly signal to potential employers their skills or get firm-specific skills, remaining in such a situation in longer or shorter periods of time depending on their signalling capabilities.	Signalling problem. Supply side.

Source: Own elaboration, based on Capsada-Munsech (2017).

The three main approaches that have driven this debate are the "human capital theory" (Becker, 1993), the "job competition model" (Thurow, 1975), and the "career mobility theory" (Sicherman and Galor, 1990) and there is a summary of their main components in Table 1, above.

According to the human capital theory (Becker, 1993), it is suggested that the overeducation phenomenon occurs due to lack of information in the labour market. That way, the overeducation phenomenon tends to be a short term one and to disappear as the workers mobility in the labour market takes place in the beginning of their careers, allowing them to learn and acquire new skills until they reach a job that is adjusted to their qualifications and competences, or until it takes for workers to be adjusted to the production necessities of the company they are in, utilising their full human capital. Under this assumption, overeducation would negligible and due to imperfect information. Workers would invest in education in order to maximise their wages and utility and firms would recruit workers in order to maximise their productivity by using their skills and competences. However, if overeducation ends up being a permanent phenomenon that persists over time and across different jobs, that constitutes a challenge to the human capital theory.

The job competition model, postulated by Thurow (1975), offers a different overview in the overeducation debate. It looks at the labour market as a training market rather than a bidding market, as it considers that most of the skills a worker gains are through on-the-job experience rather than through formal education. In this sense, the labour market acts as a form of competition for a training place in a job and not as a bidding market where, on the supply side, one wants to sell and accept a wage according to the skills that formal education has provided. As jobs are allocated by companies according to the level of education required, among other factors, to perform them, workers will depend on the relative position of their educational level and their skills in relation to other workers in order to obtain them and be able to acquiesce more skills. This way of looking at the labour market promotes that workers aim for ever higher skill levels, as only then will their relative position to others improve, eventually creating an inflation of credentials problem. This inflation of credentials on the part of workers may result in a state of overeducation, as workers may have to obtain more qualifications than necessary in order to reach a position and may also lead to a situation of persistence of overeducation, if the labour market and firms do not create more suitable positions for the educational levels of workers.

Finally, the career mobility theory (Sicherman and Galor, 1990) approach to the issue of overeducation reasons that it is because workers cannot correctly signal their skills to employers, or because they have less experience in the labour market, that they may end up in a situation of overeducation in their jobs. In this theory, this situation can only change once a worker is able to correctly signal to the potential employer their level of qualifications and skills, or when their function changes to one that correctly reflects their abilities and firm-specific skills. Thus, within the career mobility theory, overeducation is a phenomenon that can be both short-lived and persistent throughout a worker's career. Unlike in the human capital theory and the job competition model, which assume that there is homogeneity in workers' individual preferences, the career mobility theory does not make any assumption regarding that matter, only pointing out the signalling problem on the supply side of the labour market as the main reason for the existence of overeducation.

2.3. The “stepping stone” vs. “trap” hypothesis

As explained in the previous subchapter, the main theories on overskilling and overeducation cannot converge to a single explanation as to the effects of the persistence in this situation. While some theories point to the fact that it may be a purely transitional phenomenon of adaptation to the labour market, others suggest that it may bring permanent consequences for workers. These interpretations can be summed up in a question of debate, which can be translated as follows: is overskilling at the beginning of a career a “stepping stone” or a “trap”?

The “stepping stone” hypothesis has been best laid out by Sicherman and Galor (1990), where they state that overeducation acts as an investment in experience through work, paving the way for the acquisition of more skills and competences enhancing new job opportunities or promotions to correctly matched jobs. That way, overeducation can be no more than a step in the process of integration in the labour market. The “stepping stone” hypothesis, as well as the negative stigma associated with one being in a situation of unemployment right after graduation (Arulampalam, 2001), is one of the reasons advanced by the economic literature to justify the decision by young graduates to accept jobs for which they are overeducated.

However, on the other hand, and contrarily to this hypothesis, many economic studies point to the fact that this overskilling phenomenon not only is not part of a natural process of adjustment, but effectively works as a “trap” – the overskilling “trap” – in that, once a worker finds itself in a labour market situation of being overskilled for the job it is performing, its transition to a labour market situation adequate to its academic qualifications and competences is turned harder. According to McCormick (1990), the overeducation phenomena acts as a stronger negative signal to potential employers than a situation of unemployment and, moreover, according to Mavromaras and McGuinness (2012), these phenomena are not only prejudicial to the well-being of workers but also to the well-being of employers.

The work done by Frei and Sousa-Poza (2012), using 26 738 pooled observations from the first eight waves of the Swiss Household Panel (1999-2006), and applying a multinomial logit and probit models, found out that almost 90% of overqualified workers escape that state within four years, against evidence on signalling effects, and the percentage of those who remain overqualified when they change occupations within a job is higher than those who become well-matched (45,8% vs. 40,4%), but those who change employers are as equal to remain overqualified than to become well-matched in their new jobs (43,8% vs. 44,8%). They also found that overqualified workers have a higher risk of becoming unemployed, increasing the probability of job mobility. Using a fractional logit model, for 14 664 observations of the first four waves of the HILDA Survey, in Australia, McGuinness and Wooden (2009) also found that overskilled workers are 8 percentage points more likely quit their current jobs within 12 months of taking them (29% vs. 21%), and that overskilled workers expect losing jobs 17 to 27% more than their well-matched counterparts, with overskilling increasing the likelihood of voluntary and involuntary job separation, and with many overskilled workers that don’t find better and well matched jobs ending up to leave entirely the workforce. However, both studies agree that tenure and occupational experience reduce the risk of a worker becoming overqualified.

One of the main conclusions of the study conducted by Meroni and Vera-Toscano (2017), using a dynamic or iterated propensity score model, is that the acceptance of a job in which a worker is overeducated, instead of remaining in a situation of unemployment for a longer period of time, does not lead to higher probabilities of that worker being adequately employed in the future, but to higher probabilities of remaining in a job for which that worker has more skills and competences than necessary, sustaining the overeducation “trap” hypothesis contrary to the “stepping stone” hypothesis, being the “trap” more persistent through time. The results of that study also demonstrated that the persistence of overeducation is verified in all areas of study, however, it is greater for those who have graduated in Education and Humanities. These effects were studied for a sample of 10 526 graduates, five years after graduation, in thirteen European countries (the United Kingdom [Liberal Europe]; Czech Republic and Estonia [Eastern Europe]; Austria, Belgium, France, Germany and the Netherlands [Continental Europe]; Finland and Norway [Scandinavian Countries]; Italy, Portugal and Spain [Southern Europe]) and found that, for Eastern and Southern European countries, overeducation always works as a “trap”, for Scandinavian Countries and Continental Europe there are mixed results on the overeducation “trap” hypothesis, and for Liberal Europe overeducation works as a “trap” if the graduates accept their jobs right after graduation.

In their study, Baert, Cockx and Verhaest (2013), analysed a sample of 1 434 Flemish male individuals, born between 1978 and 1980, through a survey, and found that the overeducation “trap” hypothesis holds. Applying the Timing of Events methodology, they concluded that overeducation acts as a “trap” not only to young people that accept jobs right after graduation, but also to long-term unemployed young people – young people who hoped to find a job that suited their level of education but gave up doing so – as accepting a job for which they will be overeducated reduces substantially their transition to an adequate job. The study found that for accepting such a job, their monthly transition rates for an adequate one fall between 51% and 98%, depending on the period during which they have been unemployed.

The results of Acosta-Ballesteros, Osorno-del-Rosal and Rodríguez-Rodríguez (2018), with a sample of 1 930 Spanish workers between 16 and 34 years-old, collected in 2009, using a recursive bivariate probit model also do not support the career mobility theory, pointing that being in a first job in which a worker is overeducated, significantly increases in 40,2 percentage points the risk of a worker remaining overeducated in a later one, supporting the overeducation "trap" hypothesis. They also find that individuals who start their career in overeducated positions are more likely to suffer from overeducation in the present those that didn't and that that effect comes mainly from the fact of being overeducated per se.

More recently, the work done by Araújo and Carneiro (2020) analysing the time period between 1998-2012 for Portuguese graduates, and their transition to the labour market, found out that around half of Portuguese employees in the private sector experience some form of vertical mismatch in the moment when they are being hired, be it overeducation or undereducation. However, and in contrast to the previously mentioned studies, they found out that even being in a mismatched job increases the labour market experience of workers, who in turn invest in on-the-job training. The information about the skills and abilities of employees is also increased for employers over the time, leading to the necessary adjustments that, for those who keep their jobs, results in almost a complete reduction of the initial wage penalties that they suffer. The results of Araújo and Carneiro (2020) also suggest that these educational mismatches are mostly driven by unobserved characteristics innate to workers and firms, that fail to accurately account for them. Therefore, they found that over two-thirds of the wage penalty of overeducated workers and over three-fourths of the undereducated premiums are due to heterogeneity.

2.4. Evolution of the graduate labour market in the period under consideration

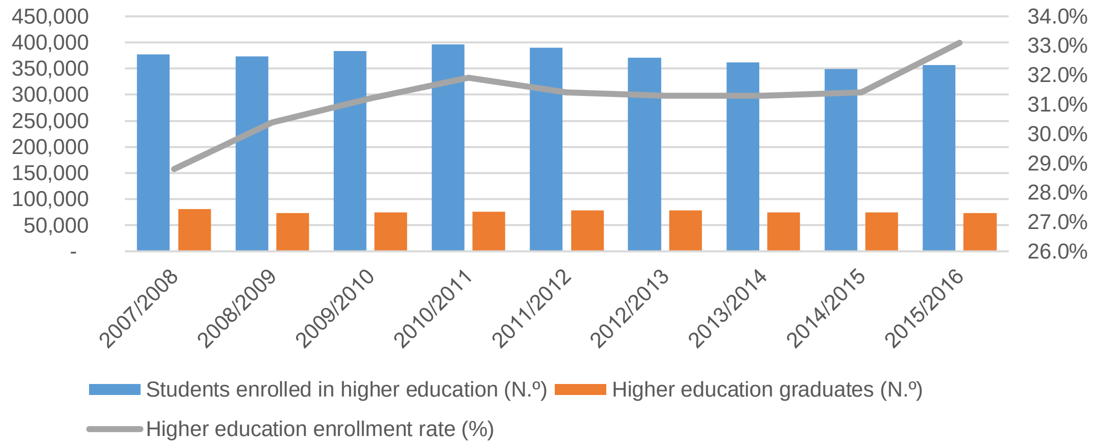
In this subchapter it is pretended to contextualize the reality of the Portuguese economy and labour market during the period in which our respondents were in university and after graduation and first years of employment, corresponding to the periods between the first survey conducted after graduation and the follow up survey.

As noted by Figueiredo et al. (2017), Portugal has long had a considerable deficit of qualifications since, at least, the last two centuries. In the mid-1970s, a quarter of the population was illiterate, and more than 35% of the population aged over 15 had no formal education at all, a situation that progressively and drastically changed after the country's democratization, which began in 1974. In 2011, about six percent of all population still had no formal education, but about 60 per cent had completed basic education and almost 40% had completed secondary education.

With regards to Higher Education, Portugal has also followed a path of success since the beginning of its democratization process. With a highly socially and regionally unequal Higher Education system whose access was, in the mid-1970s, difficult and with just over 50 000 students enrolled, Portugal has surpassed the barrier of 400 000 students enrolled in Higher Education in 2003. In the last two decades, including during our analysis period, the number of students enrolled in Higher Education varied between 349 658 and 396 268. According to the DGEEC (2016), the number of graduates of Higher Education Institutions in Portugal has also been steadily growing having reached its peak in 2007/2008 with 81 539 students graduating in that academic year. Since then, and during our analysis period the number of graduates has oscillated between 73 857 and 79 034 per academic year. The year-on-year variation in the number of students enrolled and graduated in Higher Education, demonstrated in Figure 1, can be attributed to several reasons, among others, the increased demand for accreditation of Higher Education Institutions and their courses, after 2009, which lead to the closure of some institutions and courses, demographic changes, with a decrease in the number of young people in university age in Portugal, and a strong focus must also be laid on the country's economic performance.

The Higher Education enrolment rate, that measures the percentage relationship between the number of students enrolled in Higher Education initial training courses, aged between 18 and 22 years old, and the resident population of the same age levels, has grown steadily since the democratization of access to Higher Education until the academic year of 2010/2011, when it reached a peak of 31,9%. Since then, the rate dropped 31,4% and maintained itself on that level for the next four academic years, until it grew again to 33,1% in the academic year of 2015/2016. During this period, it was also witnessed a rather significant decrease in the number of enrolled students in Higher Education as well as in the number of graduations from Higher Education. This may be justified with the fact the during these years, Portugal was under a severe financial crisis that led to an international bailout and severe austerity measures.

Figure 1 – Enrolment in Higher Education.



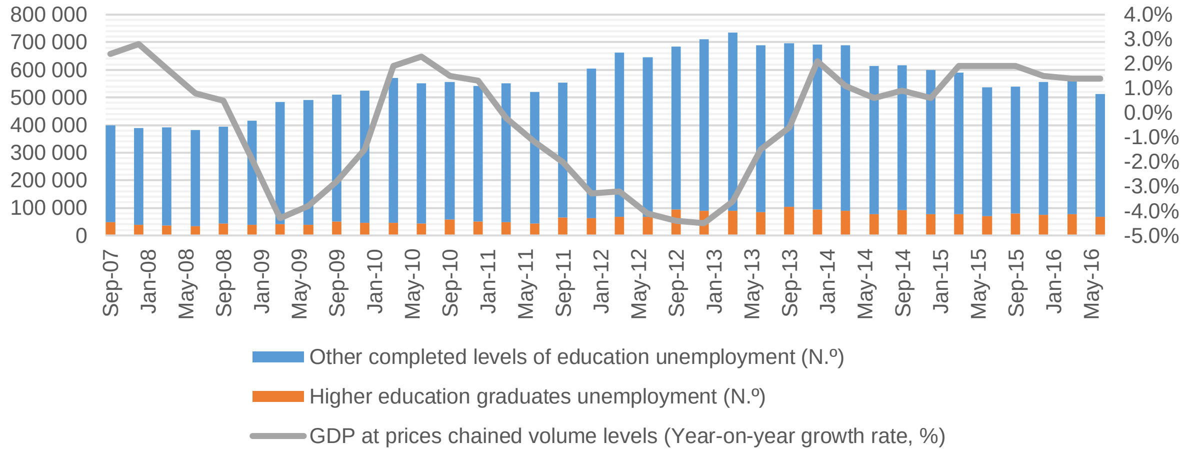
Source: own elaboration according with INE and DGEEC data.

In relation to unemployment and the economic performance of Portugal, as can be seen on Figure 2, from September of 2007 to March of 2016 unemployment numbers fluctuated along with economic growth. During this period Portugal experienced two periods of recession, which lead to the increasing numbers in unemployment. The longest recession period started in the first trimester of 2011 and ended in the third trimester of 2013 and coincided with the Portuguese sovereign debt and financial crisis, and with the implementation of the Memorandum of understanding on financial assistance to Portugal, a €78,0 billion bailout program (European Commission, 2011).

During this period of recession, which coincides with the departure of the graduates under analysis in this work from university and their entry into the labour market, total unemployment increased, from 519 000 in the second quarter of 2011, to the peak of 734 000 in the first quarter of 2013, reaching an unemployment rate of 17,5%, according to Statistics Portugal (INE, 2020).

Regarding those in unemployment who had completed Higher Education, their numbers followed the trend of general unemployment, increasing from 44 000 in the second quarter of 2011 – representing 8,5% of the total unemployed – to a peak of 103 000 in the third quarter of 2013 – representing 14,8% of the total unemployed – with the unemployment rate reaching 12,9% among those who had completed Higher Education.

Figure 2 – Relationship Between Unemployment and Economic Performance.



Source: own elaboration according with INE and DGEEC data.

3. Data and Descriptive Analysis

3.1. Alumni data

The database used in this dissertation was built by the *Observatório do Percurso Socioprofissional dos Diplomados da Universidade de Aveiro*. This Observatory has the role of regularly monitoring the employability of graduates of the University of Aveiro and of producing wide-ranging studies about their career paths after graduation.

This study uses data from two separate surveys that were conducted by the University of Aveiro through questionnaires via telephone interview in two sequential moments (up to two and five years after graduation). The first survey was conducted to the graduates of all the cycles of study conferred by the University of Aveiro in the 2008/2009 to 2010/2011 triennia. The fieldwork and data collection for the first survey took place between March and September of 2012, and the second survey was conducted at the end of 2015, approximately three years after the first one and consisted of a follow-up questionnaire with broadly similar questions. All questionnaires focused on graduates' employment situation and position, their pay as well as the adequacy of employment to their area of studies. Questions also included respondents' evaluation of their level of competences (as provided by their cycle of studies) against the skill requirements of their employment at the time. The respondents for both waves were selected using a non-proportional stratified random sampling method with the aim of guaranteeing representativeness at the course level.

For the purposes of this dissertation, graduates whose country of residence was not Portugal were excluded from the sample. These are minority populations and were not considered to be relevant to the object of this study. In the first moment of this study, of the 7 195 graduates of the University of Aveiro in the triennium 2008/2009 to 2010/2011, 2 662 were interviewed. In the second moment, all these individuals were recalled to answer a similar follow up questionnaire. Of these, 1 384 provided follow-up information about their employment and educational trajectory. This gap between the first and follow-up surveys may have caused some attrition problems between the two sub-samples. As an example, those who answered both surveys could have been those in a better employment position, or those with a smoother transition to the labour market after graduation, and thus more willing to give feedback after the initial survey. Otherwise, those who experienced more difficulties in entering the labour market could have been more easily discouraged in answering the follow up survey. Also, it is worth mentioning that, with a smaller sample in the second moment, important information about wages and transitions among mismatch states may have been lost. As such, these attrition problems will be analysed in detail in a further sub-section of this chapter.

A second important choice concerns the choice of a balanced or unbalanced panel to conduct the analysis. Not all respondents were employed and had valid earnings data in both surveys. A significant share of individuals interviewed in the first phase were inactive (actively studying, for example) and may, therefore, have valid employment information only for the follow-up questionnaire. This is a common occurrence considering that an increasing share of higher education students continue to postgraduate studies after their first-degree. Equally an important number of respondents may had been unemployed in either survey.

Table 2 – Transition matrix (employment status).

First Surveys	Follow up Survey								Total	
	Employed		Unemployed		Student/ Inactive		Missing			
Employed	800	(0,491)	49	(0,030)	30	(0,018)	750	(0,460)	1629	(0,612)
Unemployed	138	(0,345)	43	(0,108)	9	(0,023)	210	(0,525)	400	(0,150)
Student/Inactive	244	(0,385)	37	(0,058)	34	(0,054)	318	(0,502)	633	(0,238)
Total	1182	(0,444)	129	(0,048)	73	(0,027)	1278	(0,480)	2662	(1)

Source: Own elaboration. Frequency in parenthesis.

Table 2 describes the flow between such employment states between the two surveys including missing data in either survey. We can see that almost half of the responses about the employment status were lost from the first to the follow up surveys. This loss of data, as explained above, happened as only 1 384 individuals recorded responses for the follow up survey, however, it should be noted that this split in the data provided for both surveys was almost even across those who were employed, unemployed, or were student or inactive in the first surveys. As such, of the 1 629 respondents that were in employment in the first moment of this study, and of those who recorded answers for the second moment, almost all of them remained employed in the follow up survey, with only a fraction becoming unemployed. On the other hand, of those 400 unemployed individuals in the first surveys, 138 became employed and only around a tenth of them remained unemployed in the follow up survey.

Considering our research objectives, namely the objective of measuring the earnings impact of education-job mismatches in initial career years, we use the most balanced panel to conduct the analysis as we only consider data from those individuals who provided earnings data in both surveys. This results in a balanced sample that is much smaller than the overall number of graduates who were interviewed. This does not eliminate, however, problems of attrition, having in account, as we argued, that not all individuals that answered in the first moment provided data for the second moment, but equally selection problems, considering for example that the propensity to be unemployed may not be fully independent of the explanatory factors considered (fields of study, educational performance but equally the nature of the education-job match in the first survey). The results may therefore be interpreted with these limitations in mind. Also, in order to make possible biases clear, not only we explore the issue of attrition below as we present separate data for both the full sample and the balanced sample. The full sample consists of the total number of observations of the dataset that were graduated and were employed with a salary in 2012 or 2015.

The final dataset used in the study also removed doctoral graduates from our samples as they consisted of a very low number of observations in the first survey. Respondents with valid earnings data in both surveys that attained a doctoral degree between surveys were kept as part of the sample, however. Finally, we decided to remove from the sample all earnings outliers. As such, all those individuals whose wages were three times above the 99th percentile for wages were removed from the balanced sample. This results in a fully balanced dataset of approximately who were tracked across the period covered by both surveys (2012 – 2015).

3.2. Mismatch variables

Given that the main contribution of this dissertation should be the measurement and analysis of the persistence of the effects of education-job mismatches for recent graduates, it is necessary to create a set of essential variables for measuring these mismatches. These variables will serve as the focus variables of the models to be applied for the measurement and quantification of vertical and horizontal mismatches, as well as for the transition between mismatch states, or not.

Table 3 – Descriptive Statistics: Mismatch Variables.

Variable	Description	Whole sample			Balanced sample		
		N	Mean	Std	N	Mean	Std
Horizontal mismatches							
Horizontal12	There is a horizontal mismatch in the first survey	1457	0,184	0,388	672	0,171	0,377
Horizontal15	There is a horizontal mismatch in the follow up survey	1094	0,192	0,394	672	0,186	0,389
Match/Mismatch status							
Skills_Adq12	The skills acquired in HE are adequate for job performance in the first survey	1125	0,596	0,491	507	0,613	0,487
Skills_Adq15	The skills acquired in HE are adequate for job performance in the follow up survey	1090	0,581	0,494	672	0,595	0,491
Perform_Dem12	There is a demanding job performance in relation to skills learnt in the first survey	1097	0,345	0,475	492	0,362	0,481
Perform_Dem15	There is a demanding job performance in relation to skills learnt in the follow up survey	1068	0,425	0,495	658	0,441	0,497
Mismatch Status 12							
pmatch12, 0	There is a perfect match	1096	0,233	0,423	483	0,263	0,441
us12, 1	The individual is underskilled	1096	0,112	0,316	483	0,106	0,308
os12, 2	The individual is overskilled	1096	0,373	0,484	483	0,364	0,482
mismatch12, 3	There is a perfect mismatch	1096	0,282	0,450	483	0,267	0,443
Mismatch Status 15							
pmatch15, 0	There is a perfect match	1066	0,276	0,455	483	0,292	0,455
us15, 1	The individual is underskilled	1066	0,148	0,356	483	0,150	0,356
os15, 2	The individual is overskilled	1066	0,312	0,467	483	0,319	0,467
mismatch15, 3	There is a perfect mismatch	1066	0,264	0,428	483	0,240	0,428

Source: Own elaboration.

In Table 3, we present our focus variables for the study of these mismatches and their essential description. The form of measurement of these variables is presented in Table 30 in the Appendix. Next, we will present the way they are constructed and proceed to the descriptive analysis. Information for each variable is provided twice: for the whole sample and for the balanced sample. The balanced sample is a sub-group of the whole sample and it consists of all those that were employed with a salary in both 2012 and 2015. As it can be seen, the number of observations in each sub-sample varies considerably. This is because the number of observations in each sub-sample differs for each of the created variables, as we will explain throughout the description of the variables below.

3.2.1. Horizontal mismatches

The variable Horizontal was constructed from the original ordinal scale that assessed the degree of horizontal mismatch in the first and follow up surveys (represented by the numbers 12 and 15, referring to the year in which data were collected). The Horizontal variable was created on the basis of the survey question "To what extent do you consider your job/profession to fall within the training area of the course in which you graduated?". Such question exists in the two phases of the survey and takes on a binary character, as described in Table 3 (1 = horizontal mismatch; 0 = otherwise).

We can see in our balanced sample that self-perceived horizontal mismatches grew by 1,5 percentage points, from 17,1% to 18,6%, from the first to the follow up survey. This suggests that, on average, graduates' employment may have become more diverse but equally more demanding overtime, as a result of career progression.

3.2.2. Match/Mismatch status

Firstly, the variables Skills_Adq and Perform_Dem, are related with two different kinds of vertical mismatches and measure the suitability of the skills acquired in Higher Education for professional performance. The first variable is derived from the question "For the course you have completed, how do you assess the skills it has given you for your professional performance?". The second, referring to the exigence of professional responsibilities in relation to the level of skills acquired in Higher Education, is derived from the question “In view of the level of skills you have acquired in your course, how demanding do you consider the functions you have professionally?”. As can be seen in Table 3, in our balanced sample, the fraction of individuals whose skills learnt in Higher Education are adequate for performing their jobs is of around three-fifths of the sample in both surveys. In relation to the exigence of professional responsibilities relative to the level of skills acquired, in both surveys, only about two-fifths of individuals consider that their job performance is demanding (relative to their level of skills). This is a first indication that demand-side constraints may be more important than supply-side constraints. These two questions have precisely that advantage, of indicating the source of mismatch or, in other words, whether is more a question of underkilling or overskilling. In chapter 5 we chose also to make separate calculations for each of these directions of mismatch.

With the goal of further studying the underskilling and overskilling status of the individuals surveyed in the two moments (2012 and 2015) and to understand the number and level of transitions between the different states from one survey to another, we also decided to look at the combination of the answers to those two questions in order to create a set of variables that can display, for both moments, if each individual was in a job in which he considered to be a “perfect mismatch”, a “perfect match”, or to be in a “overskilled” or “underskilled” situation.

These survey questions were the ones just described that originated the Skills_Adq and Perform_Dem variables. Transforming these two ordinal questions[1] into dummy variables (1 = adequate skills; 0 = inadequate skills) and (1 = demanding performance; 0 = not demanding performance), respectively,

[1] Respondents could answer the first question on a scale ranging from 1 (“None”) to 5 (“All of them”), and we defined individuals to have adequate skills if their response equalled 4 or 5. Respondents could answer the second question on a scale ranging from 1 (“Really not demanding”) to 5 (“Very demanding”), with individuals defined to have a demanding performance if their response equalled 4 or 5.

these two binary variables, when looked together, allow us to set up the four mismatch states presented in Table 4.

The four different states originated by the crossed examination of the two questions described above, thus allowed us, both for the initial and the follow up surveys, to construct four dummy variables – pmatch, us, os, and mismatch –, one for each of the states, as described in Table 3.

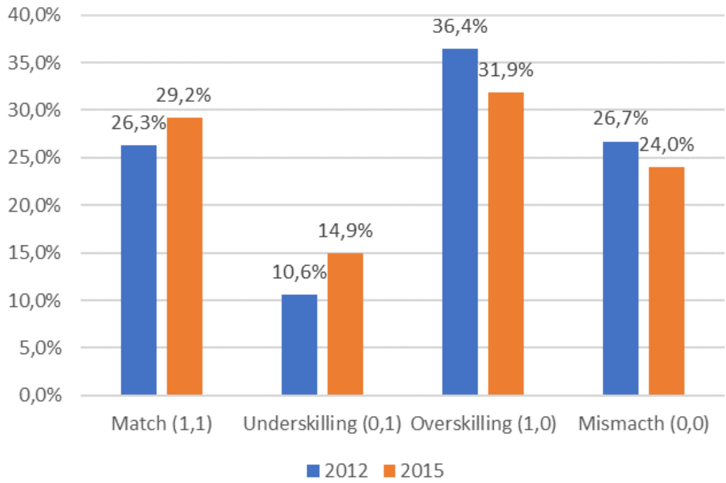
Table 4 – Skills/exigence states.

Status	State	Description
(1,1)	Perfect Match	(adequate skills, demanding performance)
(0,1)	Underskilling	(inadequate skills, demanding performance)
(1,0)	Overskilling	(adequate skills, not demanding performance)
(0,0)	Perfect Mismatch	(inadequate skills, not demanding performance)

Source: Own elaboration.

The data in Figure 3 shows that, based on the balanced dataset we constructed and following the establishment of respondents' careers, and as expected and supported by the literature on this subject, there is a decrease of 2,7 percentage points in the percentage of workers in a "perfect mismatch" situation, from 26,7% to 24,0%. There is also a rather significant decrease in "overskilled" workers, from 36,4% to 31,9%.

Figure 3 – Transition Between Mismatch States (%).



Source: Own elaboration.

As a consequence, after three years, we can also note an increase of almost three percentage points of respondents who consider themselves in a "perfect match" situation, from 26,3%, in 2012, to 29,2%, in 2015. In these situations, their qualifications and skills perfectly fit the demands of the job they perform. However, it should be noted that even though the number of respondents who considered themselves in a "perfect match" situation increased from the first moment to the second, the percentage of respondents in both moments that considered themselves in that situation was always below 30%. "Underskilling" also increased from the first moment to the second by 4,4 percentage points, from 10,6%, in 2012, to 15,0%, in 2015. Despite this increase, this was the state, in both moments, where there were fewer respondents. In contrast, and despite the stated improvements, the relative majority of respondents at both moments were in a state of "overskilling". Table 5 presents the transition matrix between states among both surveys.

Table 5 – Transition matrix (match or mismatch status).

First Survey	Follow up Survey								Total	
	P. Match		Underskilling		Overskilling		P. Mismatch			
P. Match	60	(0,472)	12	(0,094)	40	(0,315)	15	(0,118)	127	(0,263)
Underskilling	12	(0,235)	5	(0,098)	12	(0,235)	22	(0,431)	51	(0,106)
Overskilling	46	(0,261)	25	(0,142)	78	(0,443)	27	(0,153)	176	(0,364)
P. Mismatch	23	(0,178)	30	(0,233)	24	(0,186)	52	(0,403)	129	(0,267)
Total	141	(0,292)	72	(0,149)	154	(0,319)	116	(0,240)	483	(1)

Source: Own elaboration. Frequency in parenthesis.

In the remainder of this work and in addition to the focus on horizontal mismatches, we will focus in particular on the impact of the "perfect match" status as a measure of the inexistence of mismatches between education and work. It is clear from the data that, even in the follow-up survey (more than three years after graduation) less than a third of graduates are in such a match. We are, therefore, particularly interested in the demand- and supply-side determinants of achieving such a status and its earnings and career consequences. This will be one of the main focus of chapter 5.

3.3 Earnings and mismatches

Table 6 presents a set of descriptive statistics about the earnings variables that will be used along this dissertation. As the main dependent variable, we will use the log hourly wages – logwh – of the individuals recorded in both surveys.

We also show the values for monthly wages – wm_real –, and variables varwm_real and varwh_real represent the monthly, and hourly, wage difference between both surveys, respectively. All earnings variables refer to real earnings (calculated using the OECD price consumer index deflator). We also note that all wage values are at 2015 prices. It is clear from Table 6 that real wages are somewhat higher for individuals in our balanced sample, relative to all the available information in both surveys and particularly so in the follow-up survey. This is partly not a surprise, given that the balanced sample refers to individuals with greater experience.

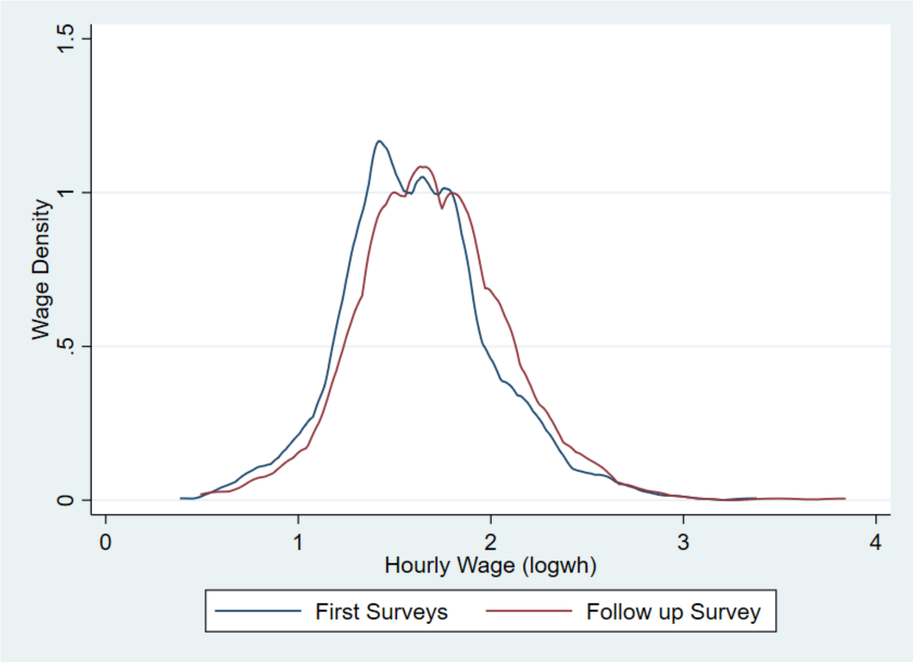
Table 6 – Descriptive Statistics: Dependent Variables.

Variable	Description	Whole sample			Balanced sample		
		N	Mean	Std	N	Mean	Std
logwh12	Natural logarithm of the hourly wage in the first surveys	1458	1,592	0,394	672	1,620	0,389
logwh15	Natural logarithm of the hourly wage in the follow up survey	1085	1,631	0,398	667	1,702	0,396
wm_real12	Real monthly wage in the first surveys	1458	964,04	435,47	672	993,81	438,79
wm_real15	Real monthly wage in the follow up survey	1085	1032,43	519,70	667	1115,38	570,22
varwm_real	Real monthly wage difference between both surveys	-	-	-	667	0,194	0,507
varwh_real	Real hourly wage difference between both surveys	-	-	-	667	0,163	0,496

Source: Own elaboration.

Figure 4 presents the hourly wage density distribution for both the responses to the first survey, conducted in 2012, and to the second survey, conducted in 2015 of the balanced sample. The main conclusion we can take from observing the wage density distribution is the increase of the average hourly wage earned by the individuals in the survey in the course of the three years. This was expected as workers progress in their careers. We can also see that three years on, there is more dispersion and less concentration in the hourly wages earned.

Figure 4 – Real Hourly Wage Density (First and Follow up Surveys).



Source: Own elaboration.

Looking now at wages from the perspective of the mismatches defined in the previous subchapter, we can observe from Table 7 that individuals who started their path in the labour market in a “perfect mismatch” situation earned considerably less than all the others, while those who started in a “perfect match” situation earned the most. In the follow up survey, we can also see that those in a “underskilling” situation had the smallest gross increase in their monthly wages, becoming the least paid, followed by those in a Perfect Mismatch situation and those in an Overskilling situation. Those in a Perfect Match situation, however, continued with substantially higher monthly wages than all others. Overall, those who started their careers in a more negative position, in a “perfect mismatch” or in a “overskilling” situation, had the slowest growth in their wages than those in a “perfect match” situation. This again reinforces our focus on this perfect match status as, from a mere descriptive stance, it appears that wage advantages are actually reinforced throughout the period covered by this study.

We can equally suggest as a hypothesis that the growth of the Portuguese minimum wage during the period under analysis in this dissertation may explain part of the increase of 172,57 euros, the second largest recorded, only behind the growth recorded by those in a “perfect match”, in the real monthly wages of those who were in a “perfect mismatch” from the first to the follow up surveys.

Table 7 – Mean real monthly wage by match/mismatch variables, by survey.

Variable	Real Monthly Wage		
	First Survey	Follow up Survey	Difference
Mismatch Status			
Perfect Match, 0	1055,04	1254,06	199,02
Underskilling, 1	976,30	1021,54	45,24
Overskilling, 2	1035,68	1089,80	54,12
Full Mismatch, 3	893,90	1066,47	172,57
Total	975,72	1079,70	103,98

Source: Own elaboration. Values at 2015 prices.

3.4. Control variables

Having already defined and quantified the main variables that we will use throughout this dissertation and what their purposes are, it is also convenient to define and describe the set of control variables that will be used in the models. These variables, which we will detail in the following sections, have information on the type and area of study of the individuals who responded to the surveys, their relative educational performance, the characteristics of the firms where they worked at the time of data collection and other data on further education and their employment situation.

3.4.1. Type of course, field of study, educational performance and further education

As in the previous tables, Table 8 presents a set of descriptive statistics about the education-related variables. Information for each variable is provided twice: for the whole sample and for the balanced sample. The variables were organized by groups. The first variables refer to the level of studies, followed by relative educational performance and the field of study. Mean values are to be read as percentages, with the exceptions of the variable Average who is represented in a 0 to 20 scale, and variable Averageq which represents the respective grades’ quartile (measured within each level and area of studies). A lower quartile indicates a higher relative grade.

Table 8 – Descriptive Statistics: Control Variables (type of course, field of study and further education).

Variable	Description	Whole sample			Balanced sample		
		N	Mean	Std	N	Mean	Std
Initial type of course							
Bachel12	Bachelor's degree	1458	0,489	0,500	672	0,476	0,500
Master12	Master's degree	1458	0,511	0,500	672	0,524	0,500
Initial field of study							
Average	Final Average	1432	14,06	1,860	662	14,04	1,834
Averageq	Final Average (quartiles)	1291	2,55	1,132	596	2,59	1,096
area1	Sciences	1307	0,236	0,425	603	0,221	0,415
area2	Engineering and Mathematics	1307	0,296	0,457	603	0,292	0,455
area3	Technology	1307	0,055	0,228	603	0,055	0,228
area4	Business	1307	0,161	0,368	603	0,177	0,382
area5	Social Sciences	1307	0,086	0,281	603	0,083	0,276
area6	Education	1307	0,050	0,219	603	0,048	0,214
area7	Arts and Humanities	1307	0,114	0,318	603	0,124	0,330
Further education							
Bachel15	Has concluded a Bachelor's degree since the first survey	325	0,028	0,164	175	0,040	0,197
Master15	Has concluded a Master's degree since the first survey	325	0,391	0,489	175	0,303	0,461
Doctor15	Has concluded a Doctoral degree	325	0,083	0,276	175	0,080	0,272

Source: own elaboration.

The initial type of course variables presented are Bachel12 and Master12, that consist of dummy variables corresponding to whether the individual graduated from a Bachelor's degree or a Master's degree, respectively, in the first period. As in the whole sample, we only have graduates from Bachelor's and Master's degrees. 47,6% of the balanced sample is composed by individuals who were initially graduates from Bachelor's degrees and the other 52,4% who were initially graduated from Master's degrees.

The variable Average represents the final average with which students graduated from the University of Aveiro. As in all public Higher Education Institutions in Portugal, the final grade of the courses leading to Bachelor's and Master's degrees in the University of Aveiro is the arithmetic average, weighted by the respective weight in credits, of the grades obtained by each student in each of the curricular units of the respective study plan in a scale from 0 to 20. As such, the final average of graduates for both the whole and balanced samples was around 14 values. The variable area, that represents the fields of study from which the individuals in our sample were initially graduated, is a categorical variable with seven different areas: Sciences (area1), Engineering and Mathematics (area2), Technology (area3), Business (area4), Social Sciences (area5), Education (area6), and Arts and Humanities (area7).[2] It is possible to see that most individuals in the balanced sample were graduated from Engineering and Mathematics, Sciences, and Business, 29,2%, 22,1% and 17,7%, respectively. Less than 10 per cent were graduated from Education, and Technology, 4,8% and 5,5%, respectively. This distribution reflects the course and student composition of the University of Aveiro.

Because the first survey was conducted both among Bachelor's and Master's degree holders and if we consider the highly likely transition from first degree to a postgraduate degree, we expect significant changes in the composition of the sample across both periods. Among those who pursued further training, we wish to capture the ones that have concluded further long-duration education after the first surveys. As so, we used the variables Bachel15, Master15 and Doctor15 to capture those individuals who concluded another Bachelor’s, Master’s or Doctoral degree, respectively.

We find out that, in the balanced sample, of the individuals who participated in the first survey – and pursued further medium/long education afterwards – 56% completed a new course, with 30,3% achieving a Master’s degree, 4% achieving a new Bachelor’s degree and 8% achieving a Doctoral degree. With this important exception, Table 8 also makes clear that there is a broadly similar distribution of characteristics in our balanced sample relative to the full datasets.

3.4.2. Job characteristics

The job characteristics variables presented below (Table 9) capture further details about the transition to employment and the potential experience held by the individuals in our sample. The timejob variable demonstrates the tenure, in months, of individuals in their current job; the employed12 variable is a dummy variable demonstrating if an individual had already a job prior to graduation in the first survey. Permanent variables are dummy variables that demonstrate if an

[2] Detailed description of the field of study areas in Table 31 in the Appendix.

individual has a permanent contract with his employer, and t_full, another dummy variable, demonstrates if an individual had a full-time job in the first and follow up surveys. The exp variable represents the potential experience of graduates in each sample, that is, the time, in months, that went from graduation until the taking of each survey.

Table 9 – Descriptive Statistics: Control Variables (job characteristics).

Variable	Description	Whole sample			Balanced sample		
		N	Mean	Std	N	Mean	Std
Job characteristics							
timejob12	Tenure in current job in the first surveys (months)	1128	48,19	71,15	508	57,26	79,07
timejob15	Tenure in current job in the follow up survey (months)	1055	58,26	72,15	642	79,04	82,15
employed12	Had a job at the time of graduation	1458	0,488	0,500	672	0,551	0,498
Employment Relationship							
Permanent12	Part of the permanent staff in the first surveys	1255	0,373	0,484	566	0,417	0,493
Permanent15	Part of the permanent staff in the follow up survey	988	0,498	0,500	600	0,618	0,486
t_full12	Has a full-time job in the first surveys	1438	0,897	0,304	663	0,906	0,291
t_full15	Has a full-time job in the follow up surveys	1094	0,947	0,224	672	0,960	0,197
Time since graduation							
exp12	Time since graduation at the first surveys (months)	1457	22,74	10,20	672	22,87	10,28
exp15	Time since graduation at the follow up survey (months)	1093	57,45	10,12	672	58,87	10,28

Source: own elaboration.

Regarding the tenure of individuals in their current jobs, as expected, it increased by about twenty months during the period between the two surveys, from average values of 57,26 months to 79,04 months, in our balanced sample. We can also observe that about half, 55,1%, of the individuals in our balanced sample already had a job before graduation. Regarding having a full-time job, the number increased from the first to the follow up survey by 5,4 percentage points from 90,6% to 96%.

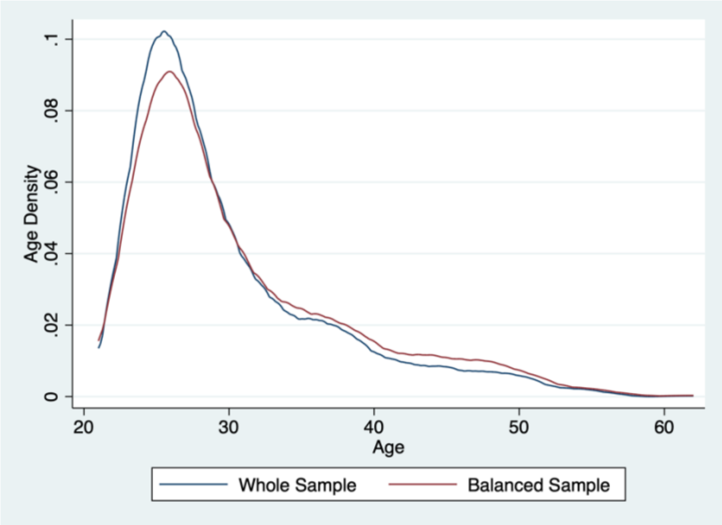
In relation to the potential experience of the graduates in our samples, we can indicate that they had 22,74 months of potential experience in the whole sample, increasing slightly to 22,87 months in the balanced sample, in the first survey. In the follow up survey, the potential experience of respondents increased to 58,87 months in the balanced sample.

Being this study about the persistence of education-job mismatches in the transition from Higher Education to employment, it is reasonable to expect that the mean age in the whole and balanced samples would be similar to that of the national graduation age. In 2013, the year after the individuals in our sample were first interviewed, that age was of 25,9 years for Bachelor's degrees or equivalent, in Portugal, according to OECD (2019).

However, in the sample of this study, the mean age recorded for the whole sample was of 29,9 years, four more years than the national Portuguese mean age of recent Higher Education graduates. These differences may arise also due to the fact that the sample collected for this dissertation includes data from individuals that graduated up to three years to the point in which the first survey was taken and, as such, this should be taken in consideration when looking at this figure. Extricating between those who had graduated from Bachelor's and Master's degrees, we record in our whole sample a mean age of 28,6 years for Bachelor's degree graduates and of 31,1 years for Master's degree graduates. If we look into the balanced sample, that mean age of the recent Higher Education graduates increases almost a full year to 30,8 years with the breakdown for type of course being of 29,3 years for Bachelor's degree graduates and of 32,1 years for Master's degree graduates.

Figure 5 presents the age density in the whole and balanced samples of this study and, although it shows that a significant proportion, more than 30 per cent, of the recent graduates have between 24 and 26 years at the time of the first survey, the median age in both the whole and balanced samples is of 27 years old and a significant number of respondents, around one third of the samples, is more than 30 years old.

Figure 5 – Age Density (for working and balanced samples).



Source: own elaboration.

When analysing the tenure in the current job values presented in Table 9, one should bear in mind these factors, as the average tenure in the current job in 2012, at the time of the first survey, was of 48,19 months (around 4 years) in the whole sample, and of 57,26 months (almost 5 years) in the balanced sample, as some of these individuals were already in the labour force before graduating from Higher Education. Another important factor to bear is that this situation may somehow affect the overall results of some of the estimations made in the next chapter. The theories of the "stepping stone" and overeducation or overskilling "traps", theories that we are working with in this study, are designed to reflect the evolution of initial job mismatches on recent graduates who are entering the labour force. Also noteworthy is the fact that our balanced sample captures graduates with more stable employment links as observable in the variables related with tenure and type of contract. This is partly expected considering that individuals that did not have an employment relationship in the first survey may have both lower tenure and more unstable contracts in the initial transition to employment. However, it is equally possible that our balanced sample selects, to a higher extent, individuals with such stable employment links.

3.4.3. Company characteristics

In this section, job characteristics refer to the variables that define the type of company in which the surveyed individuals were working in the first and follow up surveys. The variables are MicroEnt, SmallEnt, MediumEnt and LargeEnt refer, respectively, to micro enterprises (less than 10 workers), small enterprises (less than 50 workers), medium enterprises (less than 250 workers) and large enterprises (more than 250 workers). Variables AML and AMP are dummy variables that assume a unit value if an individual, in each of the surveys, is working in the Lisbon or Porto Metropolitan Areas.

Table 10 – Descriptive Statistics: Control Variables (company characteristics).

Variable	Description	Whole sample			Balanced sample		
		N	Mean	Std	N	Mean	Std
Company							
MicroEnt12	Worked in a micro enterprise in the first surveys	1379	0,255	0,436	646	0,248	0,432
MicroEnt15	Worked in a micro enterprise in the follow up survey	1073	0,198	0,398	660	0,194	0,396
SmallEnt12	Worked in a small enterprise in the first surveys	1379	0,284	0,451	646	0,271	0,445
SmallEnt15	Worked in a small enterprise in the follow up surveys	1073	0,287	0,453	660	0,273	0,446
MediumEnt12	Worked in a medium enterprise in the first surveys	1379	0,241	0,428	646	0,249	0,433
MediumEnt15	Worked in a medium enterprise in the follow up surveys	1073	0,293	0,455	660	0,317	0,466
LargeEnt12	Worked in a big enterprise in the first surveys	1379	0,220	0,415	646	0,232	0,423
LargeEnt15	Worked in a big enterprise in the follow up surveys	1073	0,223	0,416	660	0,217	0,412
Geographical Area							
AML12	Worked in the Lisbon Metro Area in the first surveys	1458	0,027	0,161	672	0,021	0,143
AML15	Worked in the Lisbon Metro Area in the follow up survey	1062	0,108	0,311	658	0,103	0,305
AMP12	Worked in the Porto Metro Area in the first surveys	1458	0,200	0,400	672	0,231	0,422
AMP15	Worked in the Porto Metro Area in the follow up survey	1062	0,248	0,432	658	0,245	0,430

Source: own elaboration.

Looking at the data for each type of company in Table 10 above, in the balanced sample, we can say that the percentage of individuals who were working in a micro enterprise declined 5,6 percentage points from the first to the follow up surveys, from 24,8% to 19,4%, while the percentage of individuals working in a medium enterprise increased 6,8 percentage points, from 24,9% to

31,7%. The share of individuals who were working in small enterprises was maintained through both surveys around 27% (27,1% to 27,3%), and those working in large enterprises briefly declined 1,5 percentage points, from 23,2% to 21,7%, from the first to the follow up surveys.

In relation to the geographical area, as it would be expected due to the geographical proximity of the University of Aveiro to the Porto region, in our balanced sample, in both surveys, almost a quarter of the respondents work in the Porto Metropolitan Area, 23,1% in the first surveys and 24,5% in the follow up survey. On the other hand, the percentage of our balanced sample working in the Lisbon Metropolitan Area increased greatly from just 2,1% of individuals in the first survey, to 10,3% of them in the follow up survey. We can equally see that there are not very significant biases in the composition of employment between the full information available in the sample and that in our balanced sample.

3.5. Attrition

In this subchapter we will analyse the attrition problems of our sample, taking into account the different time nature of the data collected and the potential questions that may be raised due to the comparability of the data.

Table 11 – Attrition Analysis (difference from the group).

Variable	Difference	95% Confidence Interval	
wm_real12	-55,220**	-100,025	-10,414
wh_real12	-0,267**	-0,520	-0,014
timefirst12	0,044	-0,963	1,052
timejob12	-16,497***	-24,799	-8,195
exp12	-0,246	-1,298	0,805
age	-1,647***	-2,360	-0,934
logwm12	-0,069***	-0,112	-0,026

***, ** and * indicate significance at 1%, 5% and 10%, respectively.

In Table 11 there is a summary of a two-sample t-test with equal variances that was conducted on the continuous variables listed above. The variables were tested to see if there were significant differences between the means of those who graduated and were employed with a salary both in 2012 and in 2015 and those who were graduated and were employed with a salary just in 2012 in order to see eventual differences between those who stayed through both surveys and those who didn't. We can see with the results of the tests that were conducted that at a 1% significance level we can reject the null hypothesis – that there are no differences between the two groups – for timejob12, age and logwm12 meaning that in these variables there are significant differences between the two groups. The same happens for wm_real12 and wh_real12 at a 5% significance.

In terms of variables wm_real12 and wh_real12, that correspond to the real monthly and hourly wages of individuals, respectively, we can attest that those individuals that provided data for 2012 and 2015 had, in 2012, higher wages than those who just provided wage data in 2012, as those who remain in the balanced sample earn, on average, more 55,22 euros than those who don't (at a 5% significance level). This can be interpreted as a good sign because by having the workers with higher wages in our balanced sample that can give us a conservative approach to the results of our final estimates. Those who stayed in the balanced sample also are, on average 1,647 years older than those who didn't, and have been working in their current jobs for a longer period of around 16,5 months.

Table 12 – Attrition analysis (chi^2 expected).

Variable	Test statistic (Pearson chi^2)	Significance level
Skills_Adq12	1,222	0,269
Perform_Dem12	1,170	0,279
Horizontal12	1,363	0,243
Bachel12	0,822	0,365
Master12	0,778	0,378
area1	1,559	0,212
area2	0,096	0,757
area3	0,003	0,958
area4	2,119	0,145
area5	0,178	0,674
area6	0,135	0,713
area7	1,193	0,275
t_full12	1,179	0,278
employed12	19,335	0,000***

***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 12 shows a summary of the expected frequencies and the Pearson chi^2 of the presented variables and its significance levels. By observing the significance levels provided we can affirm that we do not reject the null hypothesis for any of the variables except for empolyed12, meaning that all the other variables are uniform and representative of the balanced sample and that there are no significant differences. That means that for variable employed12, in our balanced sample, we ended up with a significant overrepresentation of people that were already employed when they graduated in 2012 meaning that our final results may be somewhat biased.

Apart from that conclusion, the results for the expected frequency of the education-job mismatch variables, demonstrate broadly comparable samples. Looking at the detailed descriptive, we see that in the balanced sample we stayed with a slightly bigger sample than the expected value would suggest, meaning that there are a few more individuals that have adequate skills and demanding performances in their current jobs. For variable Horizontal12, results show that in the balanced sample we have a slightly smaller number of individuals who experience an horizontal mismatch, and for variables Bachel12 and Master12, that present us the number of individuals who had completed a Bachelor or Master degrees in 2012, respectively, we can observe that in our balanced sample we ended up with a slightly smaller than expected number of individuals for Bachel12 and with a slightly bigger than expected number of individuals for Master12. Results also show that for variable area1, that represents the number of individuals in the sample that come from Sciences degrees, we have a slightly smaller than expected number of individuals in the balanced sample, for variables area2, area3, area5 and area6, that represent the number of individuals in the sample that come from Engineering and Mathematics, Technologies, Social Sciences, and Education degrees, respectively, the number of individuals in the balanced sample are about the same as expected by the test, and that for variables area4 and area7, that represent the number of individuals in the sample that come from Business, and Arts and Humanities degrees, we ended up with a slightly bigger than expected number of individuals in the balanced sample. For those who have full time jobs in 2012, represented through the t_full2 variable, results show that in the balanced sample we have a slightly bigger number of individuals than would be expected. In any case, none of these differences is statistically significant indicating, in particular, that there appears to be sufficient dispersion in mismatch status to proceed with our calculations.

4. Methodology

In this chapter, we will present the methods that will be used to study the earnings impact of initial education-job mismatches throughout graduates' first career years. We study, therefore, the earnings impact and career persistence over the first five to six years of employment of both education-job mismatches and their earnings penalties. As detailed in the previous chapter, this study focuses on data collected by the *Observatório do Percurso Socioprofissional dos Diplomados da Universidade de Aveiro* on the employment destinations of graduates from the University of Aveiro. Data were collected at two points in time: the first, in 2012, within the first years after graduation[3]; and the second, three years later, in 2015, to follow up on the first phase. The result of these two phases of data gathering, that we will be using in this study, is a two-period longitudinal dataset with information about salaries (monthly and hourly), adequacy of employment to the graduation knowledge area, the contribution of the skills conferred by the course to professional performance and the evaluation of the cycle of study against the requirements of the job in question. From these data, we were able to compute new variables about the initial and subsequent levels of over- and underskilling, and about matches and mismatches of the graduate's abilities in relation their jobs as well as earnings progression.

Additional data was also gathered about other relevant factors such as the respondents' age, the type and field of study of their degrees, the size of companies in which the graduates were working, the type of employment relationship and if there were subsequent further study periods after the first survey, among others previously described. Using these data, we hope that the control we can achieve for observed and unobserved individual effects, as well as for type of degree and field of study, will yield more reliable estimations. Importantly, we have access to data on individual grade performance at the end of the initial degree which we further normalise to take into account grade variation across cycles and fields of study

[3] As noted in subchapter 3.1. Alumni Data, the respondents of the first survey, in 2012, were randomly selected among those who graduated from the University of Aveiro within the three prior academic years: 2008/2009, 2009/2010, and 2010/2011.

The most effective way to estimate the causal effects of the treatment variables on the outcomes is through the use of a panel dataset, as is the case of this study, in which we can observe the evolution of the same variables throughout two time periods. The use of a panel fixed effects model to identify these causal effects allows us to estimate them by treating the fixed effect, an unobserved time-invariant variable bias that otherwise would be absorbed by the error term, as a parameter possible to be estimated. This unobserved time-invariant variable bias exists as workers may find themselves in situations of over- or underskilling because they may have previous innate abilities (Bauer, 2002) leading to biased results, that the use of fixed effects models with panel data can partially resolve. With that, Bauer (2002) found that when controlling for unobserved heterogeneity, the differences among adequately and inadequately skilled workers diminish or disappear.

By examining the earnings penalties associated with being overeducated depending on the level of study, Frenette (2004) also found that these vary notably according to the level of study, from 10 to 19% to college and bachelor degrees to earning penalties of just around 3% to masters degrees. However, when controlling for unobserved heterogeneity, using a fixed effects panel, these penalties decreased substantially to about 6 to 11% to college and Bachelor's degrees. More recently, and building on previous case, Carroll and Tani (2013) using an OLS estimation for the earnings function of overeducated workers and then a fixed effects model, to control for biased results due to unobserved time-invariant heterogeneity, found that the penalties young graduates suffered in the first years in the labour market had become smaller and lost their significance, following the findings of Bauer (2002) and Frenette (2004). Despite that, for older graduates that was not the case. Older graduates remained with an earnings disadvantage, suggesting that job characteristics were more related to earnings than individual ones.

A similar approach was followed by Mavromaras et al. (2013) when analysing the relationship of educational and skills mismatches with wages. Using a benchmark pooled OLS model and two panel estimations (fixed and random effects), they found that, when the overeducation equations were controlled for individual unobserved heterogeneity, the wage impacts for the overeducated and the overskilled workers, taken separately and relative to appropriately matched workers decreased and lost their significance. However, for the simultaneously overeducated and overskilled workers, the wage impacts also decreased but kept their significance over time.

One important caveat of the fixed effects model is that, although it is important for accounting and controlling for individual time-invariant unobserved heterogeneity, it does not account for individual time-variant unobserved heterogeneity and, as such, that will remain endogenous to the model (*i.e.* becoming unemployed may lead an individual to seek further training that can lead to improvements in their labour position, or an individual may gain quality experience in their first job that will not be accounted by the model). Another caveat of the fixed effects model is that the estimates that it yields may be affected by prior individual characteristics such as the likelihood of overeducation and the ability level. Frenette (2004), citing Freeman (1983), points out, however, that comparing the earnings trajectories of individuals in similar departing positions (with similar mismatch status in the first period) provides one way to account for some of such unobservable individual characteristics.

For this dissertation, we will use three types of models in order to run our estimations. We draw inspiration and guidance for our models from Frenette (2004) as well as from our own elaboration.

Firstly, we will estimate a simple logistic regression, one for each of our four focus mismatch variables (including horizontal mismatches) in order to find out the determinants of being in such a mismatch state in the first place.

$$Prob(\,mismatch_{i,t} = 1 \mid X\,) = \beta_0 + \beta_1 LEVEL_i + \beta_2 X_{i,t} + \varepsilon_{i,t} \text{ (Eq. 1)}$$

In this model, $mismatch_{i,t}$ represents each of the four focus variables to be estimated, $Skills\_Adq_{i,t}$, $Perform\_Dem_{i,t}$, $Horizontal_{i,t}$, and $pmatch_{i,t}$, $LEVEL_i$ refers to the level of study, $X_{i,t}$ being a set of control variables and $\varepsilon_{i,t}$ an error term. Here we are particularly interested in understanding which factors, mainly from an individual or education point of view, are associated with the probability of experiencing education-job mismatches, through the response probability of being mismatched. Section 5.1. presents the results of such estimations.

Then, we will use a natural log earnings model that is intended to study the economic returns to mismatch status by level of study. The model presented is as follows:

$$ln\,W_{i,t} = \beta_0 + \beta_1 LEVEL_i + \beta_2 LEVEL'_i * mismatch_{i,t} + \beta_3 X_{i,t} + \gamma_i + \sigma_{i,t} \text{ (Eq. 2)}$$

In this model, $ln\,W_{i,t}$ represents the log hourly wages of our individuals, $LEVEL_i$ refers to the level of study, $mismatch_{i,t}$ it's a dummy variable of one of each four focus variables to be estimated indicating the state of mismatch, $LEVEL_i * mismatch_{i,t}$ is the interaction between the level of study and one of the focus variables, $X_{i,t}$ being a set of control variables, γ_i an individual-specific unobserved term that is constant overtime and $\sigma_{i,t}$ a disturbance term. Here we estimate repeated cross-sections (for the two time periods, the first and follow-up surveys) as we are interested not only in the earnings returns attributed to the mismatch status but equally how these premiums or penalties evolved over time. This provides a first naïve estimate of the persistence of such effects. Section 5.2. covers the results of these estimations and we perform calculations for four separate types of mismatch.

Finally, for Section 5.3., the last model we will be using is a simple two-period fixed effects model:

$$\Delta \ln W_i = \beta_0 + \beta_1 LEVEL_i + \beta_2 OPATH_{i,t} + \beta_3 X_{i,t} + (\gamma_i - \gamma_i) + \varepsilon_{i,t} \text{ (Eq. 3)}$$

In this main model, $\Delta \ln W_i$ represents the difference between the two-periods of the natural logarithm of the wages of the individuals, $OPATH_{i,t}$ is a vector representing the pathway into or away of a perfect match or horizontal mismatch status (four states in all: two states per period in the two periods), $\varepsilon_{i,t}$ is the error term and the term $(\gamma_i - \gamma_i)$ is included for clarity but, under the assumption of time-invariant unobserved heterogeneity, this differences-out in the fixed effects model. All variables included in the model refer to time-variant characteristics that include education-related variables, taking advantage of the fact that a relatively large number of individuals shifted their educational attainment from one survey to the next, but also labour-market related variables. As argued by Frenette (2004), the advantage of considering this model is the ability to compare the earnings outcomes of graduates who share similar mismatch status in the first period but who have different trajectories (into or away from a position of perfect skills matching or horizontal mismatching). This allows us to provide estimates of the impact of skill and horizontal mismatches in earnings trajectories discounting possible biases arising from non-observable individual characteristics, at the least to the extent that these are correlated with the probability of being in a similar mismatch status in the first time period. These estimates then allows to provide more robust estimates of the earnings impact of education-job mismatches and, indirectly, of their relevance in explaining further wage inequality across the initial career years.

5. Empirical Results

The following econometric analysis tries to measure empirically the theoretically assumed hypothesis. The variables in use in the following Tables and their range of values have already been described in the Data and Descriptive Analysis chapter. We will focus specifically on four of the focus variables presented in subchapter 3.2. Mismatch Variables, namely the Skills_Adq variable, which measures whether there is a skills mismatch and the skills learnt in Higher Education are adequate (or not) for the job performance of individuals, the Perform_Dem variable, which measures whether there is a job mismatch and there is a demanding job performance in relation to the skills learnt in university, the pmatch variable, which, for each moment, tells us whether an individual is in a situation of “perfect match” between the skills he or she possesses and the demand for them in order to perform his or her job, and the Horizontal variable, which measures the existence of a horizontal mismatch. As such, firstly, through the use of simple logit models, we will try to find out what determines the probability of an individual to be in a mismatch status, or not, in both moments of our survey, for each of the four focus variables. Then, in the next subchapter, through the use of OLS estimations, we will try to find out the earnings penalties associated with being in each of our focus variables in each survey.

5.1. Determinants of a match or mismatch status

The estimates from a binary logit model on the determinants of being in a match or mismatch situation are presented in the following tables. The results presented for each of the focus variables cover both the initial and follow up surveys.

5.1.1. Determinants of having adequate skills for job performance

By looking at the results presented on Table 13 on what determines the probability of having adequate skills for job performance, for the first surveys, variables related to the Sex and Final Average (quartiles) of individuals show strong significance levels across the different models. As such, being male is very strongly and positively related to the likelihood of having adequate skills for job performance. Belonging to the lowest quartiles of the final graduation averages distribution also shows to impact negatively the likelihood of individuals having the right skills for performing their jobs.

In Model 2 and 3, although the significance level is small, being a graduate from the Business field of study is strongly negatively related to the likelihood of having adequate skills for job performance, as opposed to those from a Sciences field if study.

Table 13 – Logit coefficients: determinants of having adequate skills for job performance in the first survey.

	Model 1		Model 2		Model 3	
	Skills_ Adq12	z statistic	Skills_ Adq12	z statistic	Skills_ Adq12	z statistic
Intercept	1,057*	(1,93)	1,259**	(2,13)	0,790	(1,08)
Master's	0,148	(0,75)	0,170	(0,85)	0,188	(0,92)
Age	0,003	(0,20)	0,002	(0,18)	0,024	(1,01)
Sex	-0,860***	(-4,21)	-0,888***	(-4,25)	-0,873***	(-4,16)
Final Average (quartiles)	-0,148	(-1,61)	-0,155*	(-1,67)	-0,169*	(-1,80)
Time since graduation	0,005	(0,50)	0,004	(0,43)	0,004	(0,39)
Engineering and Mathematics [a]			0,088	(0,34)	0,075	(0,29)
Technology [a]			-0,436	(-1,06)	-0,453	(-1,10)
Business [a]			-0,861*	(-1,83)	-0,852*	(-1,81)
Social Sciences [a]			-0,492	(-1,34)	-0,531	(-1,44)
Education [a]			-0,512	(-1,17)	-0,513	(-1,17)
Arts and Humanities [a]			-0,274	(-0,90)	-0,264	(-0,86)
Employed when graduated					-0,054	(-0,24)
Tenure in current job					-0,002	(-1.04)
N	495		495		495	
Log Likelihood	-320,185		-316,032		-315,407	

*** p<0,01, ** p<0,05, * p<0,10. [a] Sciences is the base category.

Looking at the same skills adequacy variable for the follow up survey, in Table 14, we can verify the occurrence of somewhat similar results. However, three years after graduation, the being employed when graduated variable lost its significance, showing that this effect is no longer an important predictor of having adequate skills for job performance. On the other hand, variable Sex and Final Average (quartiles), continue to be related to the likelihood of having those adequate skills. Three years after graduation, being a male, and being the highest quartiles of the final graduation averages, still is a positive predictor of individuals having the adequate skills for the jobs they hold than being a female, and being in the lower quartiles of the grade distribution, with this last variable estimation being slightly reinforced in the follow up survey. In relation to the fields of study, and in relation to those who graduated from a Sciences field of study, those who graduated from an Engineering and Mathematics and Technology backgrounds, three years after the first surveys, are more significantly more likely to be in a situation where they have the adequate skills for jobs performance, showing an interesting field of study effect and maybe signalling that job experience may play a role in achieving a good match in these areas.

Table 14 – Logit coefficients: determinants of having adequate skills for job performance in the follow up survey.

	Model 1		Model 2		Model 3	
	Skills_ Adq15	z statistic	Skills_ Adq15	z statistic	Skills_ Adq15	z statistic
Intercept	0,858	(1,30)	0,482	(0,69)	0,706	(0,90)
Master's in the first surveys	0,109	(0,59)	0,147	(0,77)	0,153	(0,78)
Master's since the first surveys	0,183	(0,52)	0,147	(0,41)	0,100	(0,28)
PhD since the first surveys	0,447	(0,72)	0,510	(0,81)	0,867	(1,25)
Age	-0,016	(-1,35)	-0,014	(-1,20)	-0,022	(-1,17)
Sex	-0,441**	(-2,45)	-0,408**	(-2,23)	-0,471**	(-2,46)
Final Average (quartiles)	-0,242***	(-2,91)	-0,237***	(-2,82)	-0,251***	(-2,86)
Time since graduation	0,014*	(1,70)	0,013	(1,53)	0,015	(1,62)
Engineering and Mathematics [a]			0,514**	(2,12)	0,529**	(2,11)
Technology [a]			1,012**	(2,24)	0,968**	(2,12)
Business [a]			0,398	(1,44)	0,309	(1,08)
Social Sciences [a]			0,094	(0,28)	0,057	(0,16)
Education [a]			0,135	(0,31)	0,027	(0,06)
Arts and Humanities [a]			0,323	(1,08)	0,309	(1,00)
Employed when graduated					-0,183	(-0,91)
Tenure in current job					0,002	(1,22)
N	596		596		571	
Log Likelihood	-392,744		-388,407		-368,523	

*** p<0,01, ** p<0,05, * p<0,10. [a] Sciences is the base category.

5.1.2. Determinants of having a demanding job performance for the skills acquired

The results presented on Table 15 on the determinants of having a demanding job performance for the skills acquired in Higher Education, for the first surveys, reveal to us that almost no variable presents statistical significance, with the exceptions of Age and tenure in the current job, in Model 3, and coming from a Business field of study, in Models 2 and 3.

Although Age and tenure in the current job are significant values in determining having a demanding job performance for the qualifications acquired in Higher Education, its values are small and close to zero, ending up having also a very small determinant effect. Coming from a Business field of study, though its significance levels are small, only at 10%, reveals itself to be positively related to the likelihood of an individual having a demanding job performance in employment, in the first surveys. This result contrasts with the negative predictive power of the same variable on whether it is a determinant of having the adequate skills for job performance, indicating a possible underskilling problem in the graduates of this field of study when entering the labour market.

Table 15 – Logit coefficients: determinants of having a demanding job performance in the first survey.

	Model 1		Model 2		Model 3	
	Perform_ Dem12	z statistic	Perform_ Dem12	z statistic	Perform_ Dem12	z statistic
Intercept	-1,388**	(-2,48)	-1,385**	(-2,31)	-0,030	(-0,04)
Master's	0,299	(1,51)	0,296	(1,47)	0,233	(1,13)
Age	0,019	(-0,13)	0,020	(1,49)	-0,044*	(-1,71)
Sex	-0,026	(-0,07)	-0,050	(-0,24)	-0,110	(-0,53)
Final Average (quartiles)	-0,006	(0,59)	-0,006	(-0,07)	0,031	(0,33)
Time since graduation	0,006	(-2,48)	0,008	(0,83)	0,010	(0,94)
Engineering and Mathematics [a]			-0,214	(-0,84)	-0,190	(-0,73)
Technology [a]			-0,129	(-0,31)	-0,094	(-0,22)
Business [a]			0,806*	(1,74)	0,779*	(1,66)
Social Sciences [a]			-0,173	(-0,45)	-0,056	(-0,15)
Education [a]			-0,011	(-0,03)	-0,031	(-0,07)
Arts and Humanities [a]			-0,222	(-0,71)	-0,268	(-0,85)
Employed when graduated					0,267	(1,16)
Tenure in current job					0,006***	(2,68)
N	480		480		480	
Log Likelihood	-313,145		-310,343		-305,311	

*** p<0,01, ** p<0,05, * p<0,10. [a] Sciences is the base category.

For the follow up survey, in Table 16, variables related to the sex and age of the individuals surveyed lost their significance levels, indicating that they no longer serve to predict the likelihood of an individual to have a demanding job performance for the skills it has acquired in Higher Education, such as tenure in the current job. On the other hand, three years later, holding a Master's degree since graduation (surveyed in the first survey) gains significance and it reveals to be a positive predictor in having a demanding job for the skills acquired in all three models. This result can be linked and can demonstrate the long-term benefits of pursuing further education and achieving higher levels of qualification and its impact in finding a matched job with a corresponding level of exigence for the skills acquired.

In Model 2, being from an Engineering and Mathematics background reveals itself to be also a positive predictor in having a demanding job for the skills acquired, and in Models 2 and 3, coming from an Education field of study, has a very strongly positively related to the likelihood of having a demanding job performance, three years later, when compared to those who come from a Sciences background.

Table 16 – Logit coefficients: determinants of having a demanding job performance in the follow up survey.

	Model 1		Model 2		Model 3	
	Perform_ Dem15	z statistic	Perform_ Dem15	z statistic	Perform_ Dem15	z statistic
Intercept	-1,261*	(-1,91)	-1,578**	(-2,24)	-1,073	(-1,37)
Master's in the first surveys	0,358*	(1,94)	0,408**	(2,13)	0,384*	(1,95)
Master's since the first surveys	0,227	(0,65)	0,230	(0,65)	0,142	(0,39)
PhD since the first surveys	0,053	(0,09)	0,109	(0,19)	-0,011	(-0,02)
Age	0,008	(0,70)	0,010	(0,89)	0,002	(0,11)
Sex	-0,206	(-1,16)	-0,166	(-0,92)	-0,267	(-1,43)
Final Average (quartiles)	-0,059	(-0,73)	-0,065	(-0,79)	-0,080	(-0,94)
Time since graduation	0,014*	(1,72)	0,014	(1,63)	0,012	(1,31)
Engineering and Mathematics [a]			0,422*	(1,74)	0,394	(1,57)
Technology [a]			0,026	(0,06)	0,001	(0,00)
Business [a]			0,336	(1,22)	0,279	(0,97)
Social Sciences [a]			0,049	(0,14)	0,070	(0,20)
Education [a]			1,108**	(2,44)	1,030**	(2,23)
Arts and Humanities [a]			-0,228	(-0,74)	-0,211	(-0,67)
Employed when graduated					-0,213	(-1,07)
Tenure in current job					0,002	(1,09)
N	584		584		559	
Log Likelihood	-395,992		-389,808		-372,762	

*** p<0,01, ** p<0,05, * p<0,10. [a] Sciences is the base category.

5.1.3. Determinants of being in a "perfect match" status

By looking at the results presented on Table 17 on what determines the probability of being in "perfect match" situation, for the first surveys, only variables related to having a Master's degree, the gender of individuals and to their field of study gained significance. As such, holding a Master's degree is positively related to the likelihood of being in a "perfect match" situation, than only having a Bachelor's degree. This is an important and interesting result, as it shows the importance of further education among recent university graduates and its positive externalities when entering the labour market. Although significance levels are not high, the probability of males fitting in a perfect match situation is higher among them than among female respondents.

Also, an interesting result is that those who graduated from an Arts and Humanities field of study are more negatively related to the likelihood of being rightly employed in a "perfect match" situation, than those graduated from a Sciences background, meaning that there might be a high level of job mismatches among those who graduated from that field os study.

Table 17 – Logit coefficients: determinants of being in a "perfect match" status in the first survey.

	Model 1		Model 2		Model 3	
	pmatch12	z statistic	pmatch12	z statistic	pmatch12	z statistic
Intercept	-1,597***	(-2,58)	-1,368**	(-2,06)	-0,996	(-1,19)
Master's	0,400*	(1,82)	0,447**	(2,00)	0,376*	(1,65)
Age	0,016	(1,12)	0,016	(1,09)	-0,007	(-0,25)
Sex	-0,427*	(-1,91)	-0,445*	(-1,96)	-0,472**	(-2,05)
Final Average (quartiles)	-0,072	(-0,71)	-0,077	(-0,75)	-0,063	(-0,61)
Time since graduation	0,011	(1,02)	0,011	(0,99)	0,012	(1,06)
Engineering and Mathematics [a]			-0,073	(-0,27)	-0,066	(-0,24)
Technology [a]			-0,385	(-0,83)	-0,389	(-0,84)
Business [a]			-0,402	(-0,73)	-0,419	(-0,76)
Social Sciences [a]			-0,401	(-0,93)	-0,357	(-0,82)
Education [a]			-0,348	(-0,71)	-0,365	(-0,75)
Arts and Humanities [a]			-0,798**	(-2,18)	-0,825**	(-2,24)
Employed when graduated					0,409	(1,63)
Tenure in current job					0,001	(0,55)
N	471		471		471	
Log Likelihood	-268,842		-265,652		-264,018	

*** p<0,01, ** p<0,05, * p<0,10. [a] Sciences is the base category.

From the results provided by Table 18, for the follow up survey, we can conclude that the predictive power of having a Master's degree in the first survey on being in a "perfect match" job situation increased in the follow up survey, revealing and reinforcing the power of having a Master's degree completed in the search and finding of a job where one is in a "perfect match" situation. It should also be noted, in Model 3, the strong and positive impact of having completed a Doctoral degree in increasing the probability of being in a situation of "perfect match", reinforcing the point made earlier about the importance of pursuing further education for a job match situation.

Table 18 – Logit coefficients: determinants of being in a "perfect match" status in the follow up survey.

	Model 1		Model 2		Model 3	
	pmatch 15	z statistic	pmatch 15	z statistic	pmatch 15	z statistic
Intercept	-2,641***	(-3,09)	-3,065***	(-3,39)	-2,744***	(-2,75)
Master's in the first surveys	0,522**	(2,30)	0,638***	(2,72)	0,633***	(2,63)
Master's since the first surveys	0,460	(1,07)	0,444	(1,00)	0,325	(0,71)
PhD since the first surveys	0,661	(1,06)	0,889	(1,40)	1,168*	(1,77)
Age	0,019	(1,32)	0,023	(1,56)	0,009	(0,38)
Sex	-0,045	(-0,20)	0,081	(0,36)	0,049	(0,21)
Final Average (quartiles)	-0,143	(-1,43)	-0,137	(-1,34)	-0,137	(-1,31)
Time since graduation	0,021**	(1,97)	0,016	(1,46)	0,016	(1,42)
Engineering and Mathematics [a]			0,726**	(2,52)	0,792***	(2,66)
Technology [a]			0,946**	(2,16)	0,990**	(2,23)
Business [a]			0,533	(1,03)	0,557	(1,07)
Social Sciences [a]			0,077	(0,17)	0,197	(0,43)
Education [a]			1,467***	(3,20)	1,416***	(3,01)
Arts and Humanities [a]			-0,045	(-0,12)	-0,012	(-0,03)
Employed when graduated					-0,085	(-0,34)
Tenure in current job					0,002	(0,74)
N	471		471		457	
Log Likelihood	-278,125		-269,002		-261,025	

*** p<0,01, ** p<0,05, * p<0,10. [a] Sciences is the base category.

Still looking at the data in Table 18, we can see that the time since graduation variable has gained significance in Model 1, demonstrating to be positively related to the probability of being in a "perfect match", although showing a reduced effect. Graduates in the Engineering and Mathematics, and in the Education, fields of study, relative to graduates from a Sciences background, also displayed a higher probability of being in a "perfect match" three years after the first surveys.

5.1.4. Determinants of being in a "horizontal mismatch" status

The results presented on Table 19 on the determinants of being in a horizontal mismatch, for the first surveys, reveal to us that being a female is positively related to the likelihood of being in a position where a horizontal mismatch occurs at a very high significance level, as opposed to being a male. The same happens for those who come from a Social Sciences background who are more likely to be in such a situation, as those from a Sciences only background.

Table 19 – Logit coefficients: determinants of being in a "horizontal mismatch" status in the first survey.

	Model 1		Model 2		Model 3	
	Horizontal 12	z statistic	Horizontal 12	z statistic	Horizontal 12	z statistic
Intercept	-2,149***	(-3,30)	-2,147***	(-3,04)	-2,752***	(-2,89)
Master's	-0,935***	(-3,87)	-0,985***	(-3,95)	-1,035***	(-3,57)
Age	0,012	(0,78)	0,011	(0,71)	0,032	(1,07)
Sex	0,650***	(2,62)	0,613**	(2,44)	0,824***	(2,83)
Final Average (quartiles)	0,184*	(1,66)	0,175	(1,56)	0,251**	(1,97)
Time since graduation	-0,013	(-1,19)	-0,010	(-0,87)	-0,022	(-1,62)
Engineering and Mathematics [a]			-0,108	(-0,33)	-0,049	(-0,14)
Technology [a]			-0,278	(-0,46)	-0,244	(-0,40)
Business [a]			0,250	(0,68)	-0,254	(-0,37)
Social Sciences [a]			0,806**	(1,98)	0,785*	(1,80)
Education [a]			-0,355	(-0,53)	-0,295	(-0,43)
Arts and Humanities [a]			-0,429	(-0,91)	-0,369	(-0,77)
Employed when graduated					0,104	(0,33)
Tenure in current job					-0,003	(-0,93)
N	596		596		496	
Log Likelihood	-247,400		-243,262		-192,102	

*** p<0,01, ** p<0,05, * p<0,10. [a] Sciences is the base category.

On the other hand, as the individuals place themselves in the lower quartiles of the final graduation average distribution, the more likely it is for them to be in a horizontal mismatch, which leads us to believe that higher graduation average grades lead individuals to have more matched jobs. This result, however, is not significant in Model 2 of our estimation, and has a small significance level in Model 1. The same happens to those who graduated from a Master's degree in the first surveys as they are less likely to be in situations of horizontal mismatches, suggesting that higher qualifications lead to more adequately matched job opportunities.

Looking at the same horizontal mismatch variable for the follow up survey, with a slightly smaller sample, on what determines the probability of an individual to be in such a mismatch situation, we can see on Table 20 that the variables related to gender and the final graduation average lost their significance levels in the follow up survey.

Table 20 – Logit coefficients: determinants of being in a "horizontal mismatch" status in the follow up survey.

	Model 1		Model 2		Model 3	
	Horizontal 15	z statistic	Horizontal 15	z statistic	Horizontal 15	z statistic
Intercept	-2,481***	(-2,91)	-2,300**	(-2,55)	-2,870***	(-2,88)
Master's in the first surveys	-0,646***	(-2,76)	-0,700***	(-2,92)	-0,681***	(-2,76)
Master's since the first surveys	-0,453	(-1,01)	-0,454	(-1,00)	-0,448	(-0,98)
PhD since the first surveys	-	(-)	-	(-)	-	(-)
Age	0,011	(0,71)	0,009	(0,58)	0,042*	(1,80)
Sex	0,302	(1,31)	0,278	(1,19)	0,305	(1,26)
Final Average (quartiles)	0,088	(0,83)	0,079	(0,74)	0,048	(0,43)
Time since graduation	0,010	(0,94)	0,012	(1,11)	0,011	(1,00)
Engineering and Mathematics [a]			-0,473	(-1,51)	-0,450	(-1,40)
Technology [a]			-0,742	(-1,27)	-0,721	(-1,22)
Business [a]			-0,076	(-0,22)	-0,076	(-0,21)
Social Sciences [a]			0,066	(0,16)	0,054	(0,13)
Education [a]			0,194	(0,39)	0,288	(0,56)
Arts and Humanities [a]			-0,319	(-0,80)	-0,390	(-0,93)
Employed when graduated					0,086	(0,33)
Tenure in current job					-0,005**	(-2,37)
N	582		582		558	
Log Likelihood	-268,126		-265,537		-252,052	

*** p<0,01, ** p<0,05, * p<0,10. [a] Sciences is the base category.

The effect of having a Master's degree in the first surveys remains strongly and negatively related to the likelihood of one being in a horizontal mismatch. In

Model 3, we can also see that Age and tenure in the current job present slightly significant values, however both close to zero and, as a consequence, they do not act as determinants of being in a horizontal mismatch.

5.2. Economic returns to the match or mismatch variables

In this subchapter, for the initial and follow-up surveys, using the nature and panel size of our data, we will estimate, through the use of repeated cross-section estimates, the OLS hourly earnings estimates for all our focus variables. All the models presented here result from the estimation of Eq. 2 and follow the same design, presented in Table 21, only varying the Match/Mismatch Status variables – variables Skills_Adq, Perfrom_Dem, pmatch, and Horizontal, which measure, respectively, the suitability of the skills acquired in Higher Education for professional performance, the demand of professional responsibilities in relation to the level of skills acquired in Higher Education, the presence of a "perfect match" state, and the existence of horizontal mismatches –, as in the previous subchapter.

Table 21 – OLS models' design.

	Model 1	Model 2	Model 3	Model 4
Type of course	X	X	X	X
Type of course*Match/Mismatch Status	X	X	X	X
Personal characteristics		X	X	X
Field of study			X	X
Company and job characteristics				X

Source: Own elaboration.

In Model 1, the simplest model, we will only control for the type of course (Bachelor's or Master's) and for the interaction variable between the type of course and the Match/Mismatch Status variables. In Model 2, the variables relating to the personal characteristics of individuals will be added, namely age, sex and the final graduation average. In Model 3, information will be added regarding the area of study of each individual and, finally, in Model 4, information will be added regarding the characteristics of the firm and the work of the individuals. To the extent that the data on those individuals who had completed a Doctorate degree in the follow up survey caused some noise in the following estimates, these observations were taken from the balanced sample in order to obtain better results.

5.2.1. Presence of adequate skills for job performance

In the OLS estimation for the two periods under review, the estimation of wage returns followed the specifications set out in Table 21. In this sense, the interaction variable under analysis in this case was the one that interacted the academic degree with the suitability of the skills acquired in Higher Education for professional performance, that is, with the variable Skills_Adq, previously defined and whose description is in Table 30 in the Annex.

From the results of the estimation by the OLS method for wage returns for the first surveys, in Table 22, we can observe that the existence of a Master's degree by individuals has a positive and significant impact in the hourly wages that remains even as more variables are added to the Models, although it becomes smaller as the different models increase the specification. Having a Master’s degree offers a wage premium that can range from 13,1 to 19,7% more than the base category of just having a Bachelor’s degree. This effect remains three years after, in the follow up survey, with the wage premium showing very similar results overall.

As with the interaction variables with the competences match, or mismatch, variables we’re analysing, holding a Bachelor’s degree and having a competences mismatch, *i.e.*, inadequate skills, when compared to the base category, presents a statistically significant wage penalty across all models that assumes that monthly wages can be -9,4 to 13,7% lower to those who are in the base category, across all four models. In the follow up survey, with the exception of Model 4, these values continue to be statistically significant, although at smaller levels, and the wage penalty for that interaction variable decreases slightly, meaning that as time passes, the mismatch tends to be attenuated. As with graduates from a Master’s degree but with inadequate skills for performing their jobs, they also face a significant wage penalty when compared to adequately skilled Master’s degree graduates. However, these wage penalties are smaller than those faced by Bachelor’s degree graduates with inadequate skills, illustrating the benefits of pursuing further education, even when one may end up

Table 22 – OLS coefficients: economic returns for the first and follow up surveys (presence of adequate skills for job performance).

	First Surveys				Follow up Survey			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage
Intercept	1,567*** (0,031)	1,170*** (0,089)	1,217*** (0,094)	1,236*** (0,120)	1,634*** (0,029)	1,227*** (0,111)	1,233*** (0,117)	1,183*** (0,154)
Master's	0,180*** (0,042)	0,132*** (0,039)	0,123*** (0,039)	0,125*** (0,039)	0,182*** (0,039)	0,127*** (0,039)	0,126*** (0,040)	0,147*** (0,038)
Bachelor's*Inadequate Skills [a]	-0,147*** (0,049)	-0,099** (0,046)	-0,108** (0,047)	-0,121*** (0,046)	-0,101** (0,045)	-0,090* (0,047)	-0,082* (0,047)	-0,035 (0,045)
Bachelor's*Adequate Skills [a]	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)
Master's*Inadequate Skills [a]	-0,092** (0,046)	-0,081* (0,043)	-0,085** (0,043)	-0,078* (0,041)	-0,074* (0,040)	-0,058 (0,037)	-0,060 (0,038)	-0,062* (0,037)
Age		0,018*** (0,002)	0,017*** (0,002)	0,009*** (0,004)		0,017*** (0,002)	0,019*** (0,002)	0,014*** (0,003)
Sex		-0,077** (0,033)	-0,075** (0,033)	-0,069** (0,032)		-0,155*** (0,030)	-0,142*** (0,028)	-0,152*** (0,030)
Final Average (quartiles)		-0,057*** (0,015)	-0,057*** (0,015)	-0,047*** (0,014)		-0,023* (0,014)	-0,014 (0,013)	-0,010 (0,014)
Time since graduation		0,002 (0,002)	0,002 (0,002)	0,001 (0,002)		0,001 (0,001)	0,002 (0,001)	0,003** (0,001)
Master's since the first survey						-0,073 (0,057)	-0,077 (0,057)	-0,112** (0,055)
Engineering and Mathematics [b]			-0,090** (0,040)	-0,065* (0,039)			-0,050 (0,041)	-0,065* (0,039)
Technology [b]			0,036 (0,066)	0,076 (0,064)			0,054 (0,068)	-0,050 (0,064)
Business [b]			0,013 (0,076)	0,053 (0,074)			0,010 (0,046)	0,014 (0,046)

Table 22 – (continuation).

Social Sciences [b]			-0,086 (0,059)	-0,107* (0,060)			-0,119** (0,058)	-0,132** (0,055)
Education [b]			0,055 (0,071)	0,079 (0,068)			-0,042 (0,073)	-0,118* (0,069)
Arts and Humanities [b]			-0,014 (0,049)	0,011 (0,048)			-0,023 (0,051)	-0,035 (0,048)
Micro Enterprise [c]				0,050 (0,051)				-0,043 (0,058)
Medium Enterprise [c]				0,174*** (0,037)				0,061* (0,033)
Large Enterprise [c]				0,132*** (0,040)				0,114*** (0,036)
Lisbon Metro Area				-0,011 (0,185)				0,181*** (0,046)
Employed at time of graduation				0,031 (0,035)				-0,007 (0,031)
Seniority in current job				0,000 (0,000)				0,000 (0,000)
Permanent Staff				0,053 (0,037)				0,069** (0,029)
Full-time job				0,062 (0,056)				-0,127 (0,085)
N	507	495	495	465	667	591	591	491
R^2	0,093	0,224	0,241	0,325	0,072	0,203	0,214	0,331

Standard errors in parentheses. * $p < 0{,}10$, ** $p < 0{,}05$, *** $p < 0{,}01$. [a] Master's*Adequate Skills is the base category. [b] Sciences is the base category. [c] Small Enterprise is the base category. Bachelor's*Adequate Skills presents no results due to collinearity issue.

with inadequate skills for performing their jobs. In the follow up survey, the values presented for this interaction variable lose their statistical significance in Models 2 and 3. However, in Models 1 and 4, the presented values for the hourly wage penalty are smaller than for the initial surveys. This can mean that, in the long run, even if an individual becomes skills mismatched, the fact that it holds a higher academic position, when compared with holding a lower one, can have a less negative impact on hourly earnings.

We can also observe that the personal characteristics of individuals all have a high level of statistical significance. As expected, and consistent with the economic literature, ageing has a positive impact on wages, such as the final graduation average, while the values of the latter decrease with the higher specification of the models. Belonging to the lower quartiles of the distribution of the final graduation averages can have a negative impact on the hourly wages that, for the first surveys, can go from -5,5 to -4,6% for every hour worked. The final graduation averages, however, lose their statistical significance in the follow up survey, with the exception of Model 2, however with a smaller wage penalty. On the other hand, there is also a significant wage penalty associated with being female that, differing among Models, can go from a hourly wage penalty of -6,7 to -7,4%, in the first survey, and that, three years after, in the follow up survey, can more than double that value.

As for the fields of study of the individuals in the sample, few of the variables presented show statistical significance. For the first surveys, individuals graduated from Engineering and Mathematics face a wage penalty that can range from -6,3 to -8,0% when compared to those graduated from a Sciences field of study. Also, Model 4 shows that those graduated from a Social Sciences background also face a statistically significant wage penalty when compared to those graduated in Sciences of about -10,1%. In the follow up survey, these wage penalties are sustained, with those earned by the Social Sciences being increased by around 2 percentage points, and with the graduates from the field of study of Education showing also a wage penalty of around -11,1% in relation to those graduated from a Sciences course.

The results also show that there is a significant wage premium for working in a Medium or Large Enterprises in relation to working on a Small Enterprise, which serves as a base category. Workers in Medium Enterprises have a wage premium of around 19,0%, the highest premium, while workers in Large Enterprises get an hourly wage premium of 14,1% in relation to the base category of being employed in a Small Enterprise. These wage premiums are still significant in the follow up surveys, with the wage premiums slightly decreasing three years on. Being employed in the Lisbon Metropolitan Area also shows a highly significant wage premium in the follow up survey, meaning that those who work there earn, on average, more 19,8% than those who don't. There is also another wage premium associated with being on the permanent staff, with a wage premium of 7,1%, in the follow up survey, when compared to those who aren't.

5.2.2. Presence of a demanding job performance

From the results of the estimation by the OLS method for the hourly wage returns for the first surveys, in Table 23, we can see that holding a Master's degree is statistically significant and presents a high wage premium for all four Models with values varying between 9,6 to 21,7%, in relation to only holding a Bachelor's degree. These wage premiums, however, decrease slightly in the follow up survey, showing some signs of convergence with those Bachelor's degree holders as time passes. Regarding the interaction variables, in this section, it interacts the academic degree of individuals with the demand of professional responsibilities in relation to the level of skills acquired in Higher Education. According to the results for each model, these interaction variables are not statistically significant for the first surveys, meaning that not having a demanding job performance, *i.e.*, a job mismatch, is not that significant at the entry level of the labour market. In Model 1 of the follow up survey, a Bachelor's degree graduate who does not have a demanding job performance has a wage penalty of about -12,9% in its hourly wage. The interaction variable between being a Master's degree holder and not having a demanding job performance, in the follow up survey, shows a wage penalty close to -5,9%, when compared to the base category of having a demanding job performance in relation to the skills acquiesced in Higher Education, in Model 4. These results, for Models 2 to 4 of the follow up surveys, however significant, do not present high levels of statistical significance.

Table 23 – OLS coefficients: economic returns for the first and follow up surveys (presence of a demanding job performance).

	First Surveys				Follow up Survey			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage
Intercept	1,554*** (0,044)	1,188*** (0,096)	1,232*** (0,102)	1,249*** (0,127)	1,676*** (0,036)	1,282*** (0,117)	1,304*** (0,124)	1,282*** (0,159)
Master's	0,196*** (0,057)	0,114** (0,053)	0,111** (0,053)	0,092* (0,052)	0,136*** (0,046)	0,102** (0,047)	0,091* (0,048)	0,113** (0,045)
Bachelor's*Not Demanding Performance [a]	-0,055 (0,054)	-0,062 (0,049)	-0,056 (0,049)	-0,056 (0,048)	-0,138*** (0,047)	-0,103** (0,048)	-0,112** (0,049)	-0,098** (0,046)
Bachelor's*Demanding Performance [a]	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)
Master's*Not Demanding Performance [a]	-0,065 (0,047)	-0,037 (0,043)	-0,035 (0,043)	0,009 (0,042)	-0,045 (0,040)	-0,040 (0,037)	-0,039 (0,037)	-0,061* (0,036)
Age		0,018*** (0,002)	0,017*** (0,002)	0,009** (0,004)		0,017*** (0,002)	0,016*** (0,002)	0,013*** (0,003)
Sex		-0,086*** (0,033)	-0,085** (0,033)	-0,079** (0,032)		-0,160*** (0,031)	-0,161*** (0,031)	-0,145*** (0,030)
Final Average (quartiles)		-0,061*** (0,015)	-0,062*** (0,015)	-0,055*** (0,014)		-0,026* (0,014)	-0,026* (0,014)	-0,023* (0,013)
Time since graduation		0,002 (0,002)	0,003 (0,002)	0,002 (0,002)		0,001 (0,001)	0,001 (0,001)	0,003** (0,001)
Master's since the first survey						-0,072 (0,059)	-0,078 (0,059)	-0,123** (0,056)
Engineering and Mathematics [b]			-0,080* (0,041)	-0,055 (0,040)			-0,054 (0,041)	-0,068* (0,039)
Technology [b]			0,023 (0,067)	0,062 (0,064)			0,062 (0,069)	-0,042 (0,065)
Business [b]			-0,019 (0,078)	0,025 (0,075)			0,007 (0,047)	0,013 (0,046)

Table 23 – (continuation).

Social Sciences [b]			-0,100 (0,062)	-0,131** (0,062)			-0,128** (0,058)	-0,137** (0,056)
Education [b]			0,041 (0,072)	0,066 (0,069)			-0,049 (0,075)	-0,130* (0,071)
Arts and Humanities [b]			-0,018 (0,050)	0,014 (0,049)			-0,019 (0,051)	-0,029 (0,048)
Micro Enterprise [c]				0,031 (0,052)				-0,051 (0,059)
Medium Enterprise [c]				0,181*** (0,039)				0,057* (0,034)
Large Enterprise [c]				0,132*** (0,041)				0,112*** (0,037)
Lisbon Metro Area				0,037 (0,187)				0,174*** (0,046)
Employed at time of graduation				0,025 (0,036)				-0,004 (0,031)
Seniority in current job				0,000 (0,000)				0,000* (0,000)
Permanent Staff				0,077** (0,038)				0,070** (0,030)
Full-time job				0,071 (0,059)				-0,125 (0,085)
N R^2	492 0,069	480 0,211	480 0,224	451 0,313	653 0,074	579 0,203	579 0,216	479 0,338

Standard errors in parentheses. * $p < 0{,}10$, ** $p < 0{,}05$, *** $p < 0{,}01$. [a] Master's*Demanding Performance is the base category. [b] Sciences is the base category. [c] Small Enterprise is the base category. Bachelor's*Demanding Performance presents no results due to collinearity issues.

With regard to personal characteristics, these are statistically significant for the first survey and, there is a small wage premium associated with age and higher final graduation averages, while there is a wage penalty for being female. As in the previous section, the already large wage penalty associated with being a female almost more than doubles in the follow up survey, and can reach, per Model 2 of the follow up survey, a penalty of -14,9% per hour worked when compared to the monthly wages of males. The penalty of being in the lower quartiles of the final graduation averages also decreases its statistical significance in the follow up survey and presents lower values. Those who already had a Master's degree in the first surveys present a wage penalty in the follow up survey of around -11,6%, possibly signalling up the effect of already being in employment and those who enter the labour market earning higher hourly wages.

As regards the field of study, in this estimation, for the first survey, only in Model 3 do the areas of Engineering and Mathematics present statistically significant results, in which graduates from these fields presenting wage penalties of around -7,7%, in relation to those who graduated from the Sciences field of study. In Model 4, for the first surveys, being graduated from a Social Sciences background show a wage penalty of -12,3% when compared to those who come from a Sciences background. These wage penalties are consistent and significant in the follow up survey, with those coming from the field of study of Education also earning a wage penalty of -12,2% on the hourly wages, when compared to Sciences graduates.

As for the company characteristics, for the first surveys, there is a wage premium for those working in a Medium Enterprises of 19,8% per hour worked and in a Large Enterprise of around 14,1% compared with those working in a Small Enterprise. As it happened in the previous section, these wage premiums are maintained statistically significant in the follow up surveys, with the wage premium associated with working in a Medium Enterprise decreasing to 5,9%, and with the wage premium of working a Large Enterprise also decreasing, but less, reaching 11,9%, when compared to individuals working in a Small Enterprise. Working in the Lisbon Metropolitan Area, in the follow up survey, also presents a high and significant wage premium of 19,0%, in relation to those who don't work in that geographical area, demonstrating the better opportunities of working around the capital city of Portugal. A wage premium is also associated with being on the permanent staff, in the follow up survey.

5.2.3. Presence of a "perfect match"

From the results of the OLS estimation of wage returns for the initial surveys, in Table 24, we can see that holding a Master's degree has statistical significance for Models 1 and 2, in the first surveys, and it presents a wage premium that can vary across both models from 11,1 to 15,8%, opposed to just being a Bachelor's degree holder. The value for this variable loses its statistical significance in the follow up survey, with the exception of Model 4, that maintains the wage premium of those who have a Master's degree at around the same levels.

As for the interaction variables, in this section they interact between the academic degree of the individuals and the permanence, or not, in a state of "perfect match". The estimation results for the four Models, in the first surveys, do not present statistical significance for any of the interaction variables, with the exception of Model 1, where it shows a wage penalty for those Bachelor's degree graduates who are not in a perfect match of -10,1%, when compared to those perfectly matched. In the follow up survey, the interaction variables gained statistical relevance, and thus, Models 1 to 3 show that there is a significant wage penalty for Bachelor's degree graduates who are not in a "perfect match" situation of -12,9 to -17,9% per hour worked, and for Master's degree holders who are also not in a "perfect match" situation, for all 4 models, that can range from -8,9 to -10,7% when compared to those who are perfectly matched. Given their statistical significance, this set of results provides an interesting conclusion in that not being in a "perfect match" situation brings a higher wage penalty for those who graduated from a 1st Cycle degree than those who graduated from a 2nd Cycle degree, when compared to perfectly matched individuals with the same level of academic qualifications, and these wage penalties only show up after individuals are in the labour market and not at the entry level.

Table 24 – OLS coefficients: economic returns for the first and follow up surveys (presence of a "perfect match").

	First Surveys				Follow up Survey			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage
Intercept	1,603*** (0,054)	1,206*** (0,101)	1,265*** (0,107)	1,280*** (0,132)	1,788*** (0,055)	1,363*** (0,137)	1,382*** (0,142)	1,349*** (0,178)
Master's	0,147** (0,069)	0,105* (0,063)	0,094 (0,063)	0,095 (0,062)	0,067 (0,066)	0,094 (0,063)	0,089 (0,063)	0,114* (0,059)
Bachelor's*Not Perfect Match [a]	-0,107* (0,061)	-0,073 (0,056)	-0,079 (0,056)	-0,063 (0,055)	-0,197*** (0,063)	-0,138** (0,059)	-0,140** (0,059)	-0,089 (0,056)
Bachelor's*Perfect Match [a]	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)
Master's*Not Perfect Match [a]	-0,055 (0,051)	-0,046 (0,046)	-0,045 (0,047)	-0,015 (0,046)	-0,113** (0,045)	-0,108** (0,043)	-0,109** (0,043)	-0,093** (0,041)
Age		0,018*** (0,002)	0,017*** (0,002)	0,009** (0,004)		0,015*** (0,002)	0,015*** (0,002)	0,010*** (0,004)
Sex		-0,083** (0,033)	-0,083** (0,034)	-0,077** (0,033)		-0,145*** (0,033)	-0,146*** (0,033)	-0,137*** (0,033)
Final Average (quartiles)		-0,062*** (0,015)	-0,063*** (0,015)	-0,057*** (0,015)		-0,030** (0,015)	-0,029* (0,015)	-0,025* (0,014)
Time since graduation		0,002 (0,002)	0,003 (0,002)	0,002 (0,002)		0,001 (0,002)	0,002 (0,002)	0,003* (0,002)
Master's since the first survey						-0,095 (0,065)	-0,103 (0,065)	-0,097 (0,063)
Engineering and Mathematics [b]			-0,088** (0,042)	-0,061 (0,041)			-0,048 (0,042)	-0,073* (0,040)
Technology [b]			0,033 (0,068)	0,073 (0,065)			0,045 (0,067)	-0,061 (0,064)
Business [b]			-0,013 (0,078)	0,029 (0,075)			0,043 (0,078)	-0,011 (0,078)

Table 24 – (continuation).

Social Sciences [b]			-0,100 (0,062)	-0,133** (0,063)			-0,135** (0,062)	-0,149** (0,059)
Education [b]			0,051 (0,073)	0,077 (0,071)			-0,060 (0,073)	-0,143** (0,070)
Arts and Humanities [b]			-0,017 (0,051)	0,012 (0,050)			-0,015 (0,050)	-0,039 (0,048)
Micro Enterprise [c]				0,019 (0,052)				-0,088 (0,073)
Medium Enterprise [c]				0,172*** (0,038)				0,042 (0,035)
Large Enterprise [c]				0,110*** (0,041)				0,073* (0,041)
Lisbon Metro Area				0,019 (0,188)				0,194*** (0,049)
Employed at time of graduation				0,023 (0,036)				0,007 (0,034)
Seniority in current job				0,000 (0,000)				0,001* (0,000)
Permanent Staff				0,085** (0,038)				0,061* (0,032)
Full-time job				0,074 (0,059)				-0,056 (0,099)
N R^2	483 0,069	471 0,212	471 0,228	442 0,315	479 0,069	467 0,189	467 0,204	395 0,301

Standard errors in parentheses. * $p < 0,10$, ** $p < 0,05$, *** $p < 0,01$. [a] Master's*Perfect Match is the base category. [b] Sciences is the base category. [c] Small Enterprise is the base category. Bachelor's*Perfect Match presents no results due to collinearity issues.

The personal characteristics of individuals show statistical significance for the first survey in all models, and values consistent with those presented in the previous sections, namely the wage penalty for being female and the wage premium associated with age (which is decreasing according to more variables are added to the successive Models, and over time) and being in the first quartiles of the final graduation average (also decreasing over time). The wage penalty for being a female increases significantly in the follow up survey, with wage penalties achieving -12,8 to -13,6% when compared to male workers.

As for the fields of study, in this estimate, for the first survey, in Model 3, only those graduated from the Engineering and Mathematics field of studies present a statistically significant wage penalty of around -8,4% in relation to Science graduates, and a graduate from a Social Sciences course, in Model 4, presents a wage penalty of around -12,5% when compared to an individual from a Sciences background. In the follow up survey, as in previous models, the value of the wage penalties of those who come from an Engineering and Mathematics, and Social Sciences, backgrounds are maintained, with the first decreasing slightly and the second increasing slightly. Those graduated from Education courses also face a wage penalty in the follow up survey, when compared to those from a Sciences background, of about -13,3%.

There are wage premiums associated with not working in a Small Enterprise, which serves as a base category, with the largest belonging to workers in Medium Enterprises who have a premium of more than 18,7% per hour worked in relation to those workers, followed by individuals working in Large Enterprises, with a premium of more than 11,6% of the hourly wage. In the follow up survey, the wage premium of working in a Medium Enterprises disappears as the wage premium of working a Large Enterprise is slightly reduced to 7,6%, when compared to those working in a Small Enterprise. The wage premium associated with working in the Lisbon Metropolitan Area is significant and presents high values, reaching 21,4% in the follow up survey, demonstration the better career opportunities in this area.

5.2.4. Presence of “horizontal mismatch”

From the results of the estimation by the OLS method for the wage returns for the first surveys, in Table 25, we can see that holding a Master's degree is statistically significant and presents a high wage premium that ranges from 41,1 to 49,2% across all four Models, when compared to only having a Bachelor’s degree. This wage premium is sustained in the follow up survey, although showing slightly decreased values. Regarding the interaction variable, in this section, it interacts the academic degree of individuals with the existence, or not, of a horizontal mismatch. According to the results for each model, these interaction variables are statistically significant, showing that a Bachelor’s degree graduate who does not have a horizontal mismatch has a wage premium 24,0 to 28,0% higher vis-à-vis the base category of having such a horizontal mismatch, in the first surveys. The interaction variable between being a Master's degree holder and having a horizontal mismatch, in the first survey, shows a wage penalty of 20,1 to 23,6% vis-à-vis the base category of not having such a mismatch. This wage premiums and penalties, in the follow up survey, are also statistically significant, although its values are smaller for both premiums and penalties, potentially meaning that, as time passes, these differences tend to be attenuated.

With regard to personal characteristics, these are statistically significant and, as in the previous sections. There is a small wage premium according to age and the final graduation average – by being placed in the first quartiles of the final graduation average distribution –, while there is a wage penalty for being female. This penalty is higher than 8% in terms of wage returns. For the follow up survey, the effects of the final graduation average are still significant, although with decreasing values, and the wage penalty associated with being a woman more than doubles across all three models, in relation to being a man.

With regards to the field of study of the individuals, for the first surveys, only being a graduate from the field of study of Engineering and Mathematics presents statistically significant values for both models, with a wage penalty associated that can range from -6,1 to -6,8% when compared to be a Sciences.

Table 25 – OLS coefficients: economic returns for the first and follow up surveys (presence of horizontal mismatches).

	First Surveys				Follow up Survey			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage	Hourly Wage
Intercept	1,345*** (0,042)	0,915*** (0,088)	0,941*** (0,093)	0,973*** (0,124)	1,436*** (0,046)	1,003*** (0,120)	1,015*** (0,125)	1,044*** (0,156)
Master's	0,400*** (0,047)	0,354*** (0,048)	0,344*** (0,048)	0,365*** (0,051)	0,372*** (0,050)	0,320*** (0,052)	0,311*** (0,052)	0,275*** (0,050)
Bachelor's*No Horizontal Mismatch [a]	0,215*** (0,048)	0,243*** (0,050)	0,242*** (0,050)	0,259*** (0,052)	0,204*** (0,052)	0,213*** (0,054)	0,208*** (0,054)	0,155*** (0,051)
Bachelor's*Horizontal Mismatch [a]	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)
Master's*Horizontal Mismatch [a]	-0,212*** (0,063)	-0,198*** (0,056)	-0,190*** (0,056)	-0,195*** (0,067)	-0,144*** (0,055)	-0,113** (0,052)	-0,116** (0,052)	-0,135*** (0,050)
Age		0,019*** (0,002)	0,019*** (0,002)	0,011*** (0,003)		0,017*** (0,002)	0,017*** (0,002)	0,014*** (0,003)
Sex		-0,068** (0,028)	-0,068** (0,028)	-0,065** (0,031)		-0,155*** (0,030)	-0,156*** (0,030)	-0,143*** (0,029)
Final Average (quartiles)		-0,045*** (0,013)	-0,046*** (0,013)	-0,044*** (0,014)		-0,024* (0,014)	-0,024* (0,014)	-0,022* (0,013)
Time since graduation		0,000 (0,001)	0,001 (0,001)	0,001 (0,002)		0,002 (0,001)	0,002 (0,001)	0,004** (0,001)
Master's since the first survey						-0,067 (0,056)	-0,070 (0,056)	-0,107** (0,054)
Engineering and Mathematics [b]			-0,070* (0,038)	-0,063* (0,038)			-0,053 (0,040)	-0,066* (0,038)
Technology [b]			0,026 (0,064)	0,056 (0,062)			0,051 (0,067)	-0,045 (0,063)
Business [b]			0,016 (0,043)	0,027 (0,070)			0,013 (0,046)	0,022 (0,045)

Table 25 – (continuation).

Social Sciences [b]			-0,086 (0,054)	-0,095 (0,059)			-0,115** (0,057)	-0,124** (0,054)
Education [b]			0,044 (0,068)	0,065 (0,067)			-0,036 (0,072)	-0,114* (0,068)
Arts and Humanities [b]			-0,025 (0,047)	-0,002 (0,047)			-0,023 (0,050)	-0,038 (0,047)
Micro Enterprise [c]				0,055 (0,051)				-0,037 (0,057)
Medium Enterprise [c]				0,161*** (0,036)				0,064** (0,032)
Large Enterprise [c]				0,120*** (0,039)				0,122*** (0,036)
Lisbon Metro Area				-0,010 (0,180)				0,176*** (0,045)
Employed at time of graduation				0,032 (0,034)				-0,008 (0,030)
Seniority in current job				0,000 (0,000)				0,000 (0,000)
Permanent Staff				0,054 (0,036)				0,058** (0,029)
Full-time job				0,042 (0,055)				-0,132 (0,084)
N R^2	672 0,117	596 0,272	596 0,284	466 0,357	667 0,090	591 0,222	591 0,233	491 0,349

Standard errors in parentheses. * $p < 0,10$, ** $p < 0,05$, *** $p < 0,01$. [a] Master's*Not Horizontal Mismatch is the base category. [b] Sciences is the base category. [c] Small Enterprise is the base category. Bachelor's*Horizontal Mismatch presents no results due to collinearity issues.

graduate. For the follow up survey, this wage penalty is sustained, and those graduated from the fields of study of Social Sciences and Education now also present wage penalties, in relation to those graduated from the Sciences field of study, -11,7% and -10,8%, respectively.

As for the company characteristics, in the first surveys, there is a wage premium for those working in a Medium Enterprise of over 17,5% and in a Large Enterprise of around 12,7%, compared with those working in a Small Enterprise. These wage premiums prevail in the follow up survey, although the premium associated with working in a Medium Enterprise decreases three year after the initial survey by half, to 6,6%, and the wage premium of those working in Large Enterprises increases slightly to 13%, when compared to those working in Small Enterprises. The strong positive effect on wages of working in the Lisbon Metropolitan Area is also significant in the follow up survey, with those working around the Portuguese capital city earning more 19,2% per hour worked than those who don't. Being employed within the permanent staff also has a positive and significant wage effect in the follow up survey of 6,0%, when compared to those who are on limited employment contracts.

5.3. Fixed-effects models

In this final section of this dissertation, we will present the estimates of the fixed effects models on the earnings consequences of the permanence or transition between matched or mismatch status from the first to the follow up surveys. For that matter, we use simply the pmatch and horizontal variables that refer, respectively, to whether respondents are in a perfect skills match status or in a horizontal mismatch status. For each type of mismatch, we estimate two different fixed effects models. The first model was estimated using only the main mismatch variables, with control variables being added to the second model.

Thus, through the use of a data panel, we intend to assess whether being, or remaining, in a mismatch situation matters in terms of the hourly wages, taking advantage of the variation that exists over the two periods, by observing the same individuals and variations across time-variant education- or job-related characteristics.

Table 26 – Fixed effects coefficients: economic returns to skills mismatches.

	Model 1		Model 2	
	Coefficient	Robust SE	Coefficient	Robust SE
Intercept	1,612***	(0,048)	1,680***	(0,110)
Master's degree in both surveys	0,023	(0,087)	-0,033	(0,106)
Doctorate degree since the first survey	0,164	(0,143)	0,094	(0,174)
Perfect Matched in both surveys	0,117***	(0,036)	0,067*	(0,040)
Not Perfect Match in both surveys	0,081***	(0,024)	0,035	(0,028)
Newly Matched in the follow up survey	0,115***	(0,039)	0,009	(0,046)
Lost Match in the follow up survey	0,071	(0,052)	0,076	(0,056)
Micro Enterprise			-0,029	(0,049)
Medium Enterprise			0,107**	(0,042)
Large Enterprise			0,092**	(0,037)
Seniority in current job			0,000	(0,000)
Full-time job			-0,134	(0,085)
Permanent Staff			0,061**	(0,031)
Lisbon Metro Area			0,163**	(0,064)
N	962		854	
R^2	0,066		0,149	
ID	483		477	

* $p < 0{,}10$, ** $p < 0{,}05$, *** $p < 0{,}01$

Through the results of Table 26, we can see that the results for Master's degrees and Doctorates, in themselves, are not statistically significant, though they demonstrate a relatively positive effect. Although they are not significant, the results from these variables manage to clear from the model some noise that it might have, in part, due to the higher wages attributed to individuals who attained doctoral education between surveys.

By analysing Model 1 of the estimation, and observing the results that present statistical significance, we can see that being perfectly matched in both moments of this study has a positive effect on the wages of individuals across surveys of around 12,4%, while moving from a state of mismatch to a state of match carries with it a positive effect of 12,2% on hourly wages. The figures for being permanently mismatched at both moments in the study and for becoming mismatched from the first to the second – although not significant – also show positive values in the evolution of wages. However, these figures are lower than those previously presented, showing a penalty for being, or becoming, mismatched.

Looking at Model 2, we can see that most of the effects that Model 1 was capturing in the different transition categories disappear, or are diluted, when the control variables, *i.e.*, the characteristics of the labour market, are included. Thus, we can confirm that working in a medium or large enterprise brings positive wage effects over time, as well as having a job where you are part of the permanent staff, or working in the Lisbon Metropolitan Area, with a wage effect of 18,4%. Control variables appear therefore to be important, and this should be noted, as these effects may be related to the access to some types of employment, such as large enterprises, being in Lisbon Metropolitan Area, or having an effective job, that interact with the matching/mismatching effects.

Table 27 – Difference in fixed effects coefficients (pmatch).

Test	Coefficients	
	Model 1	Model 2
Perfect Match – Lost Match	0,117 – 0,071 = **0,046**	0,067 – 0,076 = **-0,009**
Not Perfect Match – New Match	0,081 – 0,115 = **-0,034**	0,035 – 0,009 = **0,026**
Perfect Match – Not Perfect Match	0,117 – 0,081 = **0,036**	0,067 – 0,035 = **0,032**

* $p < 0{,}10$, ** $p < 0{,}05$, *** $p < 0{,}01$

As such, in Table 27, for Model 1, those who were perfectly matched in the first surveys and lost their match in the follow up survey, had their hourly earnings decrease by 4,7%, when compared to those who maintained their matched status. Those who were permanently mismatched in the first surveys and became newly matched in the follow up survey, when compared to those who remained permanently mismatched, had their hourly earnings grow by 3,5%. Somewhat different results appear for differences in Model 2. However, none of the results has statistical significance.

By looking, in Table 28, at the fixed effects coefficients of being, or ceasing to be, in a situation of horizontal mismatch, in Model 1, we can say that being in a position of horizontal match in the two phases of the study translates into an average salary gain for an individual of about 8,2% on an hourly basis. On the other hand, the highest wage gain is recorded among those who move from a situation of mismatch in the first surveys to a correct horizontal match in the follow up survey, with a wage gain of around 19,4%. In relation to being in a position of horizontal mismatch in the two phases, or of losing the matched employment from the first to the second moments of the study, these values do not present statistical significance, although presenting positive signs.

Table 28 – Fixed effects coefficients: economic returns to horizontal mismatches.

	Model 1		Model 2	
	Coefficient	Robust SE	Coefficient	Robust SE
Intercept	1,592***	(0,038)	1,661***	(0,082)
Master's degree in both surveys	-0,011	(0,077)	-0,051	(0,085)
Doctorate degree since the first survey	0,140	(0,127)	0,094	(0,134)
Horizontal Match in both surveys	0,079***	(0,016)	0,026	(0,024)
Horizontal Mismatch in both surveys	0,052	(0,039)	0,078	(0,053)
New Matched in the follow up survey	0,177**	(0,084)	0,406***	(0,088)
Lost Match in the follow up survey	0,012	(0,062)	-0,022	(0,065)
Micro Enterprise			-0,023	(0,044)
Medium Enterprise			0,092***	(0,034)
Large Enterprise			0,087**	(0,038)
Seniority in current job			0,000	(0,000)
Full-time job			-0,157**	(0,064)
Permanent Staff			0,055*	(0,030)
Lisbon Metro Area			0,177***	(0,056)
N	2542		1945	
R^2	0,053		0,189	
ID	1875		1550	

* p < 0,10, ** p < 0,05, *** p < 0,01

By adding the control variables to the estimation, in Model 2, we can conclude that the effect of being in a match situation in the two moments of the study, the first and follow up surveys, is lost, while the effect of matching in the second moment of the study is reinforced, pointing to a salary increase in the order of 50%. The loss of significance of horizontal match variable may be associated, as in Table 26, with the gain in significance of the new variables related to the labour market. Thus, it is noted that the transition to employment in a Medium or Large Enterprise generates a positive impact on the salaries of individuals greater than 9%, as well as maintaining the positive effects of being effective in a job, and working in the Metropolitan Area of Lisbon, with this last one almost reaching 20% of salary premium. On the other hand, going for a full-time job seems to have a negative impact on wages.

Table 29 – Difference in fixed effects coefficients (Horizontal).

Test	Coefficients	
	Model 1	Model 2
Horizontal Match – Lost Match	0,079 – 0,012 = **0,067**	0,026 + 0,022 = **0,048**
Horizontal Mismatch – New Match	0,052 – 0,177 = **-0,125**	0,078 – 0,406 = **-0,328*****
Horizontal Match – Horizontal Mismatch	0,079 – 0,052 = **0,027**	0,026 – 0,078 = **-0,052**

* $p < 0,10$, ** $p < 0,05$, *** $p < 0,01$

The results of the tests presented in Table 29 show that moving from mismatch to match has a positive and significant effect on an individual's salary. In turn, the only statistically significant result appears in Model 2, where those who became horizontally matched in the follow up survey, from a horizontal mismatch position in the first one, when compared to those were horizontally mismatched in both surveys, experienced a wage growth of around 28,0%, demonstrating the highly positive effect of becoming matched and its compensation on earnings.

6. Conclusion

The initial motivation for this dissertation was to analyse the existence and effects of the persistence, over two questionnaire waves (an initial and a follow up survey of the same individuals), of situations of mismatches in employment associated with the transition of graduates from Higher Education Institutions into the labour market. In a national context of rapid growth in the number of Higher Education graduates, their entry into a labour market marked by an older and less qualified generation, as well as a growing, and positive, massification of Higher Education in the younger generations, combined with the existence of a rigid labour market, may contribute to the creation of situations of education-job mismatches. These may be difficult to quantify correctly for a researcher but, above all, they can be difficult to overcome for those living with them, creating situations of permanence in these states that may have negative effects on the careers and earnings of these individuals.

Taking into account the novelty and the richness of the dataset available for this study, we tried to contribute to the existing literature on overskilling and education-job mismatches through an analysis of the transition to the labour market of recent graduates of the University of Aveiro. The existence of a university level dataset brought advantages to our analysis, namely by allowing a more homogeneous sample when compared to other studies carried out on this subject. Issues related to the quality of the institution, the academic degrees conferred and the quality of the courses of the individuals in the sample also ended up being more controlled given the nature of the data collected. On the other hand, there is more heterogeneity on the side of the labour market, taking into account the existing differences in the sectors of activity, the size of companies and their location. The employment destination of the graduate sample considered in this study is, however, sufficiently diverse to allow for the study of these mismatch dynamics.

We have tried to focus our analysis on four variables to measure the phenomena of overskilling and education-job mismatches: one relative to the suitability of the skills acquired in Higher Education for professional performance, measuring the match between individual skills and required competences; one relative to the demand/exigence of professional responsibilities, measured in relation to the level of skills acquired in Higher Education; one relative to the permanence in a state of a “perfect match” between the individuals’ skills and competences required in the job; and one relative to the permanence in a state of horizontal mismatch.

Looking first at the determinants of being in a situation of match or mismatch, we can observe in most of the estimates, both for the first surveys and for the follow up survey, that there is a very strong and simple gender effect in all of them, where being a woman is always negatively related to the probability of being in a situation of match, be it related to the skills of individuals, to the specificities of the labour market side, or whether one is in a horizontal or vertical match. This is a cross-cutting and statistically significant effect that appears in most results. Another transversal result is the impact of the final graduation average as a determinant of having the right skills for professional performance and as a determinant of being horizontally matched. In this sense, the more the final graduation average of a Higher Education graduate is in the first (higher) quartiles of the distribution, the more likely it is to be in a position of adequate skills for professional performance or not to be horizontally mismatched, with high levels of significance.

Regarding the determinants of being in a perfect match situation, having a Master's degree proves to be a very positive predictor of being in that situation, and this value is further reinforced three years later in the follow-up survey. This factor, also associated with strong area effects – being graduated in the first survey from the field of study of Arts and Humanities works as a negative predictor of being perfectly matched (losing significance in the follow-up survey) and, in the second survey, being graduated from the fields of study of Engineering and Mathematics, Technology, and Education has a very positive effect in the way of being perfectly matched, compared to graduates in the area of Sciences – they also explain to what extent these skills can facilitate access to better positions in the labour market.

The main conclusion of this dissertation can be that the pursuit of studies for the second cycle of Higher Education is important, as it leads more quickly to jobs for which individuals are perfectly matched. From the point of view of wage returns, obtaining a Master's degree is extremely important, since it offers its holders the highest hourly wage premiums, which can be, in the first surveys, between 11,7 to 21,7% higher than those earned by Bachelor's degree graduates, depending on the models under analysis and, in the follow up survey, that can be 6,9 to 20% higher than Bachelor's degree graduates. As such, there is a strong Master's degree effect and pursuing it leads to better hourly wages, independently of being matched or mismatched (although mismatched Master's degree holders earn considerably less than matched Master's degree holders), although these effects tend to decrease in the follow up survey. For those who are horizontally matched, the wage premium of having a Master's degree can be greater than 40%, when compared those who only have a Bachelor's degree.

The existence of a Master's degree is also very important when interacting with the mismatch variables and for the effects that these interactions have in terms of wage returns, even in comparison with Bachelor's degree graduates. Compared to a good match situation, a Master's degree graduate that has inadequate skills for job performance has an hourly earnings penalty inferior to those of a Bachelor's degree. Both earnings penalties are still present three years later, but with smaller values, possibly showing some signs of convergence through time. However, when looking from the perspective of the exigence of the job performance, one can see that those interaction effects only appear in the follow up survey and are greater for those who are Bachelor's degree graduated with not demanding performances, as at the same time those in the same situation but with a Master's degree only have a wage penalty around -5,9%.

A Master's degree graduate that is in a horizontal mismatch situation leads to a high wage penalty at the beginning of the career. However, for the same situation, the follow up survey shows that this penalty becomes smaller showing signs of a wage convergence with the passage of time for those with a horizontal mismatch, although timid. This result can possibly mean that horizontal mismatches tend to be attenuated over time. On the other hand, it should be noted that a Master's degree graduate who is not in a "perfect match" situation, vis-à-vis a perfectly matched one, only shows wage penalties in the follow up survey. Even so, it should be pointed out that the wage penalties incurred as a result of a Master's degree graduate not being in a situation of a "perfect match" are in any case lower than the wage penalties associated with a Bachelor's degree graduate being it in a vertical or horizontal mismatch situation, thus verifying the importance of the existence of a Master's degree, even if one enters the labour market in a more negative situation.

An effect that cuts across all estimates and almost all models is related to the gender effect of individuals. As previously seen in the determinants of being in a position of match, or mismatch, being a woman served as a significant negative predictor of being perfectly matched at all levels. This negative effect of being a woman also affects wage returns, with women, in the first surveys, earning between -6,3 to -8,2% less than their male counterparts in terms of hourly wages. This negative effect is reinforced three years later in the follow-up survey, with the wage gap widening significantly to -12,8 to -14,9% compared to men, widening the gender pay gap.

Another cross-sectional effect on all estimates and models in analysis relates to the final graduation average. In subchapter 5.1., belonging to the first quartiles of the distribution of final graduation averages has proved to be an important predictor of a good match. In fact, in relation to hourly wage returns, this variable also shows a positive wage effect, *i.e.*, the better an individual's final graduation average is placed in the quartile distribution, this is transmitted in a significant wage premium in the initial surveys. However, as expected, this sign loses value and statistical significance in the follow-up survey. As individuals gain more experience in the labour market, the effect of the final graduation average decreases, losing statistical significance, as this variable ends up working as a transition and signalling effect of workers leaving university and entering the labour market, serving as a way of solving asymmetric information problems by firms.

Another cross-sectional effect on the personal characteristics of individuals, as might be expected, is related to the age factor, that is, as individuals age, this is associated with a positive, albeit small, wage premium, which may be associated with factors such as career consolidation or being already in the labour market when leaving university.

In relation to the effects of the characteristics of employers and jobs and their impact on the hourly wage returns of workers, a wage premium effect can be observed associated with the fact that an employee is working in a Medium or Large Enterprise relative to working in a Small Enterprise. These positive wage premium effects remain in the follow-up survey although, in some situations, their values decrease and even lose some statistical significance. Even so, these losses may be justified by the gain in statistical significance of the variables relating to being a member of the permanent staff and working in the Lisbon Metropolitan Area, revealing that for the labour market of influence of this university, there seems to be rigid demand effects that are important, namely access to career progression in larger firms and being geographically located close to the decision-making centres of the country.

It should also be noted that there are field of study effects on the estimates of hourly wage returns of individuals in both surveys for the variables under analysis. In this sense and taking the field of study of Sciences as the base category, it is possible to note consistently, and in the results of the first surveys, a wage penalty of those who graduated in the field of studies of Engineering and Mathematics of around -7%, a penalty which is slightly mitigated in the follow-up survey. In the follow-up survey, three years after the first data collection, strong effects from the fields of study of those who graduated in Social Sciences and Education also emerged, with penalties against graduates in the fields of Sciences of the order of -12,1% of the hourly wage returns. With regard to the remaining fields of study, these did not achieve statistically significant results.

The results obtained through this dissertation thus confirm the economic literature regarding the effects of being in a labour mismatch situation. Thus, individuals who are mismatched relative to both their skills and jobs are shown to suffer high and statistically significant wage penalties. These wage penalties, although attenuated in some cases, persist over time, underpinning the theory of education-job mismatches as a "trap".

By using a first-differences model to account for unobserved heterogeneity in subchapter 5.3., we confirm that there is a wage penalty associated with not being in a situation of adequate match, taking into account that, although there is wage growth for those who are not in a perfect matching situation, hourly earnings growth is lower than for those who are perfectly matched. Our results also showed that there is a premium in terms of wages for those who are no longer in a situation of mismatch from one moment to the next, and a penalty in terms of lower wage growth for those who lose their perfectly matched status.

Results for horizontally mismatched individuals show that graduates who are initially at a disadvantage experience relative wage growth if they find a job for which they are matched. Individuals who remain mismatched in both periods do not close the wage gap between them and those who are adequately skilled. Thus, the results suggest that upward wage mobility is a reality for some graduates who are initially mismatched.

As a final conclusion, and also taking into account the fact that certain fields of study are positively related to the probability of being in a situation of overskilling, or in another situation of mismatch, it becomes necessary for public decision-makers to create career guidance mechanisms for university students while they are still in Higher Education Institutions, as well as to encourage the continuation of studies for those who finish the 1st cycle of Higher Education. In addition, for those already in the labour market, it is also suggested the encouragement of vocational training activities in order to increase workers' skills and abilities and thus lead to the reduction of mismatches.

Several limitations of this dissertation have already been mentioned throughout the text. However, it is worth highlighting that only individuals who were active at each given moment in the labour market were analysed. This led us to necessarily focus on specific employment to employment transitions that result in a relatively small sample and exclude those who were not in the labour force at any given time from our analyses. This may have influenced the significance of some results. The available data also did not allow us to create an exact measure of the potential experience of each individual. The use of self-reported data can equally lead to measurement errors, since the criteria used are subjective and voluntary, and workers can exaggerate their views on their skills.

Finally, additional analysis on the interaction between gender and overskilling and between overskilling and the fields of study may be worthwhile to study further, as would a wider socio-economic study of the impacts on the careers and lives of recent graduates of being in an initial position of mismatch in the labour market.

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Appendices

Table 30 – Focus variables description.

Variable	Description	Measurement
Horizontal	Dummy: There is a horizontal mismatch	1 = horizontal mismatch 0 = otherwise
Skills_Adq	Dummy: The skills learnt in Higher Education are adequate for job performance	1 = adequate skills 0 = otherwise
Perform_Dem	Dummy: There is a demanding job performance in relation to skills learnt	1 = demanding performance 0 = otherwise
pmatch	Dummy: There is a perfect match among skills and performance demand	1 = perfect match 0 = otherwise
us	Dummy: The individual is underskilled (inadequate skills, demanding performance)	1 = underskilled worker 0 = otherwise
os	Dummy: The individual is overskilled (adequate skills, not demanding performance)	1 = overskilled worker 0 = otherwise
mismatch	Dummy: There is a perfect mismatch among skills and performance demand	1 = perfect mismatch 0 = otherwise

Table 31 – Field of study description.

Field of study	Description
Sciences	Physics; Chemistry; Biology; Geology; Biochemistry; Health; Meteorology; Oceanography; Marine Sciences; Biomedicine; Nursing; Radiology; Physiotherapy; Speech Therapy; Gerontology; Biomedical Materials and Devices
Engineering and Mathematics	(Physics, Chemistry, Civil, Geological, Materials, Environmental, Computer and Telematics, Mechanical, Electrotechnical, Industrial Automation, Ceramics and Glass) Engineering; Industrial Engineering and Management; Mathematics and Applications
Technology	ICT; Multimedia; New Communication Technologies; Product Design
Business	Accounting; Finance; Tourism; Commerce; Public Administration; Marketing; Management; Business Relations; Public and Local Management
Social Sciences	Economics; Psychology; Political Science; Judicial Clerk; Documentation
Education	Basic Education; Education
Arts and Humanities	Design; Music; Translation; Languages; Publishing