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Vertical, horizontal and skill mismatch: effects on wages and job satisfaction among University of Porto graduates

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M

2026

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UNIVERSIDADE DO PORTO

VERTICAL, HORIZONTAL AND SKILL MISMATCH: EFFECTS ON WAGES AND JOB SATISFACTION AMONG UNIVERSITY OF PORTO GRADUATES

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2025/2026

Acknowledgements

Reaching the end of this journey represents more than completing a dissertation. It also reflects the people and experiences that have contributed to my personal and academic growth. I would like to express my sincere gratitude to FEP and to all the lecturers who have been part of this journey, for the knowledge they shared and for the challenges that encouraged me to step outside my comfort zone and grow.

To my supervisors, Professor Ricardo Biscaia and Professor Anabela Carneiro, I would like to express my very special thanks for their guidance, availability and support throughout this process. During moments of greater doubt and uncertainty, I always found openness to discuss questions, reconsider choices and move forward with greater confidence. I am also grateful for their attention, responsiveness and contribution to the development of this dissertation, which were essential in bringing this work to completion.

To my family, and especially to my parents, Elsa and Fernando, I am deeply grateful for giving me every opportunity and support I needed to pursue my studies, but above all for believing in me at times when I found it difficult to believe in myself. To my sister Mara, for showing me what it means to fight for our dreams, and to my brother José Fernando, for inspiring my curiosity, my desire to keep learning and my ambition to always strive for more.

To my boyfriend, António, who has been with me since the very beginning of this journey, thank you for sharing not only the achievements, but also the doubts, fears and most difficult moments. It has now been nine years of growing side by side, going through different stages of our lives and supporting each other through every one of them. Having you with me throughout this journey made this stage even more special.

To my grandfather Manuel, for all the affection and presence throughout these years. To my grandparents Sofia, Albino and Augusta, who are no longer with us, I like to believe that they accompanied me throughout this journey and were cheering me on at every stage.

Finally, to my friends, thank you for all the conversations, shared moments and times of relaxation that made this journey lighter. Being able to share the doubts, difficulties and good moments with you made everything even more special.

Abstract:

The expansion of higher education and the growing heterogeneity of graduate employment raise questions about the match between graduates' education, skills and job requirements. This dissertation examines vertical mismatch, horizontal mismatch and skill mismatch among University of Porto graduates and their associations with wages and job satisfaction. The analysis uses the 2024 and 2025 waves of the University of Porto Graduate Survey, combining 1,211 graduates observed approximately two years after completing their degree. Vertical mismatch compares attained and required education, horizontal mismatch captures the alignment between field of study and employment, and skill mismatch measures the number of skills in underskilling and overskilling across 12 competencies. Wage associations are estimated using OLS within a Mincerian wage-equation framework, while job satisfaction is analysed using ordered probit models. In the joint wage model, undereducation is associated with hourly wages around 12.4% higher than those of adequately matched graduates, while a one-unit increase in horizontal mismatch is associated with approximately 2.8% lower wages. Each additional skill in underskilling and overskilling is associated with reductions of around 1.3% and 1.0%, respectively. For job satisfaction, a one-unit increase in horizontal mismatch is associated with a 6.8 percentage-point lower probability of reporting being very satisfied, while each additional skill in underskilling and overskilling is associated with reductions of around 2.5 and 3.6 percentage points. Overeducation loses statistical significance in the joint specifications for both outcomes. Robustness checks show that horizontal and skill mismatch results remain broadly stable, whereas vertical mismatch is more sensitive to measurement. The findings highlight the importance of considering multiple dimensions of mismatch when assessing graduates' labour market integration.

JEL codes: J24; J28; J31

Keywords: Labour market mismatch; Vertical mismatch; Horizontal mismatch; Skill mismatch; Wages; Job satisfaction; Higher education graduates

Resumo:

A expansão do ensino superior levanta questões sobre a correspondência entre a formação dos diplomados e as exigências dos postos de trabalho. Esta dissertação analisa o desajustamento vertical, horizontal e de competências entre diplomados da Universidade do Porto e a sua associação com os salários e a satisfação no emprego. A análise utiliza as edições de 2024 e 2025 do Inquérito aos Diplomados da Universidade do Porto, reunindo 1.211 diplomados observados aproximadamente dois anos após a conclusão do grau. O desajustamento vertical compara a educação adquirida com a requerida, o horizontal capta a correspondência entre área de formação e emprego, e o de competências mede competências em *underskilling* e *overskilling*. As associações com os salários são estimadas por OLS, com base na equação salarial de Mincer, enquanto a satisfação no emprego é analisada através de modelos *ordered probit*. No modelo salarial conjunto, a *undereducation* está associada a salários horários cerca de 12,4% superiores, enquanto um aumento de uma unidade no desajustamento horizontal está associado a salários aproximadamente 2,8% inferiores. Cada competência adicional em *underskilling* e *overskilling* está associada a reduções de cerca de 1,3% e 1,0%, respetivamente. Na satisfação no emprego, um aumento de uma unidade no desajustamento horizontal está associado a uma redução de 6,8 pontos percentuais na probabilidade de declarar estar muito satisfeito, enquanto cada competência adicional em *underskilling* e *overskilling* está associada a reduções de 2,5 e 3,6 pontos percentuais. A *overeducation* perde significância estatística nas especificações conjuntas para ambos os resultados. Os testes de robustez mostram maior estabilidade nos resultados do desajustamento horizontal e de competências, enquanto o vertical é mais sensível à forma como é medido. Os resultados reforçam a importância de considerar múltiplas dimensões de desajustamento na integração dos diplomados no mercado de trabalho.

Códigos JEL: J24; J28; J31

Palavras-chave: Desajustamento no mercado de trabalho; Desajustamento vertical; Desajustamento horizontal; Desajustamento de competências; Salários; Satisfação no emprego; Diplomados do ensino superior

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1. Introduction

Education constitutes an important investment in human capital, as the knowledge and skills acquired through education may enhance individuals' productivity and subsequent labour market outcomes (Becker, 1993). This relationship also occupies a central place in the Mincerian tradition, which links schooling to individual earnings (Mincer, 1974), while the positive relationship between education and wages is widely documented in the empirical literature (Card, 1999). More recent evidence indicates that individuals with higher educational attainment tend to experience higher earnings and more favourable employment prospects (OECD, 2025). In Portugal, the growth of higher education has coincided with a substantial increase in the number of graduates entering the labour market and greater heterogeneity in the jobs they hold (Figueiredo et al., 2017).

However, the benefits associated with education also depend on how graduates' qualifications and skills are matched to employment. Labour market mismatch may arise when a job does not correspond to a graduate's level of education, field of study or skills. Analysing this phenomenon therefore helps to assess how closely graduates' educational backgrounds and skills align with the requirements of the jobs they perform (McGuinness, 2006; Desjardins & Rubenson, 2011).

Previous empirical evidence suggests that the different forms of labour market mismatch may be associated with labour market outcomes in distinct ways. Regarding wages, overeducation has frequently been associated with lower earnings relative to adequately matched workers, although the magnitude of this association may be sensitive to unobserved worker and firm heterogeneity (McGuinness, 2006; Araújo & Carneiro, 2023). Horizontal mismatch has also been associated with wage penalties, particularly when there is a weak correspondence between field of study and occupation (Robst, 2007; Nordin et al., 2010). Evidence on skill mismatch likewise indicates that an inadequate use of workers' skills may be associated with lower earnings (Allen & van der Velden, 2001; Inácio, 2023).

The consequences associated with mismatch extend beyond wages. Job satisfaction provides an additional dimension of graduates' professional experience and may be particularly related to the effective use of their skills at work. Evidence from Allen and van der Velden (2001) suggests that skill mismatch, particularly the underutilisation of skills, has a stronger association with job satisfaction than educational mismatch. McGuinness and

Sloane (2011) also report lower job satisfaction among overskilled graduates when different dimensions of mismatch are considered simultaneously, as well as greater satisfaction when employment is more closely aligned with the graduate's field of study. Considering both wages and job satisfaction therefore provides a broader picture of how different forms of mismatch are associated with graduates' labour market experiences.

Studying graduates from the University of Porto provides a particularly relevant setting for this analysis. University of Porto is among the Portuguese institutions best positioned in major international university rankings (University of Porto, n.d.). It is therefore relevant to examine whether different forms of labour market mismatch are also present among graduates from an institution with a high level of academic recognition and how these situations are associated with their outcomes at the beginning of their careers. Identifying mismatch in this context makes it possible to assess whether the correspondence between education and employment remains a relevant issue even among graduates from a particularly highly regarded university environment, without implying that the patterns observed can be directly generalised to Portuguese graduates as a whole.

Within this framework, the present dissertation analyses vertical mismatch, horizontal mismatch and skill mismatch among University of Porto graduates approximately two years after completing their degree. The analysis first characterises the incidence of the different forms of mismatch. Subsequently, it examines their association with wages and job satisfaction, considering not only each dimension separately but also how the results change when the different forms of mismatch are included simultaneously. Accordingly, the dissertation addresses two central research questions: how vertical mismatch, horizontal mismatch and skill mismatch are associated with the real hourly wages of University of Porto graduates approximately two years after graduation, and how these three dimensions of mismatch are associated with their job satisfaction over the same post-graduation stage.

The empirical analysis uses two consecutive waves of the University of Porto Graduate Survey. The 2024 wave covers graduates from the 2021/2022 academic year, while the 2025 wave covers graduates from 2022/2023, with both groups observed approximately two years after completing their degree. Despite some adaptations between the questionnaires, the two waves have a broadly similar structure and contain common or harmonisable information on academic characteristics, employment, wages, job satisfaction,

and the correspondence between education, skills, and work. The final analytical sample, combining the two waves, consists of 1,211 graduates.

Vertical mismatch is identified by comparing the graduate's attained level of education with the level normally required to perform the job. Horizontal mismatch is measured through the degree of correspondence between the graduate's field of study and the job performed. Skill mismatch, in turn, is measured by comparing, across 12 skills, the levels possessed by graduates with the levels required in their respective jobs, with separate measures constructed for the number of skills in underskilling and overskilling. The association between mismatch and wages is estimated using OLS within a Mincerian wage-equation framework, with the logarithm of real hourly wages as the dependent variable, while job satisfaction is analysed using ordered probit models. The specifications control for demographic, academic and employment-related characteristics and are complemented by several robustness checks.

This study is relevant for analysing different dimensions of labour market mismatch among University of Porto graduates, providing recent evidence on a specific group of graduates observed at a comparable stage of their transition into the labour market. The analysis further contributes to understanding how educational level, field of study and skills are related to wages and job satisfaction, by considering these different dimensions of mismatch within a common empirical framework. In doing so, the study may also contribute, at the institutional level, to a better understanding of graduates' labour market integration and of the correspondence between the education acquired and the requirements of the jobs they perform.

The remainder of the dissertation is structured as follows. Chapter 2 reviews the main theoretical perspectives on labour market mismatch and the empirical evidence concerning vertical, horizontal and skill mismatch and their relationships with wages and job satisfaction. Chapter 3 introduces the data, explains the construction of the mismatch measures and presents the econometric approach. Chapter 4 reports and interprets the empirical results in light of the existing literature. Chapter 5 concludes by summarising the main findings, discussing the study's limitations and identifying directions for future research.

2. Literature review

2.1. Theoretical approaches to mismatch in the labour market

Labour market mismatch is frequently understood as the result of frictions in the process of matching workers' characteristics with job requirements. Search costs, mobility constraints and slow adjustments between the supply of qualifications and the demand for skilled labour help to explain why, particularly at the beginning of their working lives, individuals may accept jobs that do not fully correspond to their profiles and why such situations may persist for some time (Araújo & Carneiro, 2023). In a context in which these frictions were of limited importance, a more efficient match between qualifications and jobs would be expected, with wage returns more closely aligned with productivity. These frictions may therefore limit the extent to which human capital is rewarded in the job actually held. A classic starting point for framing the relationship between education, productivity, and remuneration is Human Capital Theory (Becker, 1993).

Becker (1993) argues that education and training can be understood as investments in human capital, since they involve present costs in return for expected gains in future productivity. Within this framework, the accumulation of human capital translates into greater skills and productive capabilities, which are reflected in higher real earnings over the life cycle (Becker, 1993). The Mincerian approach reinforces this perspective by relating educational attainment and experience to individual wages, constituting one of the most influential empirical foundations for estimating the returns to education (Mincer, 1974). The empirical literature has generally found a positive association between educational attainment and wages, although the magnitude of these returns varies across countries, groups of workers and institutional contexts (Psacharopoulos, 1994; Card, 1999; Oreopoulos, 2006).

From the perspective of Human Capital Theory, the relationship between education, productivity and remuneration follows a relatively linear logic, insofar as higher levels of education increase individuals' productivity and, through this channel, their wages. This perspective suggests that, in an efficient labour market, workers would tend to be matched to jobs that closely correspond to their qualifications and skills. Mismatch would therefore arise, at most, as a temporary phenomenon that could be corrected in the long run (Desjardins & Rubenson, 2011).

Nevertheless, in situations of mismatch, the job may not allow the accumulated human capital to be fully utilised, potentially resulting in wages below those expected given the worker's level of education or qualifications. This outcome contrasts with the prediction that education should result in its full productive use and in corresponding levels of remuneration (McGuinness, 2006; Desjardins & Rubenson, 2011). This limitation justifies the consideration of other theoretical perspectives capable of explaining the different forms of mismatch.

Unlike Human Capital Theory, Signalling Theory emphasises that educational credentials may influence recruitment and remuneration not only because of their potential productive content, but also because they convey information to employers in a context of information asymmetry (Spence, 1973; Dobbs et al., 2008). Since employers cannot observe the productive quality of candidates ex ante, they use educational attainment as an indirect indicator of characteristics that are difficult to observe at the time of recruitment (Spence, 1973). An academic degree therefore acts as a signal that may improve a candidate's position in the recruitment process by conveying information about characteristics that employers cannot directly observe when making hiring decisions (Spence, 1973; Dobbs et al., 2008).

Within this framework, mismatch may emerge in a context in which education operates as a signal in a market characterised by information asymmetry. When educational credentials influence employers' expectations regarding productivity and affect recruitment and remuneration decisions, individuals have incentives to invest in further education in order to improve their relative position in the labour market, even when that investment does not correspond to the effective requirements of the job (Spence, 1973). As the average level of education among candidates increases, firms may respond by raising formal entry requirements without making proportional changes to the content of the jobs, thereby generating qualification inflation and, consequently, mismatches between the level of education attained and that required, without necessarily implying a mismatch in skills (Quintini, 2011). This theory is therefore particularly useful for explaining situations of overeducation. Nevertheless, overeducation may coexist with overskilling, particularly when additional education also corresponds to a genuine increase in skills that are not fully utilised in the job (Desjardins & Rubenson, 2011). While Signalling Theory emphasises education as a source of information about the candidate, Job Competition Theory shifts the focus towards the job and the process through which candidates are allocated to vacancies.

Job Competition Theory offers an alternative explanation for mismatch by locating the determination of wages primarily within the job itself. According to this theory, remuneration mainly reflects the characteristics and requirements of the job, while education plays an essentially allocative role in the recruitment process (Thurow, 1975; Quintini, 2011). From this perspective, employers use educational attainment as a practical criterion for ranking candidates, since it is interpreted as an indicator of lower training costs and a greater capacity to adapt to the job (Thurow, 1975). As the proportion of highly educated candidates increases, the incentives to accumulate credentials in order to preserve one's relative position in the hiring queue become stronger, even when the tasks associated with the job do not require that level of education (Thurow, 1975; Desjardins & Rubenson, 2011). This mechanism has been associated with credentialism, understood as the use of education as an instrument for rationing and selecting access to employment opportunities (Berg, 1970; Quintini, 2011).

As with Signalling Theory, this perspective helps explain overeducation, since educational attainment may rank candidates even when schooling does not closely match the job's actual requirements. The framework may also help explain horizontal mismatch when vacancies cannot be filled by candidates from the most closely related fields of study, or when field-specific education carries less weight in recruitment (Montt, 2017). Since remuneration is primarily linked to the characteristics of the job, additional education beyond job requirements is expected to generate little or no additional wage return (McGuinness, 2006; Quintini, 2011). However, the theory also allows for the possibility that undereducated and underskilled workers may, in some cases, obtain more demanding jobs and earn more than would be expected on the basis of their formal profiles (Desjardins & Rubenson, 2011).

Assignment Theory provides a complementary perspective by emphasising that wages reflect the interaction between worker and job characteristics. The central element of this theory concerns the way in which individual capabilities and the technical requirements of jobs are combined, meaning that a worker's productive contribution depends on the job to which that worker is assigned (Sattinger, 1993). From this perspective, the fundamental economic problem consists of matching workers with different productive characteristics to jobs that vary in complexity. When this matching process is inefficient, efficiency losses may arise, since earnings are jointly shaped by workers' characteristics and the characteristics of

the jobs they occupy. The return to education may therefore differ depending on whether the job requires more or less education than that held by the worker (Sattinger, 1993).

This theory is particularly relevant for understanding skill mismatch, since it focuses on the extent to which workers' skills align with what their jobs actually require (Desjardins & Rubenson, 2011). At the same time, it also provides a useful framework for analysing forms of educational mismatch, as it recognises that the wage returns to education vary according to the worker-job match and the specific requirements of the role (Sattinger, 1993; McGuinness, 2006). This reasoning may also be extended to horizontal mismatch, since the alignment between field of study and occupation reflects both employers' demand for particular skills and the availability of workers trained in the relevant field. When this correspondence fails, wage penalties may arise because of the limited use of field-specific skills or the costs associated with adapting to roles in a different field (Montt, 2017). In addition to its effects on wages, this limited use of productive potential is frequently identified as one of the main causes of job dissatisfaction, since workers may feel unable to apply the skills they have acquired (Allen & van der Velden, 2001).

In contrast to the previous theories, which tend to examine mismatch as a static inefficiency or an allocation failure, Career Mobility Theory introduces a crucial temporal dimension into the understanding of this phenomenon. According to Sicherman and Galor (1990), overeducation, particularly when observed at the beginning of a career, does not necessarily represent a structural labour market problem, but may instead constitute a transitional and strategic stage of an individual's working life. Within this model, individuals may voluntarily accept jobs for which they possess more education than required when those jobs offer opportunities for future career progression. Additional education therefore functions as an investment that facilitates subsequent promotions and the accumulation of relevant experience for occupational advancement (Sicherman & Galor, 1990).

In this respect, the theory helps to explain the incidence of overeducation and overskilling among young workers, since some of these mismatches may reflect transitional stages in their professional trajectories rather than permanent labour market failures (Desjardins & Rubenson, 2011). When this interpretation holds, overeducation tends to be corrected over the life cycle as workers acquire experience, obtain more information about the labour market and move into jobs that are better suited to their profiles (Desjardins & Rubenson, 2011). The rationality of this process is reinforced by the idea that, when the

expected progression does not materialise, workers tend to leave the organisation voluntarily and seek opportunities elsewhere that are more compatible with their occupational trajectories (Sicherman & Galor, 1990).

The theoretical approaches discussed above become particularly relevant when considering the growth of higher education. In Portugal, Figueiredo et al. (2017) examined the consequences of the rapid growth of higher education for young graduates' transition into the labour market and showed that, between 2000 and 2010, the growing number of graduates coincided with greater diversity in the types of jobs they entered. In particular, the authors distinguish between traditional graduate occupations, new graduate occupations and latent graduate occupations, demonstrating that these groups differ in terms of the skills required, how fully graduates are able to use their knowledge and skills at work, and the incidence of overeducation, overskilling and education-job mismatch. The expansion of higher education should therefore not be interpreted as an automatic cause of mismatch, but rather as a context in which the growing supply of graduates and the increasing heterogeneity of jobs make their integration into the labour market more complex (Figueiredo et al., 2017). An increase in the supply of graduates may intensify competition for skilled jobs (Thurow, 1975; Desjardins & Rubenson, 2011), reinforce the use of educational credentials in recruitment processes (Spence, 1973; Quintini, 2011), and increase the importance of matching workers' characteristics with job requirements (Sattinger, 1993; Figueiredo et al., 2017).

2.2. Understanding the different dimensions of labour market mismatch

A common distinction in the literature is between educational mismatch and skill mismatch. Early research focused primarily on indicators based on education and qualifications. However, skill mismatch gained increasing prominence as education came to be recognised as an imperfect proxy for the skills relevant to the job (Sgobbi & Suleman, 2013; McGuinness et al., 2018).

According to Somers et al. (2019), educational mismatch refers to a discrepancy between an individual's educational attainment and the requirements of the job. This discrepancy may concern either the level of education or the field of study relevant to the job. Pimenta and Pereira (2019) frame the concept of educational mismatch by distinguishing between a macro and a micro perspective. While the macro-level perspective focuses on imbalances between labour supply and job vacancies, the micro-level approach considers

how workers' education corresponds to the educational demands of their jobs. Within this micro perspective, the literature usually distinguishes between vertical mismatch, expressed through overeducation and undereducation, and horizontal mismatch.

The debate on overeducation was brought to the forefront by Freeman (1976), whose work highlighted the emerging gap between rising educational attainment and the structure of available jobs. Since then, academic interest in overeducation has grown substantially, particularly from the late 1980s onwards, and the literature has evolved into a broad set of conceptual and empirical approaches (McGuinness, 2006).

McGuinness (2006) defines overeducation as a situation in which a worker possesses a higher level of education than that required by the job, whereas undereducation refers to the opposite case, in which the worker's level of education is below that required. Sánchez-Sánchez and McGuinness (2015) describe overeducation and undereducation as forms of vertical mismatch that focus specifically on the worker's educational level relative to job requirements. Cedefop (2024) adds that this form of mismatch may be conceptualised in terms of education measured by years of education or training. In this context, overeducation describes situations in which individuals with more education occupy jobs in which that level of education is not required (Mavromaras et al., 2010).

The terminology used to describe this form of mismatch is not always consistent. Desjardins and Rubenson (2011) use education mismatch and qualification mismatch in closely related ways, presenting overeducation and undereducation as equivalent to overqualification and underqualification. Montt (2017), for example, measures overqualification by assessing whether workers' educational attainment exceeds the level regarded as appropriate for their job. In institutional sources, however, qualification mismatch is sometimes used in a broader sense, referring to situations in which workers possess qualifications that differ from those required by their jobs. Within this broader definition, being overqualified means holding a qualification above the level required (Cedefop, 2024; ILO, 2014). Cedefop (2024) reinforces this broader interpretation by noting that qualifications may extend beyond the level of education and may also be understood in terms of the type of qualification, including components such as work experience. Accordingly, under broader approaches, vertical mismatch is associated not only with overeducation and undereducation, but also with overqualification and underqualification (Desjardins & Rubenson, 2011; Cedefop, 2024).

The match between education and employment is not, however, determined solely by the quantity of schooling. It may also involve the correspondence between the individual's field of education and that required by the job (McGuinness et al., 2018; Pimenta & Pereira, 2019; Somers et al., 2019). Indeed, an individual's level of education may correspond to that required by the occupation, while the field of the job remains unrelated to the individual's field of education (Sloane, 2003). Somers et al. (2019) describe horizontal mismatch as a lack of correspondence between the individual's field of study and the field associated with the job. Robst (2007) reinforces this perspective by showing that the match depends not only on the quantity of schooling, but also on the type of schooling. The author measures mismatch using individuals' self-assessed degree of relatedness between their field of study in higher education and their current job. Montt (2017) further systematises this distinction by classifying field-of-study mismatch as horizontal mismatch because it relates to the type of education, in contrast to vertical mismatch, which concerns the level of education.

It is important, however, to distinguish between education and skills, as these are not equivalent concepts. Educational mismatch is frequently regarded as an imperfect proxy for skill mismatch, since education may provide only an approximation of the skills relevant to the job without capturing them fully. The correspondence between the two therefore tends to be only partial (Sgobbi & Suleman, 2013; European Commission, 2015; McGuinness et al., 2018). This is related to the fact that educational attainment constitutes an incomplete measure of human capital, as it summarises in a single variable potentially substantial heterogeneity in the abilities and aptitudes of individuals with the same level of education (Hartog, 2000; Verhaest & Omey, 2010). Moreover, education refers to formal qualifications held at a particular point in time and may vary in content across countries and cohorts, even for the same level of attainment, whereas skills are dynamic and may be acquired, developed or lost throughout the life cycle (Flisi et al., 2017).

Consequently, holding a degree does not guarantee mastery of the skills required for a particular job, nor does possessing a higher level of education than required necessarily imply a surplus of skills (Allen & van der Velden, 2001; Mavromaras et al., 2010). Using data from the REFLEX project covering higher education graduates, Sánchez-Sánchez and McGuinness (2015) show that overeducation and overskilling are only moderately correlated. This suggests that educational mismatch and skill mismatch capture related but distinct dimensions of the correspondence between the individual and the job.

A common micro-level definition of skill mismatch, focusing on the job, describes it as a misalignment between the skills possessed by the worker and those required by the job. This approach is consistent with methods that combine measures of individuals' skills with information on the use of those skills at work (Desjardins & Rubenson, 2011; Badillo-Amador & Vila, 2013). The concept may, however, also be used in a broader sense and at different levels of analysis. Cedefop (2024), for example, defines skill mismatch as an imbalance between the skills and qualifications possessed by the workforce and those required by the labour market. This definition is close to the macro-level perspective presented by Brunello and Wruuck (2019), which focuses on aggregate imbalances between the supply of and demand for skills. Under broader uses of the concept, the literature includes forms such as skill shortages, skill surpluses, skill gaps, skills obsolescence, overskilling and underskilling. Some taxonomies may also incorporate dimensions associated with the level and field of education (Cedefop, 2024; McGuinness et al., 2018). This conceptual diversity makes it necessary to clarify the specific dimension of mismatch examined in each study.

Brunello and Wruuck (2019) organise this heterogeneity by distinguishing between macro- and micro-level analysis. At the micro level, mismatch may take the form of overskilling or underskilling. Overskilling refers to situations in which workers possess skills above the level required by their jobs or do not fully utilise those skills, whereas underskilling describes cases in which the skills possessed are insufficient to meet job requirements. Allen and van der Velden (2001) use closely related terminology, referring to the underutilisation of skills as skill underutilisation and to insufficient skills as skill deficit. Following the same logic of comparing possessed and required skills, Berlingieri and Erdsiek (2012) identify skill surpluses and skill deficits in specific skills at the individual level. For this purpose, they compare, for each skill, the level possessed by the worker with the level required by the job.

At the macro level, Brunello and Wruuck (2019) distinguish between skill shortages and skill surpluses. Skill shortages arise when employers are unable to find workers with the necessary skills in the labour market available to them and at the prevailing wage. Skill surpluses correspond to the opposite situation, in which there are more workers possessing particular skills than there are jobs demanding them. The authors also emphasise that the existence of skill shortages does not necessarily imply skill mismatch when vacancies remain

unfilled. However, shortages may generate mismatch if firms recruit underskilled workers because of a lack of suitable candidates.

Skill gaps, in turn, refer to the extent to which workers lack the skills required to perform their current jobs and are typically identified through employers' perceptions of skill deficiencies within firms (McGuinness et al., 2017). Another relevant form is skills obsolescence, which is associated with skills becoming less useful or no longer being required in the labour market, for example because of technological or organisational change. It may also reflect the deterioration of skills resulting from a lack of use (Cedefop, 2024).

These distinctions are particularly relevant to the present dissertation, which simultaneously examines the level of education required by the job, the correspondence between the field of education and the job performed, and the match between the skills possessed and those required. Throughout this dissertation, skill mismatch refers to mismatch at the job level, distinguishing between overskilling and underskilling. Vertical mismatch is operationalised as the mismatch between the individual's level of education and that required by the job, distinguishing between overeducation and undereducation. Horizontal mismatch, in turn, refers to a lack of correspondence between the individual's field of education and the job performed.

2.3. Approaches to measuring labour market mismatches

There is no consensus on how labour market mismatch should be measured, and different methodological approaches capture distinct dimensions of the phenomenon. The measurement method chosen may influence both the estimated incidence of mismatch and the factors identified as its determinants (Verhaest & Omey, 2010; McGuinness et al., 2018).

Educational mismatch can be measured in different ways, depending on whether vertical or horizontal mismatch is being examined. In the case of vertical mismatch, which is frequently operationalised through the concepts of undereducation and overeducation, three main methods can be used: self-assessment, job analysis and realised matches (Verhaest & Omey, 2010; McGuinness et al., 2018).

In the job analysis (JA), or job evaluation method, educational requirements are established on the basis of analyses of the tasks associated with each occupation. Rather than inferring this level from the schooling observed among workers, the method relies on expert assessments indicating the typical level of schooling needed to perform the job (Leuven &

Oosterbeek, 2011; McGuinness et al., 2018). An important advantage of this approach is that job requirements are assessed independently of the worker's own perception, providing an external benchmark for the level of education required. However, it is also a demanding method in terms of data collection and updating, and the assessments may become outdated as the content and requirements of jobs evolve (Flisi et al., 2017; McGuinness et al., 2018). Moreover, despite relying on expert assessments, the definition of job requirements may still involve some degree of judgement and subjectivity (McGuinness et al., 2018).

The self-assessment method relies on workers' own perceptions of the qualification level required either to obtain the job or to perform it (McGuinness et al., 2018). This approach may take two main forms: indirect self-assessment (ISA), in which the worker indicates the minimum level of education considered necessary to obtain or perform the job, and direct self-assessment (DSA), in which individuals directly assess the fit between their level of education and the job, classifying themselves as overeducated, undereducated, or matched (Verhaest & Omey, 2010). One of the main advantages of self-assessment is that workers possess detailed information about the specific content and requirements of their own jobs, allowing the measure to incorporate job-specific information that may be difficult to observe externally. In survey-based research, it also provides information directly at the individual level, which can be related to other characteristics of the worker and the job (Leuven & Oosterbeek, 2011; McGuinness et al., 2018). Nevertheless, this approach may suffer from subjective bias and cannot be applied retrospectively when the relevant question is not included in the available dataset. Moreover, when the assessment is based on the level needed to obtain the job, it may approximate the credentials gap more closely than the level actually needed to perform it, particularly in contexts where employers raise hiring requirements due to an excess supply of workers. Similarly, bias may persist if individuals inflate the status of their job or adjust their responses to their ambitions and expectations (Verhaest & Omey, 2010; McGuinness et al., 2018).

The realised matches method, also known as the empirical method, identifies educational mismatch by comparing workers' educational attainment with the level commonly observed within the same occupation. The required level of education is inferred from the mean or modal level of education within each occupation. Workers above this reference level are considered overeducated, while those below it are considered undereducated (Leuven & Oosterbeek, 2011; McGuinness et al., 2018).

Verdugo and Verdugo (1989) operationalise the realised matches method by estimating the required educational level using the average schooling observed among workers in the same occupation and classifying as overeducated those individuals whose schooling exceeded this value by more than one standard deviation. Later, Kiker et al. (1997) proposed an alternative approach, defining the required educational level by the mode of schooling observed among workers in the same occupation.

The main advantage of this method lies in its applicability to existing microdata containing information on schooling and occupation, which facilitates analyses with large samples and cross-country comparisons (McGuinness et al., 2018). However, this approach does not incorporate direct information on the skill requirements of the job. By relying on the mean or modal credentials observed within each occupation, it tends to approximate more closely the levels of education associated with access to employment, that is, to get, than those currently needed to perform the job, that is, to do (McGuinness et al., 2018). Furthermore, due to sample size limitations, modal schooling is often calculated for broad occupational groups, which may conceal relevant differences between jobs within the same occupational category (McGuinness et al., 2018; Verhaest & Omey, 2010). Finally, because occupational averages are influenced by workers with longer tenure, the indicator may reflect historical entry requirements and generate incorrect classifications when those requirements have changed for more recent cohorts (McGuinness et al., 2018).

In simplified terms, horizontal mismatch can be measured using two main approaches. The first corresponds to a subjective measure, based on the individual's self-assessment of the degree of relationship between their current job and the field of education. The second is an objective measure constructed using correspondences between fields of study and occupational codes. Under this approach, individuals are classified as horizontally mismatched when their occupation is not considered compatible with their field of education (Somers et al., 2019).

Although these measures are relatively simple to operationalise, the correspondence between field of study and occupational codes is not always clear, since many fields of education provide skills applicable to several jobs, and the relationship between education and employment depends on the specific tasks of the job (Robst, 2007). For this reason, subjective measures may better capture the specific content of the work, although they may be subject to self-assessment bias, whereas objective measures reduce dependence on

individual perception but may be sensitive to the degree of aggregation of the tables or matching rules used (Somers et al., 2019). It is important to note that, because they are based on the correspondence between formal education and occupation, these measures mainly describe the fit between the field of education and employment and may not capture informal skills acquired after graduation, namely through professional experience and workplace training (McGuinness et al., 2017; Somers et al., 2019).

Overskilling and underskilling are typically assessed using subjective measures, which rely on workers' own assessment of how their skills compare with the requirements of their jobs (McGuinness et al., 2018). These two forms of mismatch are typically identified through separate questions. Sánchez-Sánchez and McGuinness (2015), for instance, use two global self-assessment questions to measure overskilling and underskilling separately. In addition to these overall measures, the authors examine overskilling across 19 specific skills by comparing, for each skill, the level individuals report possessing with the level required in their current job.

Compared with education-based indicators, subjective measures of overskilling can capture a wider range of mismatch by taking into account skills developed both within and outside formal education. This allows workers' abilities to be assessed in relation to the demands of their current jobs, including competencies acquired through work experience and training. However, subjective measures of overskilling and underskilling also present important limitations. Responses may be influenced by individual perceptions, workers may take into account skills that are not relevant to their current tasks, and global measures provide limited information about which particular skills are underused (McGuinness et al., 2018).

2.4. Empirical evidence: wages and job satisfaction

The empirical literature has documented the consequences of labour market mismatch for both wages and job satisfaction. However, the observed effects vary according to the dimension of mismatch considered. In particular, the evidence suggests that educational mismatch tends to exhibit a stronger association with wages (Allen & de Weert, 2007; Allen & van der Velden, 2001), whereas some studies attribute greater importance to skill mismatch in explaining job satisfaction (Allen & van der Velden, 2001; McGuinness & Sloane, 2011). These differences highlight the importance of distinguishing between the various dimensions of mismatch when analysing their effects on labour market outcomes.

With regard to vertical mismatch, the literature has documented a significant relationship between the form of mismatch and wages. The interpretation of these effects depends, however, on the reference group considered. When compared with adequately matched workers with the same level of education, overeducated workers tend to earn lower wages, whereas undereducated workers tend to earn higher wages. By contrast, when the comparison is made between workers employed in jobs with similar educational requirements, surplus education continues to yield some return, although lower than the return to required education, while education below the required level is associated with a penalty (Hartog, 2000; McGuinness, 2006).

Evidence for Portugal is consistent with these findings. Kiker et al. (1997) show that education acquired beyond the level required by the job yields a positive wage return, although lower than the return associated with required education. More recently, using data from the Eurograduate Survey 2022 on Portuguese higher education graduates, Inácio (2023) identifies a penalty of approximately 12.5% associated with overeducation relative to adequately matched workers with the same level of education, as well as a positive association between undereducation and earnings. Araújo and Carneiro (2023), in turn, show that the wage differentials associated with overeducation and undereducation are substantially reduced when unobserved worker and firm heterogeneity is taken into account. In the year of hiring, for example, the penalty associated with overeducation falls from approximately 6.9% in the baseline model to around 1.4% when worker and establishment fixed effects are included simultaneously.

The different dimensions of mismatch are associated with labour market outcomes in distinct ways. Allen and van der Velden (2001) identify a negative association between overeducation and wages, while skill underutilisation exhibits a particularly strong negative association with job satisfaction. The authors conclude that skill mismatches are better predictors of job satisfaction than educational mismatches. Allen and de Weert (2007) also find wage penalties associated with overeducation, whereas measures of skill mismatch have smaller wage effects and show no common pattern across the countries analysed. With regard to job satisfaction, working below one's educational level is associated with lower satisfaction, while higher levels of skill use are associated with greater satisfaction. Among UK graduates analysed as part of the REFLEX project, McGuinness and Sloane (2011) identify wage penalties associated with overeducation for both men and women, whereas the

penalty associated with overskilling is statistically significant only for men. When measures of vertical mismatch and skill mismatch are considered simultaneously, overskilling is associated with lower job satisfaction for both sexes. Thus, the dimension of mismatch most strongly associated with wages is not necessarily the one that exhibits the strongest relationship with job satisfaction.

The evidence on horizontal mismatch also points to wage differences, although the results vary considerably across fields of study and national contexts. Robst (2007) finds, on average, lower earnings among graduates whose jobs are unrelated to their field of study, but the magnitude of the penalty differs substantially across fields. While fields such as engineering, computing, and health professions are associated with sizeable penalties, the effects are not statistically significant in fields such as liberal arts and languages. Nordin et al. (2010) likewise identify earnings penalties among Swedish graduates working in occupations outside their field of education, of approximately 20% for men and 12% for women, relative to graduates from the same field of education who work in matched occupations.

The intensity of the mismatch between field of study and occupation also appears to matter. Reis (2018) proposes a continuous measure based on the distance between the tasks associated with the field of study and those required by the occupation, showing that workers classified as mismatched constitute a highly heterogeneous group. The results indicate that wage penalties tend to increase as the distance between education and occupation increases, suggesting that it is not only the existence of horizontal mismatch that matters, but also the degree of distance between the skills associated with the field of study and those used in the job. In particular, when the distance measure is used to represent mismatch, an increase of 0.10 is associated with a 6% reduction in hourly labour earnings.

However, the wage consequences of horizontal mismatch may also depend on its coexistence with other forms of mismatch. Montt (2017) shows that field-of-study mismatch without overqualification is associated with a wage penalty of only around 3%, whereas the coexistence of the two forms of mismatch is associated with a penalty of approximately 25%. The author further shows that, in most of the countries analysed, working outside one's field of study is not associated with a statistically significant wage penalty when the worker remains in a job that is compatible with their qualification level.

Beyond wages, horizontal mismatch may also be associated with job satisfaction. The review by Somers et al. (2019) generally identifies an association between horizontal mismatch and less favourable labour market outcomes, including lower job satisfaction, although the magnitude of the effects varies across studies, fields of study, and measurement methods. This heterogeneity is consistent with the possibility that the skills acquired in some fields are more easily transferable to other occupations. McGuinness and Sloane (2011) also find a positive association between the correspondence between field of study and employment and job satisfaction.

The evidence on skill mismatch points to different consequences for wages and job satisfaction. In the case of overskilling, negative associations are generally identified with both outcomes, although its relationship with job satisfaction appears to be particularly important. In a comprehensive review of the literature, McGuinness et al. (2018) identify an average wage penalty associated with overskilling that is smaller than that observed for overeducation, while also reporting evidence of negative consequences for job satisfaction. A similar overall pattern is reported by Mateos-Romero and Salinas-Jiménez (2018), who conclude that educational mismatch tends to play a greater role in explaining wages, whereas job satisfaction is generally more closely associated with skill mismatch. This difference is in line with Allen and van der Velden (2001) and McGuinness and Sloane (2011), suggesting that the actual underutilisation of workers' capabilities may be particularly relevant to their subjective evaluation of their job.

In the Portuguese context, Inácio (2023) also finds a negative relationship between overskilling and earnings, whereas underskilling does not exhibit a statistically significant association. For a worker classified as fully overskilled, the estimated penalty is 10.68%, falling to approximately 7.44% when educational mismatch is included simultaneously in the model, while remaining statistically significant.

Green and Zhu (2010) distinguish between different forms of overqualification depending on whether or not they are accompanied by skill underutilisation. The authors show that overqualified workers who also experience skill underutilisation face larger wage penalties and lower job satisfaction. Sánchez-Sánchez and McGuinness (2015), in turn, distinguish a general measure of overskilling from the underutilisation of 19 specific skills and show that the negative associations of overeducation and overskilling with wages and job satisfaction remain largely unchanged after these measures are included. These findings

suggest that mismatch may reflect a broader underutilisation of workers' potential rather than merely the underutilisation of specific skills.

By contrast, undereducation and underskilling have received less attention in the literature, and the available evidence is less conclusive (McGuinness et al., 2018). Regarding wages, undereducation has been associated with higher earnings relative to adequately matched workers with a similar level of education (Verhaest & Omey, 2012). For underskilling, Allen and de Weert (2007) find positive and statistically significant wage associations in some countries and statistically insignificant results in others, while Inácio (2023) finds no statistically significant association with earnings. Regarding job satisfaction, van der Velden and Verhaest (2017) show that small skill deficits may be associated with greater learning opportunities without necessarily reducing satisfaction. Mateos-Romero and Salinas-Jiménez (2018), however, find a negative and statistically significant association between underskilling and job satisfaction, whereas Sánchez-Sánchez and McGuinness (2015) report a positive association. The relationship between undereducation and job satisfaction is also less clear, with Mateos-Romero and Salinas-Jiménez (2018) finding a weak negative association and Sánchez-Sánchez and McGuinness (2015) finding no statistically significant relationship. Overall, the evidence on undereducation and underskilling therefore appears less uniform than that concerning overeducation and overskilling.

3. Data and empirical strategy

The empirical strategy adopted in this dissertation was designed to address two central research questions:

- **Q1:** What is the association between vertical mismatch, horizontal mismatch and skill mismatch and the wages of University of Porto graduates approximately two years after graduation?
- **Q2:** What is the association between these three dimensions of mismatch and the job satisfaction of University of Porto graduates approximately two years after graduation?

To address these questions, measures of vertical mismatch, horizontal mismatch and skill mismatch are constructed from graduates' responses to the survey and subsequently incorporated into the econometric models, together with a set of individual, academic and employment-related characteristics.

The organisation of this chapter follows this empirical strategy. Section 3.1 presents the survey and the sample construction process. Section 3.2 describes the construction of the measures of vertical mismatch, horizontal mismatch and skill mismatch. Section 3.3 presents descriptive statistics for the variables used in the analysis, beginning with the dependent variables, followed by the main explanatory variables and, finally, the control variables. Section 3.4 outlines the econometric strategy, distinguishing between the wage model and the job satisfaction model. Finally, Section 3.5 describes the robustness checks used to assess the sensitivity of the main results, while Section 3.6 discusses the main methodological limitations of the analysis.

3.1. Survey and sample construction

The data used in this dissertation result from a graduate survey conducted by the University of Porto. This survey was designed to monitor the employment situation of former students and to collect information on their trajectories following the completion of higher education. It covers graduates holding bachelor's, master's and doctoral degrees and has the primary aim of monitoring graduates' professional trajectories, thereby producing information that is useful both for evaluating the education provided and for improving institutional policies relating to graduate employability. According to the information contained in the questionnaire, the data collected are also intended to fulfil the legal

requirement to disclose information on graduates' employment situation periodically under the Portuguese Legal Framework for Higher Education Institutions (*Regime Jurídico das Instituições de Ensino Superior*, RJIES). The survey questions used to construct the variables included in the empirical analysis, together with their corresponding response options, are presented in Annex A.

The present analysis considers two consecutive survey waves. The first refers to graduates' situation as at 1 October 2024 and covers individuals who completed their degree in the 2021/2022 academic year. The second refers to graduates' situation as at 1 October 2025 and covers those who completed their degree in the 2022/2023 academic year. In both cases, graduates are observed approximately two years after completing their degree, allowing for the analysis of a comparable stage in the transition into the labour market.

For the purposes of this dissertation, the two survey cohorts are combined into a single analytical dataset. This approach is justified, first, by the fact that both surveys focus on consecutive cohorts of graduates from the University of Porto and examine their professional situation at a similar stage of their postgraduate career, approximately two years after completing their degree. This temporal proximity makes the two waves more comparable than observations collected at more distant points in time. Furthermore, although some adaptations were made to the questionnaires, particularly in the case of graduates with a PhD, the two cohorts have a broadly similar structure and contain common or harmonisable information on academic trajectories, employment status, job characteristics, wages, job satisfaction and perceptions of the correspondence between education, skills and employment. Combining the two waves therefore increases the sample size and strengthens the empirical analysis without compromising the consistency of the main variables used.

The survey design comprised a short version, filled in approximately 5 minutes, after which the graduates were asked if they wanted to continue further in the questionnaire, for a second set of questions lasting an additional 10 minutes. Therefore, there are valid short-form responses and valid long-form responses. A response is considered a valid short-form response when the respondent completes the questionnaire up to the end of its first section. A valid long-form response corresponds to cases in which the respondent completes the entire questionnaire and, therefore, a valid long-form response is always simultaneously a valid short-form response. This distinction is relevant to the present dissertation because

only long-form responses contain all the information required to construct the three dimensions of mismatch examined in the analysis: vertical mismatch, horizontal mismatch and skill mismatch.

The analysis was further restricted to individuals aged 50 or under. Although all graduates are observed approximately two years after completing their degree, older individuals may have long and well-established employment trajectories that pre-date graduation. In such cases, wages, job characteristics and mismatch status may reflect, to a greater extent, the professional experience accumulated before obtaining the degree, thereby reducing comparability with graduates who are at an earlier stage of their working lives. The age restriction therefore seeks to increase the homogeneity of the sample in terms of employment trajectories. This choice is consistent with concerns raised in the graduate mismatch literature regarding the use of cohorts that are relatively comparable in terms of education and labour market experience, which may help mitigate, although not eliminate, potential issues arising from unobserved heterogeneity (McGuinness & Sloane, 2011).

Table 1 summarises the sample construction process, from the valid long-form responses to the final samples used in the wage and job satisfaction models.

Table 1 – Construction of the analytical sample

Sample construction	**Observations**
Valid long responses	1,978
Valid long responses and employed graduates	1,382
After restricting the sample to individuals aged 50 or under	1,337
After excluding missing or inconsistent mismatch information	1,211
Wage analysis sample	1,093
Job satisfaction analysis sample	1,210

In addition, observations with missing or inconsistent values in the variables required to construct the mismatch measures were excluded. Following these exclusions, the analytical sample consists of 1,211 graduates.

Since wages and job satisfaction are analysed as separate dependent variables, two different estimation samples were defined. The wage models include only individuals with valid information on hourly wages, resulting in a sample of 1,093 observations. The job satisfaction models include individuals with valid information on satisfaction with their

employment situation, resulting in a sample of 1,210 observations. This approach makes it possible to use the largest number of observations available for each dependent variable and avoids excluding individuals from the job satisfaction analysis solely because they do not report valid wage information.

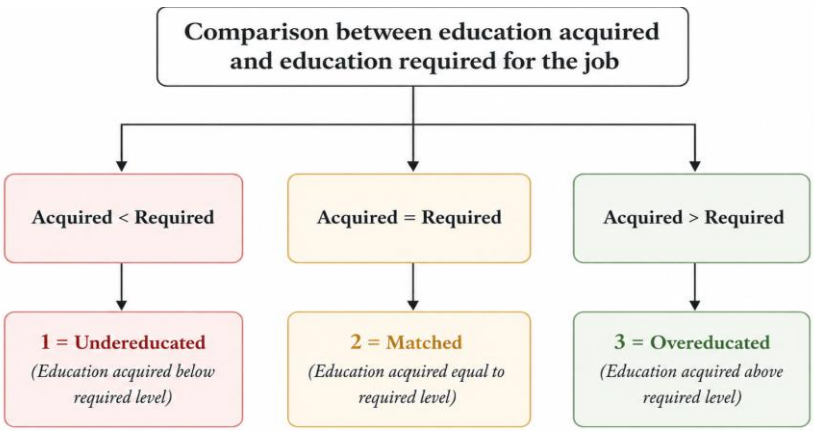
3.2. Measuring the different types of mismatch

3.2.1. Vertical mismatch

Vertical mismatch is identified by comparing the level of education acquired by the individual with the level of education normally required to perform the job. The required level is obtained from the survey question: "What level of education is normally required to perform this job?", with response categories ranging from below higher education to a doctoral degree. As the required level is reported by the graduate, this corresponds to an indirect self-assessment measure, as discussed in Section 2.3. These categories reflect the level of formal education considered necessary to perform the job and are coded according to the same educational scale used for the individual's acquired level of education.

To ensure comparability between acquired and required education, both were coded according to a common five-level scale. For acquired education, bachelor's degrees were assigned to level 3, master's and integrated master's degrees to level 4, and doctoral degrees to level 5. Based on this comparison, individuals were classified as undereducated when their acquired level of education was lower than the level required for the job, matched when the two levels were equal, and overeducated when their acquired level was higher. The resulting variable takes the value 1 for undereducated individuals, 2 for matched individuals, and 3 for overeducated individuals, as illustrated in Figure 1.

Figure 1 – Construction of the vertical mismatch variable



Source: Own elaboration

3.2.2. Horizontal mismatch

The measurement of horizontal mismatch is based on the following survey question: 'Would you say that, at the survey reference date, your job was aligned with your field of study?' Responses are recorded on an ordered scale from 1 to 5, where 1 corresponds to 'No, not at all', 3 corresponds to 'Partially', and 5 corresponds to 'Yes, absolutely'. Since the original scale measures the degree of alignment between the graduate's field of study and current job, it was reversed so that higher values indicate greater horizontal mismatch. The resulting variable therefore ranges from 1, indicating the highest level of alignment, to 5, indicating the lowest. The variable is entered linearly in the econometric models.

3.2.3. Skill mismatch

To measure skill mismatch, the analysis draws on a set of 12 skills included in the survey. For each skill, employed respondents were asked two separate questions. The first asked them to assess the level of that skill required by their job, while the second asked them to assess their own level of the same skill. In both cases, responses were recorded on a scale from 1 to 7, where 1 indicates a very low level and 7 a very high level. The 12 skills considered in the analysis are presented in Table 2.

Table 2 – Skills included in the skill mismatch measure

1.	Mastery of your own field or discipline
2.	Analytical thinking
3.	Ability to rapidly acquire new knowledge
4.	Ability to coordinate activities
5.	Ability to work productively with others
6.	Ability to make your meaning clear to others
7.	Ability for applied use of information and communication technologies (ICT, e.g., text processing, working with tables, retrieve information from the internet, e-mail)
8.	Ability for advanced use of information and communication technologies (ICT, e.g., programming, syntax in statistical software)
9.	Ability to come up with new ideas and solutions
10.	Willingness to question your own and others' ideas
11.	Ability to present products, ideas or reports to an audience
12.	Ability to write and speak in a foreign language

Source: U.Porto Survey 2024/2025

The construction of the skill mismatch measure builds on the comparison between skills possessed and skills required used by Allen and de Weert (2007) and Berlingieri and Erdsiek (2012). More specifically, it is based on the difference between the skill level reported

by the individual and the level of the same skill required in their current job. Accordingly, for each skill j and each individual i, the following difference was calculated:

$$Gap_{ij} = SkillOwn_{ij} - SkillRequired_{ij}$$

where Gap_{ij} represents the difference between the level of skill j possessed by individual i and the level of that skill required in the job. $SkillOwn_{ij}$ denotes the skill level reported by the graduate, while $SkillRequired_{ij}$ denotes the level of that skill required by the tasks performed in the job. Following Berlingieri and Erdsiek (2012), a one-point tolerance margin around matching was applied. Differences of one point in either direction between the skill level possessed and the level required are therefore treated as relatively minor variations rather than as clear cases of mismatch. Accordingly, only differences greater than one point in absolute value are classified as skill mismatch.

The classification of each skill is defined as follows:

$$\textbf{Skill mismatch}_{ij} = \begin{cases} \text{underskilling}, & \text{if } Gap_{ij} < -1 \\ \text{well matched}, & \text{if } Gap_{ij} = -1, 0, 1 \\ \text{overskilling}, & \text{if } Gap_{ij} > 1 \end{cases}$$

Values above 1 indicate that the individual possesses a higher level of the skill than that required in the job, corresponding to situations of overskilling. Values of -1, 0 and 1 indicate that the skill is well matched, while values below -1 indicate that the level of the skill possessed is lower than that required, corresponding to situations of underskilling. Following this classification for each skill, two individual measures of skill mismatch were constructed. The first corresponds to the total number of skills in which the graduate is classified as underskilled, while the second corresponds to the total number of skills in which the graduate is classified as overskilled. Thus, for each individual, instances of skill deficit and skill surplus were summed across the 12 skills considered in the analysis.

Both variables range from 0 to 12 and correspond to the number of skills in which each graduate experiences underskilling or overskilling, respectively. Higher values indicate that a mismatch occurs across a larger number of skills. For example, an individual may be classified as underskilled in 2 skills, well matched in 6 skills and overskilled in 4 skills.

3.3. Descriptive statistics

This section presents descriptive statistics for the main variables used in the empirical analysis. As noted above, the wage and job satisfaction models are estimated using slightly different samples because wage information is missing or invalid for some individuals. However, the comparison of the main observable characteristics across the two samples reveals very similar values. For this reason, whenever possible, the descriptive analysis is based on the full analytical sample of 1,211 graduates.

The analysis begins with the outcome variables used in the empirical models. As reported in Table 3, the mean real hourly wage is €11.15, with a standard deviation of €5.66, indicating substantial variation in graduates' earnings. Mean job satisfaction is 3.85 on a scale from 1 to 5, placing it above the midpoint of the scale. This indicates that, on average, graduates assess their employment situation relatively favourably. However, the standard deviation of 1.04 and the presence of responses across the entire scale show that this assessment is not uniform, with some graduates also reporting low levels of job satisfaction.

Table 3 – Descriptive statistics of outcome variables

Variable	N	Mean	St. Dev.	Min	Max
Real hourly wage (€)	1,093	11.15	5.66	4.91	29.16
Job satisfaction	1,210	3.85	1.04	1	5

Turning to the main explanatory variables, Table 4 presents the distribution of graduates according to their vertical mismatch status. Overall, 48.22% of graduates are vertically mismatched. Overeducation is the most prevalent form of vertical mismatch, affecting 39.47% of the sample, while undereducation accounts for 8.75% of graduates. The remaining 51.78% are adequately matched, meaning that their level of education corresponds to the level normally required for their jobs.

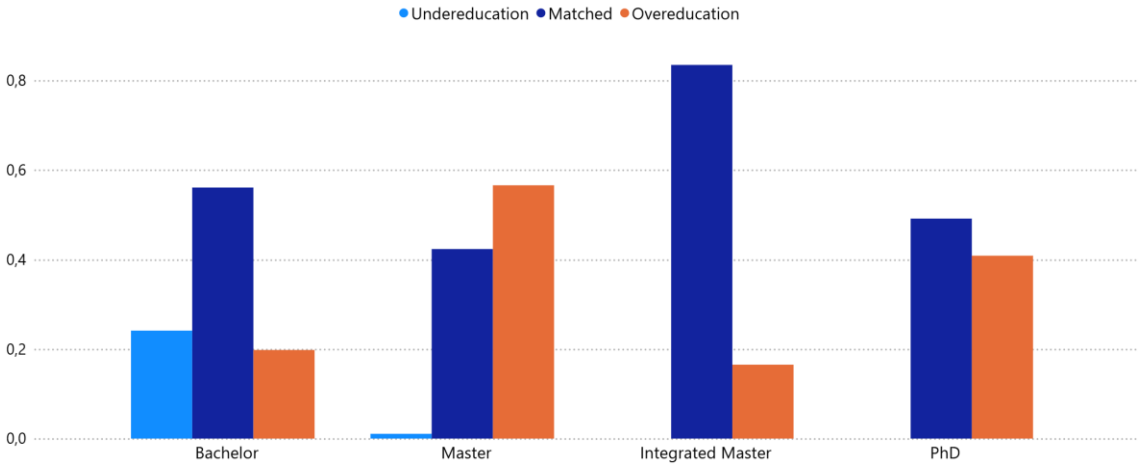
Table 4 – Distribution of graduates by vertical mismatch

Vertical mismatch	N (%)
Undereducated	106 (8.75)
Adequately matched	627 (51.78)
Overeducated	478 (39.47)
Total	**1,211 (100)**

The distribution by degree level, presented in Figure 2, shows that adequately matched graduates predominate among bachelor's and integrated master's graduates, accounting for 56.04% and 83.47% of each group, respectively. By contrast, overeducation

is most prevalent among master's graduates (56.54%). Undereducation is mainly concentrated among bachelor's graduates (24.15%) and is absent among integrated master's and PhD graduates. For PhD graduates, this absence is expected by construction, since a doctoral degree is the highest educational level considered in the measure.

Figure 2 – Distribution of vertical mismatch by degree level (%)



Source: U.Porto Survey 2024/2025. Own elaboration

The analysis then considers the extent to which graduates' employment is aligned with their field of study. As shown in Table 5, the distribution of the horizontal mismatch measure is concentrated at the lower end of the scale. In particular, 50.04% of graduates are in category 1 and 27.91% in category 2, together accounting for 77.95% of the sample. By contrast, only 11.48% fall into categories 4 or 5. The measure has a mean of 1.90 and a standard deviation of 1.17. Overall, these results indicate that most graduates are employed in jobs that are relatively closely related to their field of study, although some heterogeneity remains within the sample.

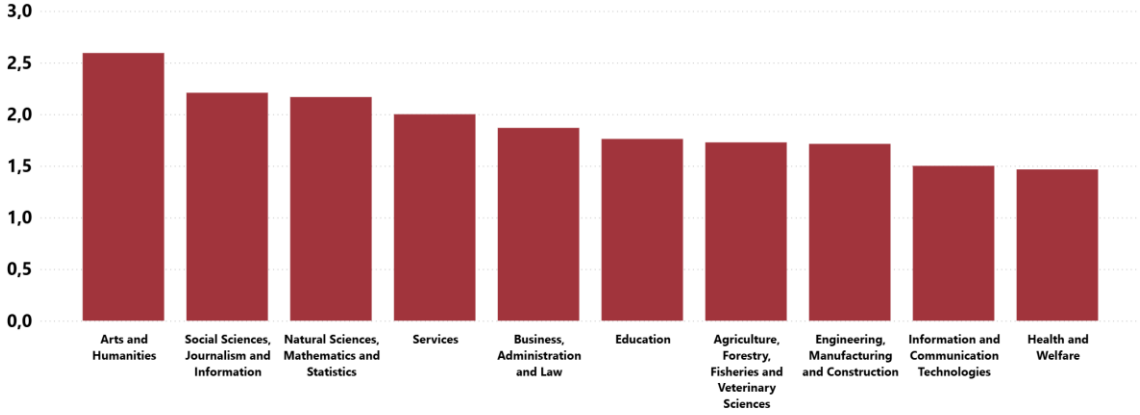
Table 5 – Distribution of horizontal mismatch scores

Horizontal mismatch	N (%)
1 (No horizontal mismatch)	606 (50.04)
2	338 (27.91)
3 (Partial horizontal mismatch)	128 (10.57)
4	61 (5.04)
5 (Full horizontal mismatch)	78 (6.44)
Total	**1,211 (100)**

To complement this analysis, Figure 3 presents the mean horizontal mismatch score by field of study. Graduates in Arts and Humanities record the highest mean value, at 2.59, indicating a weaker correspondence between their field of study and current employment.

By contrast, graduates in Health and Welfare have the lowest mean value, at 1.47, suggesting a closer relationship between their education and the professional activity they perform.

Figure 3 – Average horizontal mismatch score by field of study



Note: Scores range from 1 to 5, with higher scores indicating a weaker correspondence between the graduate's field of study and current job. Graduates with an unknown field of study are not included in the figure.

Source: U.Porto Survey 2024/2025. Own elaboration

Regarding skill mismatch, Table 6 presents the distribution of graduates according to the number of skills classified as cases of underskilling or overskilling. In the case of underskilling, 65.24% of graduates have no skills more than one point below the level required by their job, while 34.76% experience underskilling in at least one skill. More specifically, 29.40% experience underskilling in between one and four skills, and only 5.37% in five or more skills.

Overskilling is more prevalent. Only 39.55% of graduates do not report any skill above the level required, while 60.45% experience overskilling in at least one skill. In the full sample, 44.92% experience overskilling in between one and four skills and 15.52% in five or more skills.

Table 6 – Distribution of skill mismatch by number of mismatched skills

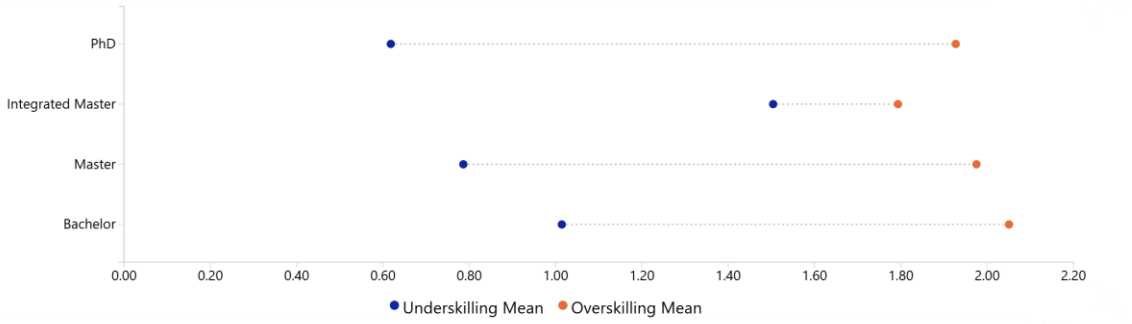
Number of mismatched skills	Underskilling N (%)	Overskilling N (%)
0 skills	790 (65.24)	479 (39.55)
1-4 skills	356 (29.40)	544 (44.92)
5 or more skills	65 (5.37)	188 (15.52)
Total	**1,211 (100)**	**1,211 (100)**

In the full sample, graduates are underskilled in an average of 0.92 skills and overskilled in an average of 1.98 skills. Figure 4 complements this analysis by presenting these mean values by degree level. The mean number of skills affected by overskilling is

higher than the corresponding mean for underskilling across all degree levels, confirming that skill levels exceeding job requirements constitute the dominant pattern. Integrated master's graduates have the highest mean level of underskilling, corresponding to 1.50 skills, while doctoral graduates record the lowest value, at 0.62. Concerning overskilling, differences across degree levels are less pronounced, ranging from 1.79 skills among integrated master's graduates to 2.05 among bachelor's graduates.

Integrated master's graduates display a particularly distinctive pattern. This is the degree level with the highest proportion of vertically matched graduates and, at the same time, the highest mean number of skills affected by underskilling. This contrast shows that a match between the level of education and the job does not necessarily imply the absence of deficits in specific skills.

Figure 4 – Average number of underskilled and overskilled skills by degree level



Source: U.Porto Survey 2024/2025. Own elaboration

Table 7 presents the correlations between the different mismatch measures. Overall, the observed associations are small in magnitude, suggesting that the measures capture related but distinct dimensions of the mismatch between education and employment. The positive correlation between overeducation and overskilling, at 0.22, suggests that these two forms of mismatch are related but far from equivalent. This is consistent with Allen and van der Velden (2001), who find only a relatively weak relationship between educational and skill mismatches.

The strongest positive correlation is observed between horizontal mismatch and overeducation, with a coefficient of 0.29, followed by the correlation between horizontal mismatch and overskilling, at 0.25. The association between horizontal mismatch and overeducation is consistent with Montt (2017), who shows that field-of-study mismatch and overqualification may coexist, while remaining conceptually distinct. Taken together, the

relatively modest correlations reinforce the idea that vertical, horizontal and skill mismatch capture different dimensions of labour market mismatch.

Table 7 – Correlations between mismatch measures

Variable	(1)	(2)	(3)	(4)	(5)
(1) Undereducation	1.000				
(2) Overeducation	−0.2501*	1.000			
(3) Horizontal mismatch	0.078*	0.2881*	1.000		
(4) Underskilling	0.0791*	−0.1069*	−0.0522	1.000	
(5) Overskilling	−0.0934*	0.2246*	0.2463*	−0.2116*	1.000

Note: * $p < 0.05$.

Having described the outcome variables and the main explanatory variables, the remainder of the section characterises the individual, academic and employment-related characteristics used as controls in the econometric models. The individual characteristics of the analytical sample are presented in Table 8. Women account for 59.70% of the sample, while men represent 40.30%. The average age is approximately 28 years, with a standard deviation of 5.8 years, indicating that the sample consists mainly of graduates at relatively early stages of their professional careers.

Table 8 – Individual characteristics of the analytical sample

Variable	Category	N	%	Mean	St. Dev.
Sex	Female	723	59.70	—	—
	Male	488	40.30	—	—
Age	—	1,211	—	28.316	5.829

The academic profile of the sample, presented in Table 9, shows a greater concentration of graduates holding a master's degree, who account for 46.74% of the total, followed by bachelor's degree holders at 34.19%. Graduates holding an integrated master's degree or a doctoral degree represent smaller shares of the sample, accounting for 9.99% and 9.08%, respectively. International experience during the course of their studies is reported by approximately one-quarter of the sample, suggesting that most graduates did not undertake international mobility during the degree programme they completed.

Table 9 – Academic characteristics of the analytical sample

	Category	*N (%)*
Degree level	Bachelor	414 (34.19%)
	Master	566 (46.74%)
	Integrated Master	121 (9.99%)
	PhD	110 (9.08%)
International Experience	Yes	300 (24.77%)
	No	911 (75.23%)

Field of study represents another important dimension of the sample profile, since the correspondence between academic background and employment may vary substantially across fields of study. The distribution presented in Table 10, based on the broad fields of the Portuguese version of CITE-F 2013, shows the highest concentration in Engineering, Manufacturing and Construction, which accounts for 27.33% of the sample, followed by Social Sciences, Journalism and Information at 16.27%. By contrast, some fields are only weakly represented, including Agriculture, Forestry, Fisheries and Veterinary at 0.91% and Information and Communication Technologies at 2.15%. The category Unknown field of study accounts for 10.07% of the observations and corresponds to cases in which the field of study is not identified in the available classification.

Table 10 – Field of study distribution of the analytical sample (CITE-F 2013)

Field of study	**N**	**%**
01 - Education	46	3.80
02 - Arts and Humanities	118	9.74
03 - Social Sciences, Journalism and Information	197	16.27
04 - Business, Administration and Law	121	9.99
05 - Natural Sciences, Mathematics and Statistics	90	7.43
06 - Information and Communication Technologies	26	2.15
07 - Engineering, Manufacturing and Construction	331	27.33
08 - Agriculture, Forestry, Fisheries and Veterinary	11	0.91
09 - Health and Welfare	116	9.58
10 - Services	33	2.73
Unknown field of study	122	10.07
Total	**1,211**	**100.00**

The employment profile provides further context regarding the conditions under which graduates are integrated into the labour market. Table 11 presents some of the main employment characteristics, including working-time arrangements, employment in the public sector, contract type and the country in which the individual is employed.

Table 11 – Employment characteristics of the analytical sample

		N (%)
Full-time	Yes	1,044 (86.21%)
	No, part-time	167 (13.79%)
Public sector	Yes	293 (24.19%)
	No	918 (75.81%)
Contract type	Fixed-term contract	255 (21.06%)
	Uncertain-term contract	141 (11.64%)
	Open-ended contract	502 (41.45%)
	Other / Not applicable / Unknown	313 (25.85%)
Portugal	Yes	1,069 (88.27%)
	No	142 (11.73%)

Note: For presentation purposes, the categories "Other", "Not applicable" and "Unknown" are grouped in this table. The original contract type categories are retained in the econometric models.

The employment structure of the sample shows that graduates are predominantly employed full-time and are strongly concentrated in the Portuguese labour market. 13.79% of graduates report working part-time, and although this group represents a minority of the sample, its presence supports the use of hourly wages in the wage analysis, as this measure allows individuals working different numbers of hours to be compared and prevents observed wage differences from merely reflecting variation in monthly hours worked.

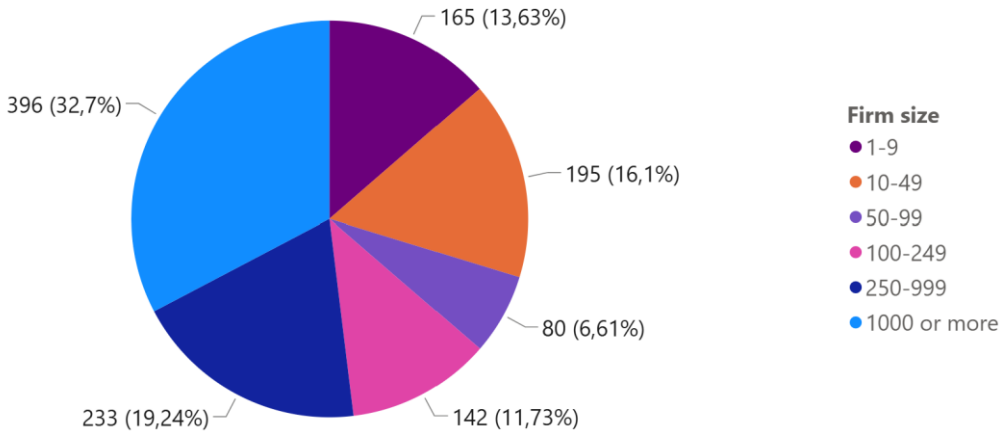
Regarding public-sector employment, 24.19% of graduates work in the public sector, while the majority are employed outside it. This distinction is relevant to the characterisation of the sample, since public and non-public sector employment may differ in terms of contractual arrangements, institutional frameworks and working conditions. With regard to contract type, open-ended contracts are the most common arrangement, covering 41.45% of the sample. Nevertheless, a substantial proportion of graduates hold fixed-term contracts or uncertain-term contracts, which together account for 32.70% of the sample, suggesting that a relevant share of graduates remain in potentially less stable employment relationships.

The geographical dimension of employment adds another important characteristic to the analysis. Although most graduates work in Portugal, 11.73% are employed abroad. This distinction should be taken into account in the empirical analysis, particularly in the wage models, since differences across national labour markets may be associated with different wage levels.

Employer size constitutes another relevant characteristic of graduates' employment context. As shown in Figure 5, graduates are relatively distributed across employers of

different sizes, although there is a greater concentration in large organisations. In particular, 32.70% of graduates work for employers with 1,000 or more employees, making this the largest category. Considering a broader classification by employer size, 48.06% of graduates work in organisations with fewer than 250 employees, while 51.94% are employed in organisations with 250 or more workers. This distribution shows that the sample includes graduates employed both in small and medium-sized organisations and in larger organisational structures.

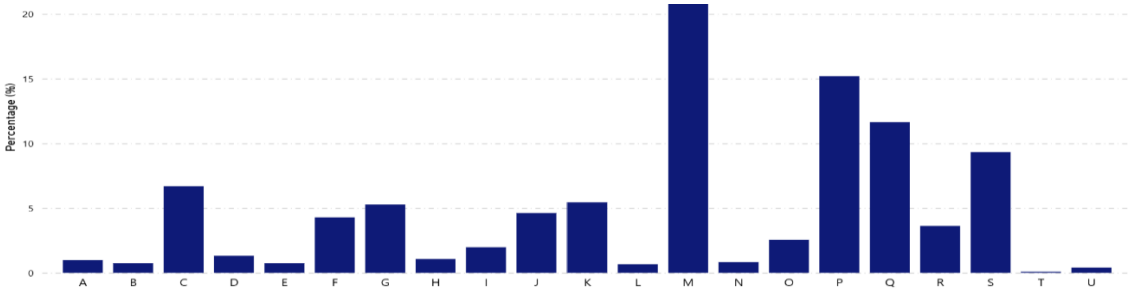
Figure 5 – Distribution of graduates by firm size



Source: U.Porto Survey 2024/2025. Own elaboration

The employment profile is further complemented by the distribution of graduates across sectors of economic activity and occupational groups, presented in Figures 6 and 7, respectively. At the sectoral level, the highest concentration is observed in sector M, corresponding to Professional, scientific and technical activities, which accounts for 22.46% of the sample, followed by sector P, Education, and sector Q, Human health and social work activities, representing 15.19% and 11.64%, respectively. Despite this concentration, the sample is also distributed across other sectors of economic activity, including Other service activities, Manufacturing, Financial and insurance activities and Wholesale and retail trade.

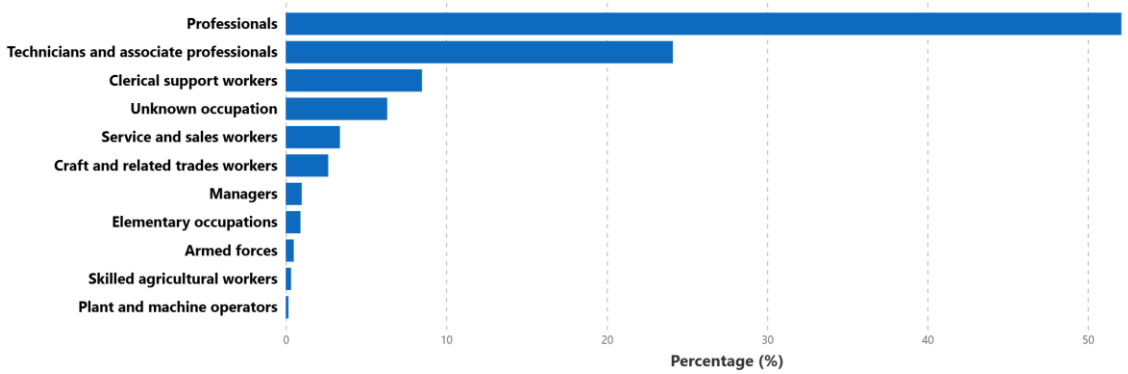
Figure 6 – Distribution of graduates by sector of activity



Source: U.Porto Survey 2024/2025. Own elaboration

A strong occupational concentration in skilled groups accompanies this sectoral distribution. More than half of graduates are classified as Professionals, accounting for 52.11% of the sample, followed by Technicians and Associate Professionals at 24.11%. Together, these two groups represent approximately three-quarters of the sample, while the remaining occupational categories account for smaller shares.

Figure 7 – Distribution of graduates by occupation



Source: U.Porto Survey 2024/2025. Own elaboration

The correspondence between each sector code and the respective sector of economic activity is presented in Annex B.

3.4. Econometric strategy for wages and job satisfaction

Two types of econometric models are used in this study. To assess the association between the different forms of mismatch and wages, ordinary least squares (OLS) estimation is employed. To analyse the association between mismatch and job satisfaction, an ordered probit model is used, since the dependent variable is measured on a scale from 1 to 5, with higher values corresponding to higher levels of satisfaction.

3.4.1. Wage model

For the wage analysis, an adaptation of Mincer's (1974) wage equation was used to examine the association between the different forms of *mismatch* and graduates' wages. The survey provides information on graduates' gross monthly wages and normal weekly working hours (see Annex A), allowing the corresponding hourly wage to be calculated. For this purpose, the formula[1] for determining hourly remuneration established in Article 271 of the Portuguese Labour Code (Law No. 7/2009 of 12 February) was used.

[1] $\frac{(Rm*12)}{(52*n)}$, where Rm denotes monthly remuneration and n denotes normal weekly working hours.

The hourly wage, rather than the monthly wage, was used to account for differences in working hours across graduates. This measure reduces the influence of differences in working time on wage comparisons, since higher monthly wages may reflect a greater number of hours worked rather than necessarily higher remuneration per unit of working time. This choice is also consistent with studies on labour market mismatch, such as Araújo and Carneiro (2023), who use hourly wages in their wage equations.

Since the dataset combines surveys with reference dates of 1 October 2024 and 1 October 2025, wages were expressed in October 2024 prices. The year-on-year rate of change in the Consumer Price Index (CPI) was 2.3% in October 2025 (INE, 2025). Nominal wages reported in the 2025 survey were deflated by dividing them by 1.023, while wages reported in the 2024 survey were retained at their observed values. The natural logarithm of real hourly wages is used as the dependent variable in the econometric models.

Separate models are estimated for vertical mismatch, horizontal mismatch and skill mismatch, together with a joint model that includes all mismatch measures simultaneously. The joint specification is also estimated separately for men and women to explore potential differences in the estimated associations by sex.

The regressions are specified as follows:

$$(1)\ ln(w_i) = \beta_0 + \beta_1 Undereducation_i + \beta_2 Overeducation_i + \mathbf{X'_i}\boldsymbol{\gamma} + \varepsilon_i$$

$$(2)\ ln(w_i) = \beta_0 + \beta_1 Horizontal\ mismatch_i + \mathbf{X'_i}\boldsymbol{\gamma} + \varepsilon_i$$

$$(3)\ ln(w_i) = \beta_0 + \beta_1 Underskilling_i + \beta_2 Overskilling_i + \mathbf{X'_i}\boldsymbol{\gamma} + \varepsilon_i$$

$$(4)\ ln(w_i) = \beta_0 + \beta_1 Undereducation_i + \beta_2 Overeducation_i + \beta_3 Horizontal\ mismatch_i + \beta_4 Underskilling_i + \beta_5 Overskilling_i + \mathbf{X'_i}\boldsymbol{\gamma} + \varepsilon_i$$

where i denotes the graduate and w_i represents the real hourly wage. $Undereducation_i$ and $Overeducation_i$ are binary indicators, with graduates classified as adequately matched constituting the reference category, in accordance with the definition presented in section 3.2.1. $Horizontal\ mismatch_i$ represents the degree of misalignment between the field of study and employment, as defined in Section 3.2.2. $Underskilling_i$ and $Overskilling_i$ correspond to the number of skills in which the graduate experiences a skill deficit or skill surplus, respectively, according to the construction presented in Section 3.2.3.

The vector X_i includes the individual, academic and employment-related control variables included in the empirical models, namely sex, age, degree level, field of study, international experience, firm size, sector of activity, public sector, full-time employment, occupation, contract type and whether the graduate works in Portugal. A detailed description of these variables is provided in Appendix A. γ represents the corresponding coefficients, and ε_i denotes the error term. The models are estimated using ordinary least squares (OLS) with heteroskedasticity-robust standard errors.

3.4.2. Job satisfaction model

To analyse the association between the different forms of mismatch and job satisfaction, an ordered probit model is estimated. Job satisfaction is measured on an ordered scale from 1 to 5, where 1 corresponds to very dissatisfied and 5 to very satisfied. Since these categories have a natural ordering but the distances between consecutive levels of satisfaction cannot necessarily be assumed to be equal, an ordered probit model is appropriate due to the ordinal nature of the dependent variable.

The model simultaneously includes all mismatch measures and the full set of individual, academic and employment-related control variables. The specification is given by:

$$(5) \quad S_i^* = \boldsymbol{M_i'\beta} + \boldsymbol{X_i'\gamma} + u_i$$

where S_i^* represents the latent level of job satisfaction of graduate i, M_i includes the same mismatch measures considered in the joint wage model presented in equation (4), and X_i contains the same set of individual, academic and employment-related control variables used in the wage models. The vectors β and γ represent the coefficients associated with the mismatch and control variables, respectively, while u_i denotes the error term. The model is estimated with robust standard errors.

Observed job satisfaction, S_i, takes values from 1 to 5 and is determined by the position of the latent variable relative to the cut-off points estimated by the model:

$$(6) \quad S_i = j \text{ if } \mu_{j-1} < S_i^* \leq \mu_j,\ j = 1, \dots, 5$$

where $\mu_1, \dots, \mu_4$ denote the cut-points estimated by the model, with $\mu_0 = -\infty$ and $\mu_5 = +\infty$. The joint specification is also estimated separately for men and women to explore potential differences in the estimated associations by sex. For the full sample, average marginal effects are calculated to facilitate the interpretation of the ordered probit estimates.

A detailed description of the variables included in the models is provided in Appendix A.

3.5. Robustness checks

To assess the sensitivity of the main findings to alternative measurement choices and sample composition, three robustness checks are conducted.

First, the skill mismatch measures are reconstructed without the tolerance margin used in the baseline specification. In the main analysis, differences of -1, 0 and 1 between the level of each skill possessed by the graduate and that required by the job are classified as a match. As a robustness check, no tolerance is applied: any negative difference is classified as underskilling, while any positive difference is classified as overskilling. This allows us to assess whether the results are sensitive to the way skill mismatch is defined.

Second, the wage model is re-estimated using only graduates working in Portugal. Since the main sample also includes graduates employed abroad, this restriction improves the comparability of wage observations and allows the analysis to assess whether the main results are sensitive to differences in labour market contexts across countries.

Finally, the sensitivity of the results to the measurement of vertical mismatch is examined using an alternative direct self-assessment measure. While the main measure compares the graduate's attained level of education with the level required for the job, the alternative measure is based on the survey question, "Would you say that your qualifications were appropriate for your job?", answered on a five-point scale. Responses 1 and 2 are classified as underqualification, response 3 as matched, and responses 4 and 5 as overqualification. The wage and job satisfaction models are then re-estimated using this alternative measure while retaining the remaining mismatch measures and the full set of controls.

3.6. Methodological limitations

This dissertation is subject to some methodological limitations that should be considered when interpreting the results. First, given the cross-sectional nature of the data, the analysis cannot fully account for unobserved heterogeneity across individuals and jobs, which may be simultaneously related to the occurrence of mismatch and to the outcomes analysed. The relevance of this issue has been documented in the literature for both wages (Araújo & Carneiro, 2023) and job satisfaction (Mavromaras et al., 2013), suggesting that

unobserved heterogeneity may account for part of the estimated associations between mismatch and these outcomes.

In addition, the different mismatch measures, as well as the dependent variables, are constructed using information reported by the graduates themselves. This may introduce measurement error arising from the subjective nature of the responses, a limitation already discussed in Section 2.3 of this dissertation.

In the case of skill mismatch, the measure used may not fully capture the complexity of the phenomenon, as it is based on the number of mismatched skills and does not identify whether mismatch in specific skills has different associations with wages or job satisfaction. In turn, the horizontal mismatch measure is entered linearly in the regressions, which assumes similar differences between consecutive categories of the ordinal scale.

4. Results

4.1. Effects of labour market mismatch on wages

Table 12 presents the OLS estimates of the association between the three dimensions of labour market mismatch and graduates' real hourly wages. For each dimension, four models are estimated, starting with a specification including only the corresponding mismatch variables and progressively introducing individual, academic and employment-related controls. This structure makes it possible to assess how the magnitude and statistical significance of the estimated associations change after accounting for observable differences across graduates.

For vertical mismatch, undereducation becomes significant after academic controls and overeducation after individual controls; both remain significant in the full model. In column (4), undereducated graduates earn approximately 13.9% higher hourly wages[2] than adequately matched graduates, while overeducation is associated with a wage penalty of approximately 5.3%. These results follow the pattern generally identified in the literature when matched workers with the same level of education constitute the reference group. In particular, Inácio (2023) also finds a wage premium associated with undereducation and a wage penalty associated with overeducation among Portuguese graduates when vertical mismatch is analysed separately. The positive association for undereducation is also consistent with Verhaest and Omey (2012), who report higher earnings among undereducated workers relative to adequately matched workers with a similar educational level.

Horizontal mismatch exhibits a negative and statistically significant association with hourly wages across all specifications. The coefficient decreases in magnitude from -0.0853 in column (5) to -0.0377 in the fully specified model (8). Thus, each one-unit increase in the horizontal mismatch scale is associated with approximately 3.7% lower hourly wages. This result is consistent with previous evidence of wage penalties associated with field-of-study mismatch (Robst, 2007; Nordin et al., 2010).

[2] Since the dependent variable is in logarithmic form, coefficients are converted into percentage changes using $100 \times [\exp(\beta) - 1]$.

Table 12 – OLS estimates of the association between vertical, horizontal and skill mismatch and hourly wages

	Vertical mismatch				Horizontal mismatch				Skill mismatch			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Undereducation	0.0245	0.0562	0.194***	0.130***								
	(0.0486)	(0.0461)	(0.0494)	(0.0388)								
Overeducation	-0.0026	-0.0580**	-0.0865***	-0.0541**								
	(0.0285)	(0.0276)	(0.0259)	(0.0252)								
Horizontal mismatch					-0.0853***	-0.0809***	-0.0568***	-0.0377***				
					(0.0115)	(0.0111)	(0.0108)	(0.0107)				
Underskilling									-0.0222***	-0.0178***	-0.0181***	-0.0133***
									(0.0065)	(0.0059)	(0.0053)	(0.0049)
Overskilling									-0.0216***	-0.0277***	-0.0207***	-0.0147***
									(0.0056)	(0.0049)	(0.0045)	(0.0039)
Controls:												
Individual		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Academic			Yes	Yes			Yes	Yes			Yes	Yes
Employment				Yes				Yes				Yes
Constant	2.307***	1.818***	1.919***	2.788***	2.468***	2.010***	2.111***	2.926***	2.370***	1.913***	2.056***	2.877***
	(0.0169)	(0.0753)	(0.0767)	(0.121)	(0.0252)	(0.0733)	(0.0759)	(0.125)	(0.0192)	(0.0754)	(0.0772)	(0.120)
Observations	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093
R-squared	0.0003	0.1099	0.2917	0.5292	0.0510	0.1495	0.2907	0.5291	0.0205	0.1316	0.2873	0.5296

Notes: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the logarithm of hourly wages. Columns (1), (5) and (9) include only the respective mismatch measures. Columns (2), (6) and (10) add individual controls; columns (3), (7) and (11) additionally include academic controls; and columns (4), (8) and (12) further include employment controls. Controls: 1) Individuals: age, sex; 2) Academic: degree level, field of study (CITE-F 2013), international experience; 3) Employment: firm size, sector, public-sector employment, full-time employment, occupation, type of contract, country of work.

Regarding skill mismatch, both underskilling and overskilling display negative and statistically significant coefficients across all models. In the fully specified model, column (12), each additional skill for which underskilling is observed is associated with approximately 1.3% lower hourly wages, while each additional skill for which overskilling is observed is associated with an approximately 1.5% reduction. The negative association for overskilling is consistent with Inácio (2023), who also reports a wage penalty associated with overskilling among Portuguese higher education graduates.

When the five mismatch measures are included simultaneously, in regression (13) of Table 13, undereducation remains positively and statistically significantly associated with hourly wages. Undereducated graduates earn approximately 12.4% higher wages than matched graduates. Horizontal mismatch, underskilling and overskilling remain negatively associated with wages, corresponding to reductions of approximately 2.8% per additional unit of horizontal mismatch, 1.3% per additional skill in underskilling and 1.0% per additional skill in overskilling, respectively.

The main change relative to the models in Table 12 concerns overeducation. The wage penalty of approximately 5.3% observed when vertical mismatch is analysed separately decreases to around 2.9% and is no longer statistically significant once the remaining dimensions of mismatch are included simultaneously. This result suggests that part of the association initially observed for overeducation may be related to the coexistence of other forms of mismatch. This interpretation is also consistent with the positive, although moderate, correlations previously observed between overeducation, horizontal mismatch and overskilling (see Table 7).

Table 13 – OLS estimates of all mismatch dimensions and wage determinants, overall and by sex

Variables	**All mismatches**	**Men**	**Women**
	(13)	(14)	(15)
Undereducation	0.117***	0.0859	0.119***
	(0.0384)	(0.0690)	(0.0452)
Overeducation	-0.0294	-0.0029	-0.0399
	(0.0259)	(0.0477)	(0.0305)
Horizontal mismatch	−0.0280**	-0.0244	-0.0232*
	(0.0114)	(0.0213)	(0.0127)
Underskilling	−0.0132***	-0.0166*	-0.0104
	(0.0049)	(0.0087)	(0.0064)
Overskilling	−0.0105**	0.0013	-0.0219***
	(0.0042)	(0.0068)	(0.0051)

Sex (omitted: Male)			
Female	−0.102***	———	———
	(0.0209)		
Age	0.00802***	0.0068*	0.0079**
	(0.00288)	(0.0040)	(0.0039)
Degree level (omitted: Bachelor)			
Master	0.156***	0.0899	0.164***
	(0.0290)	(0.0561)	(0.0327)
Integrated Master	0.0561	-0.0972	0.0776
	(0.0539)	(0.107)	(0.0642)
PhD	0.127	-0.0466	0.171
	(0.117)	(0.216)	(0.132)
Field of study (omitted: Engineering, Manufacturing and Construction)			
Education	−0.0321	-0.154**	0.0765
	(0.0559)	(0.0780)	(0.0704)
Arts and Humanities	−0.149***	-0.152	-0.132***
	(0.0426)	(0.0928)	(0.0490)
Social Sciences, Journalism and Information	−0.0499	-0.0540	-0.0447
	(0.0310)	(0.0642)	(0.0384)
Business, Administration and Law	0.0133	-0.0114	0.0199
	(0.0355)	(0.0678)	(0.0409)
Natural Sciences, Mathematics and Statistics	−0.0693	-0.0159	-0.0777
	(0.0475)	(0.0877)	(0.0533)
Information and Communication Technologies	0.136**	0.0370	0.194*
	(0.0594)	(0.0763)	(0.0991)
Agriculture, Forestry, Fisheries and Veterinary Sciences	−0.267***	-0.0891	-0.317***
	(0.0595)	(0.108)	(0.0850)
Health and Welfare	0.0112	0.212*	-0.0102
	(0.0591)	(0.123)	(0.0675)
Services	−0.0771	-0.125	0.0487
	(0.0866)	(0.133)	(0.0909)
Unknown field of study	0.231**	0.342*	0.228**
	(0.101)	(0.191)	(0.104)
International experience (omitted: No)			
Yes	0.0813***	0.121***	0.0723**
	(0.0262)	(0.0424)	(0.0306)
Firm size (omitted: 1,000 employees or more)			
1–9 employees	−0.213***	-0.231***	-0.188***
	(0.0377)	(0.0724)	(0.0447)
10–49 employees	−0.122***	-0.135**	-0.121***
	(0.0336)	(0.0590)	(0.0406)
50–99 employees	−0.0977**	-0.162**	-0.0968*
	(0.0442)	(0.0716)	(0.0571)
100–249 employees	−0.0482	-0.0560	-0.0369
	(0.0363)	(0.0623)	(0.0426)
250–999 employees	−0.00225	-0.0110	-0.0027
	(0.0248)	(0.0405)	(0.0327)

Public sector (omitted: No)			
Yes	0.104***	0.0630	0.131***
	(0.0309)	(0.0580)	(0.0377)
Full-time employment (omitted: No)			
Yes	−0.0414	-0.152**	0.0369
	(0.0444)	(0.0746)	(0.0540)
Contract type (omitted: Open-ended contract)			
Fixed-term contract	−0.133***	-0.223***	-0.106***
	(0.0252)	(0.0450)	(0.0312)
Uncertain-term contract	−0.130***	-0.206***	-0.0929***
	(0.0308)	(0.0579)	(0.0357)
Other	0.0463	-0.370	0.171
	(0.128)	(0.348)	(0.120)
Not applicable	−0.203***	-0.198***	-0.215***
	(0.0330)	(0.0623)	(0.0399)
Unknown	−0.136**	-0.184*	-0.114*
	(0.0524)	(0.109)	(0.0611)
Country of work (omitted: Abroad)			
Portugal	−0.503***	-0.498***	-0.495***
	(0.0462)	(0.0682)	(0.0608)
Constant	2.879*** (0.123)	3.161*** (0.226)	2.661*** (0.133)
Observations	1,093	440	653
R-squared	0.539	0.550	0.559

Notes: Robust standard errors in parentheses: ***p<0.01, ** p<0.05, * p<0.1. The regression includes the full set of individual, academic and employment controls. Sector of activity and occupation controls are included in the estimation but are not reported in the table for brevity.

In the case of underskilling, the result obtained differs from that reported by Allen and de Weert (2007), despite the similarity between the measures used. As in this dissertation, the authors identify situations in which the level of particular skills is more than one point below the level required by the job and subsequently aggregate these situations into a measure of skill shortage. However, while underskilling is negatively and statistically significantly associated with wages in the present dissertation, Allen and de Weert (2007) find a positive and significant association in Germany and the United Kingdom and statistically insignificant results in the remaining countries analysed. The comparison for overskilling is less direct, since Allen and de Weert (2007) do not construct a symmetric measure of skill surplus. Other studies, such as Mateos-Romero and Salinas-Jiménez (2018), also report negative associations for overskilling but use categorical measures comparing overskilled individuals with a matched reference group, differing from the count-based measure used here.

An important feature of the measures used here is that underskilling and overskilling are not mutually exclusive at the individual level, since a graduate may have a deficit in some skills while possessing an excess of others. In the joint model (13), both measures display negative associations of similar magnitude. This similarity raises the possibility that, in the

case of wages, the extent of the mismatch between graduates' skill profiles and job requirements may be particularly relevant, beyond the specific direction of that mismatch. This interpretation is consistent with the logic of Assignment Theory, according to which productivity depends on the match between workers' productive characteristics and job requirements (Sattinger, 1993).

To assess this possibility, a test of equality between the underskilling and overskilling coefficients was performed. The test does not reject the null hypothesis of coefficient equality ($p = 0.577$), indicating that there is no evidence that the associations of the two forms of skill mismatch with wages are statistically different. As a complementary analysis (see Appendix B), a measure corresponding to the total number of skills in mismatch was also considered. Its coefficient is negative and statistically significant, indicating an approximately 1.1% reduction in hourly wages for each additional skill in mismatch. Taken together, these results suggest that, in this sample, a greater number of skills in mismatch is associated with lower wages, with no statistical evidence that this association differs between underskilling and overskilling.

Regressions (14) and (15) of Table 13 present the results separately by sex. Among the mismatch variables, only underskilling is statistically significant for men, at the 10% level, with each additional skill for which underskilling is observed being associated with approximately 1.6% lower hourly wages. Among women, undereducation displays a positive and statistically significant association, corresponding to wages approximately 12.6% higher than those of matched female graduates. Horizontal mismatch and overskilling, in turn, exhibit negative and statistically significant associations, corresponding to reductions of approximately 2.3% per additional unit of horizontal mismatch and 2.2% for each additional skill for which overskilling is observed, respectively.

In addition to the mismatch variables, several controls included in regression (13) display relevant associations with wages. Women earn approximately 9.7% lower hourly wages than men, holding the remaining observed characteristics constant. International experience, in turn, is associated with wages approximately 8.5% higher.

A clear pattern also emerges with respect to firm size. Graduates working in small firms with 1 to 9 employees earn approximately 19.2% lower hourly wages than those

working in firms with 1,000 or more employees. This wage difference tends to decrease as firm size increases and becomes statistically insignificant for the larger firm-size categories.

Contract type also displays a relevant association. Compared with holding open-ended contracts, those with fixed-term or uncertain-term contracts earn approximately 12% lower wages. By contrast, employment in the public sector is associated with approximately 11% higher hourly wages, holding the remaining characteristics constant.

Finally, some wage differences are observed across fields of study relative to Engineering, Manufacturing and Construction. In particular, graduates in Arts and Humanities and Agriculture, Forestry, Fisheries and Veterinary Sciences earn approximately 13.8% and 23.4% lower wages, respectively. In comparison, the area of Information and Communication Technologies is associated with wages approximately 14.6% higher.

4.2. Effects of labour market mismatch on job satisfaction

Table 14 presents the ordered probit estimates of the association between labour market mismatch and job satisfaction. In the full sample, undereducated graduates are positively and statistically significantly associated with job satisfaction relative to adequately matched graduates, whereas no significant difference is found for overeducated graduates. Horizontal mismatch, underskilling and overskilling exhibit negative and statistically significant coefficients, indicating a lower propensity to report higher levels of job satisfaction.

Table 14 – Ordered probit estimates of the association between labour market mismatch and job satisfaction, overall and by sex

	Full sample	**Men**	**Women**
Female	-0.135* (0.0708)	———	———
Undereducated	0.317** (0.130)	0.329 (0.200)	0.341** (0.172)
Overeducated	0.0886 (0.0822)	0.0663 (0.137)	0.102 (0.108)
Horizontal mismatch	-0.231*** (0.0352)	-0.179*** (0.0562)	-0.272*** (0.0474)
Underskilling	-0.0841*** (0.0184)	-0.0471 (0.0295)	-0.107*** (0.0250)
Overskilling	-0.123*** (0.0135)	-0.108*** (0.0202)	-0.139*** (0.0181)
All controls	Yes	Yes	Yes
Observations	1,210	488	722
Pseudo R^2	0.1132	0.1443	0.1366
Marginal effects full sample			

	S = 1	S = 2	S = 3	S = 4	S = 5
Undereducated	-0.0166***	-0.0304***	-0.0348**	-0.0150	0.0968**
	(0.0060)	(0.0116)	(0.0143)	(0.0112)	(0.0416)
Overeducated	-0.0055	-0.0092	-0.0097	-0.0014	0.02580
	(0.0051)	(0.0085)	(0.0090)	(0.0018)	(0.0240)

Horizontal mismatch	0.0139***	0.0239***	0.0254***	0.0043*	-0.0676***
	(0.0027)	(0.0039)	(0.0041)	(0.0023)	(0.0101)
Underskilling	0.0051***	0.0087***	0.0092***	0.0016*	-0.0246***
	(0.0012)	(0.0020)	(0.0021)	(0.0009)	(0.0053)
Overskilling	0.0074***	0.0127***	0.0134***	0.0023*	-0.0359***
	(0.0011)	(0.0016)	(0.0016)	(0.0013)	(0.0039)

Note: Robust standard errors are reported in parentheses.***p<0.01, ** p<0.05, * p<0.1. All models include the full set of individual, academic and employment-related controls. Adequately matched graduates constitute the reference category for vertical mismatch. The lower panel reports average marginal effects for the full sample for each job satisfaction category, $S = 1, \dots, 5$, where higher values indicate greater job satisfaction.

Looking at the average marginal effects for the highest satisfaction category, $S = 5$, undereducated graduates are around 9.7 percentage points more likely to report the highest level of job satisfaction than matched graduates. By contrast, a one-unit increase in horizontal mismatch is associated, on average, with a 6.8 percentage-point reduction in the probability of being very satisfied. For skill mismatch, each additional skill in underskilling is associated with a reduction of about 2.5 percentage points in this probability, while each additional skill in overskilling is associated with a reduction of around 3.6 percentage points. The positive association between undereducation and job satisfaction differs from the evidence reported by Mateos-Romero and Salinas-Jiménez (2018), who find a negative association, and Sánchez-Sánchez and McGuinness (2015), who find no statistically significant relationship. This result therefore reinforces the less conclusive evidence surrounding the relationship between undereducation and job satisfaction.

Overeducation shows a particularly relevant change across specifications. The estimates in which each mismatch dimension is analysed separately, while retaining the full set of controls, are reported in Annex C. In these specifications, overeducation is negatively and statistically significantly associated with job satisfaction. However, in the joint model reported in Table 14, this association is no longer statistically significant once horizontal mismatch and skill mismatch are included simultaneously. As also observed for wages, the association initially identified for overeducation is therefore not robust to the simultaneous inclusion of the remaining mismatch dimensions.

Horizontal mismatch is negatively and statistically significantly associated with job satisfaction, and this association remains significant when the other mismatch dimensions are considered simultaneously. This result is consistent with McGuinness and Sloane (2011),

who also find evidence that a closer correspondence between field of study and employment is associated with higher levels of job satisfaction.

The results for skill mismatch are consistent with Mateos-Romero and Salinas-Jiménez (2018), who likewise find negative and statistically significant associations between both overskilling and underskilling and job satisfaction. Although the magnitudes are not directly comparable because of differences in the construction of the skill mismatch measures, the similarity in sign and statistical significance points to a comparable pattern.

The estimates by sex reveal some differences in the observed patterns. Among men, only horizontal mismatch and overskilling are negatively and statistically significantly associated with job satisfaction. Among women, undereducation is positively associated with job satisfaction, whereas horizontal mismatch, underskilling and overskilling exhibit negative and statistically significant associations. Overeducation is not statistically significant for either group.

4.3. Robustness analysis

Tables 15 and 16 present the robustness checks for wages and job satisfaction, respectively. Overall, the findings for horizontal and skill mismatch remain broadly stable across specifications, whereas vertical mismatch is more sensitive to its measurement.

For wages, column (1) presents the baseline specification. In column (2), the skill mismatch measures are reconstructed without applying the one-point tolerance margin. The signs and statistical significance of the main results remain broadly unchanged: undereducation continues to be positively and statistically significantly associated with wages, while horizontal mismatch, underskilling and overskilling remain negative and statistically significant. Overeducation remains statistically insignificant.

Column (3) restricts the sample to graduates working in Portugal. The results remain broadly similar to the baseline specification, as undereducation, horizontal mismatch, underskilling and overskilling retain both their signs and statistical significance. The main change concerns overeducation, which becomes negatively associated with wages and statistically significant at the 10% level, indicating some sensitivity of this result to the composition of the sample.

In column (4), the main vertical mismatch measure, based on the comparison between the level of education attained and that required for the job, is replaced by the

alternative direct self-assessment measure described in Section 3.5. Neither underqualification nor overqualification is statistically significantly associated with wages, whereas horizontal mismatch, underskilling and overskilling remain negative and statistically significant. One possible explanation for the difference relative to the main measure lies in the wording of the question itself, since, as discussed in Section 2.2, the concept of qualifications may have a broader meaning than formal educational attainment. The alternative measure may therefore capture broader aspects of qualification-job fit beyond the correspondence between attained and required levels of education that characterises the main vertical mismatch measure.

Table 15 – Robustness analysis of the association between labour market mismatch and real hourly wages

Variables	**Baseline specification**	**No tolerance in skill mismatch**	**Portugal-only sample**	**Alternative vertical measure**
	(1)	(2)	(3)	(4)
Undereducation	0.117*** (0.0384)	0.119*** (0.0390)	0.0871** (0.0371)	0.0702 (0.0532)
Overeducation	-0.0294 (0.0259)	-0.0291 (0.0258)	-0.0439* (0.0241)	0.0141 (0.0206)
Horizontal mismatch	−0.0280** (0.0114)	-0.0296*** (0.0112)	-0.0253** (0.0116)	−0.0339*** (0.0117)
Underskilling	−0.0132*** (0.0049)	-0.0096*** (0.0034)	-0.0084* (0.0047)	−0.0131*** (0.0050)
Overskilling	−0.0105** (0.0042)	-0.0097*** (0.0034)	-0.0133*** (0.0040)	−0.0121*** (0.0042)
All controls	Yes	Yes	Yes	Yes
Observations	1,093	1,093	968	1,092

Notes: Robust standard errors are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All specifications include the full set of controls used in the baseline model. In column (4), undereducation and overeducation refer to underqualification and overqualification, respectively.

Regarding job satisfaction, column (5) presents the baseline specification. When skill mismatch is reconstructed without applying any tolerance in column (6), the signs and statistical significance of the main mismatch variables remain unchanged. In column (7), the alternative vertical mismatch measure is again used. Neither underqualification nor overqualification is statistically significant, whereas horizontal mismatch, underskilling and overskilling remain negatively and statistically significantly associated with job satisfaction.

Table 16 – Robustness analysis of the association between labour market mismatch and job satisfaction

Variables	**Baseline specification**	**No tolerance in skill mismatch**	**Alternative vertical measure**
	(5)	(6)	(7)
Undereducation	0.317** (0.130)	0.306** (0.130)	-0.0777 (0.177)
Overeducation	0.0886 (0.0822)	0.0703 (0.0824)	-0.0902 (0.0698)
Horizontal mismatch	-0.231*** (0.0352)	-0.246*** (0.0347)	-0.223*** (0.0346)
Underskilling	-0.0841*** (0.0184)	-0.0358*** (0.0133)	-0.0823*** (0.0185)
Overskilling	-0.123*** (0.0135)	-0.0846*** (0.0112)	-0.120*** (0.0133)
All controls	Yes	Yes	Yes
Observations	1,210	1,210	1,210

Notes: Robust standard errors are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All specifications include the full set of controls used in the baseline model. In column (7), undereducation and overeducation refer to underqualification and overqualification, respectively.

Overall, the robustness checks show that the results for horizontal mismatch and skill mismatch remain broadly consistent in sign and statistical significance across the different specifications considered, while vertical mismatch displays some sensitivity to how it is measured.

5. Conclusions

Completing higher education does not necessarily ensure that the education acquired is fully utilised in employment. The benefits of education also depend on the match between workers' profiles and job characteristics, and mismatches may arise in educational level, field of study or skills. This issue is particularly relevant at the beginning of graduates' careers, when labour market entry may involve a process of adjustment between their education and job opportunities. Against this background, this dissertation analysed vertical mismatch, horizontal mismatch and skill mismatch among University of Porto graduates, examining their relationship with wages and job satisfaction. The analysis showed that mismatch remains relevant even among graduates from a highly regarded university.

The analysis used two consecutive waves of the University of Porto Graduate Survey, conducted in 2024 and 2025, comprising 1,211 graduates observed approximately two years after completing their degree. This allowed the analysis to focus on an early career stage. The three dimensions of mismatch were considered both separately and jointly, making it possible to assess whether the associations observed for each dimension remain when the others are taken into account. Wages were analysed using OLS models within a Mincerian wage-equation framework, while job satisfaction was analysed using ordered probit models.

Taken together, the results show that, approximately two years after graduation, different forms of labour market mismatch are already significantly associated with graduates' labour market outcomes. Regarding wages, undereducation remains positively and statistically significantly associated in the joint model, corresponding to hourly wages around 12.4% higher than those of adequately matched graduates. By contrast, a one-unit increase in horizontal mismatch is associated with approximately 2.8% lower wages, while each additional skill in underskilling and overskilling is associated with reductions of around 1.3% and 1.0%, respectively. The negative associations found for both forms of skill mismatch further suggest that the number of mismatched skills may matter for wages beyond the specific direction of the mismatch. Overeducation is initially negatively associated with wages, but this association loses statistical significance once the remaining dimensions of mismatch are included simultaneously. This indicates that focusing only on the adequacy of educational level may provide an incomplete picture, as different forms of mismatch may coexist within the same job.

Job satisfaction also reveals important differences across mismatch dimensions. Horizontal mismatch, underskilling and overskilling are negatively and statistically significantly associated with job satisfaction, indicating that poorer alignment between education, skills and employment is related not only to economic outcomes but also to graduates' assessment of their jobs. In particular, a one-unit increase in horizontal mismatch is associated with a 6.8 percentage-point lower probability of reporting being very satisfied, while each additional skill in underskilling or overskilling is associated with reductions of around 2.5 and 3.6 percentage points, respectively. Undereducation is positively associated with job satisfaction, whereas overeducation is again not statistically significant when the different mismatch dimensions are considered jointly.

These findings show that the match between education and employment should not be assessed solely through educational level. In the sample analysed, horizontal mismatch and skill mismatch show relatively consistent negative associations with both wages and job satisfaction. The robustness checks support this pattern, as results for these two dimensions remain broadly stable across alternative specifications, whereas vertical mismatch is more sensitive to how it is measured. This highlights the value of considering different dimensions of mismatch simultaneously when assessing graduates' labour market integration.

The study nevertheless has some limitations. As University of Porto graduates may differ from those of other institutions, the findings cannot be directly generalised to the broader population of Portuguese graduates. In addition, the observational nature of the data allows associations to be identified but does not permit causal relationships to be established, as unobserved individual or job characteristics may still be related to the outcomes examined. Some measures also rely on graduates' own assessments and, in the case of skill mismatch, the measure captures the number of mismatched skills but does not identify whether mismatch in specific skills has different associations with wages or job satisfaction. Finally, observing graduates approximately two years after completing their degree provides insight into an important stage of labour market entry, but does not allow us to determine whether these mismatches are temporary or persist throughout their careers.

In this context, future research could follow graduates over time to assess whether early-career mismatch is temporary or persistent. Future studies could also examine individual skills separately to identify whether mismatch in specific skills has different associations with wages and job satisfaction

6. Appendices

Appendix A – Definition of Variables Used in the Empirical Models

Variable	Definition
Dependent variables	
Log real hourly wage	Logarithm of the graduate's gross hourly wage, expressed in 2024 prices.
Job satisfaction	Self-reported job satisfaction, measured on an ordered scale from 1 = very dissatisfied to 5 = very satisfied.
Mismatch variables	
Undereducation	Dummy variable equal to 1 if attained education is below the level required for the job, 0 otherwise.
Overeducation	Dummy variable equal to 1 if attained education is above the level required for the job, 0 otherwise.
Horizontal mismatch	Ordinal variable ranging from 1 to 5, where higher values indicate a lower degree of alignment between field of study and current job.
Underskilling	Number of skills, from 0 to 12, for which the possessed level is more than one point below the required level.
Overskilling	Number of skills, from 0 to 12, for which the possessed level is more than one point above the required level.
Controls	
Individual controls	
Female	Dummy variable equal to 1 if female, 0 if male.
Age	Age of the graduate, in years, at the survey reference date.
Academic controls	
Degree level	Categorical variable: Bachelor, Master, Integrated Master and PhD. Bachelor is the reference category in the regressions.
Field of study	Categorical variable based on the broad fields of CITE-F 2013. Engineering, Manufacturing and Construction is the reference category.
International experience	Dummy variable equal to 1 if the graduate undertook international experience during the degree, 0 otherwise.
Employment controls	
Firm size	Categorical variable: 1–9, 10–49, 50–99, 100–249, 250–999 and 1,000 or more employees. The reference category is 1,000 or more employees.
Sector of activity	Main sector of activity of the firm or organisation.
Public sector	Dummy variable equal to 1 if the graduate works in the public sector, 0 otherwise.
Full-time employment	Dummy variable equal to 1 if the graduate works full-time, 0 otherwise.
Occupation	Categorical variable based on the occupational group of the graduate's current job.
Contract type	Categorical variable: open-ended, fixed-term, uncertain-term, other, not applicable and unknown. Open-ended contract is the reference category.
Work in Portugal	Dummy variable equal to 1 if the graduate works in Portugal, 0 if working abroad.

Appendix B – OLS estimates of the association between labour market mismatch and real hourly wages using an aggregate skill mismatch measure

Variables	**All mismatches**
Undereducation	0.116*** (0.0384)
Overeducation	-0.0283 (0.0258)
Horizontal mismatch	−0.0276** (0.0113)
Total skill mismatch	−0.0113*** (0.0036)
All controls	Yes
Constant	2.876*** (0.122)
Observations	1,093
R-squared	0.539

Notes: Robust standard errors are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. Total skill mismatch is defined as the sum of the number of skills in underskilling and the number of skills in overskilling and ranges from 0 to 12. Higher values indicate a greater extent of skill mismatch. The model includes the full set of controls used in the main specification.

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8. Annexes

Annex A – U.Porto Graduate Survey questions used in the empirical analysis

Variable	Survey item	Question
International experience	A2	Did you have any experience abroad in the context of the degree you completed (i.e. student mobility, internship, language courses, etc.)? Yes / No.
Employment status	A13	Were you working on 1 October 2025? Yes / No.
Country of work	A19	Where were you working? Portugal / Another country.
Contract type	A20	What type of contract did you have on 1 October 2025? Fixed-term contract / uncertain-term contract / open-ended contract / Other.
Weekly working hours	A21	What was the number of hours per week established in your employment contracts? Include all jobs, if applicable; exclude overtime.
Gross monthly earnings	A22	What were your gross monthly earnings? Include regular additional payments and all jobs.
Horizontal mismatch	A23	Would you say that your job on 1 October 2025 was aligned with your field of study? 1 = Not at all; 3 = Partially; 5 = Absolutely.
Job satisfaction	A26	Overall, how satisfied were you with your employment situation? 1 = Very dissatisfied; 3 = Neither satisfied nor dissatisfied; 5 = Very satisfied.
Firm size	E6	What was the total number of people working in the organisation/company, including all workplaces where applicable? 1–9 / 10–49 / 50–99 / 100–249 / 250–999 / 1,000 or more.
Sector of activity	E7	What was the main sector of activity of the organisation/company where you worked? Sections A–U of the economic activity classification.
Public sector	E8	Was your job in the public sector? Yes / No.
Full-time employment	E9	Was your job full-time? Include self-employment. Yes / No, part-time.
Occupation	E10	What was your occupation? Occupational categories provided in the survey.
Required education, vertical mismatch	E13	What level of education was normally required to perform this job? Below higher education / Higher professional technical education / Bachelor's degree or equivalent / Master's degree or equivalent / Doctoral degree.
Required skill level	G2	For each of the 12 skills, rate the level required in your current job. 1 = Very low to 7 = Very high
Possessed skill level	G3	For each of the same 12 skills, rate your current level. 1 = Very low to 7 = Very high
Alternative vertical mismatch	E14	Would you say that your qualifications were appropriate for your job? 1 = Qualifications significantly below those required; 3 = Qualifications aligned with those required; 5 = Qualifications significantly above those required.

Note: Survey items follow the section coding of the U.Porto Graduate Survey: A = Essential Information; E = Employment; G = Competences. Item wording and codes refer to the 2025 survey; equivalent items were used for 2024. Information on sex, age, degree level and field of study is obtained directly from the administrative dataset and is therefore not included in this table.

Annex B – Correspondence between Sector Codes and Sectors of Economic Activity

Code	Sector of activity
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households as employers
U	Activities of extraterritorial organisations and bodies

Note: Sector codes correspond to the one-letter sections (A–U) of the economic activity classification used in the U.Porto Graduate Survey.

Annex C – Ordered probit estimates of the association between vertical, horizontal and skill mismatch and job satisfaction

	Vertical mismatch				Horizontal mismatch				Skill mismatch			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Undereducation	0.422***	0.410***	0.496***	0.452***								
	(0.109)	(0.110)	(0.127)	(0.127)								
Overeducation	-0.201***	-0.215***	-0.280***	-0.168**								
	(0.0659)	(0.0677)	(0.0717)	(0.0806)								
Horizontal mismatch					-0.275***	-0.276***	-0.301***	-0.280***				
					(0.0308)	(0.0307)	(0.0321)	(0.0345)				
Underskilling									-0.0770***	-0.0814***	-0.0817***	-0.0832***
									(0.0172)	(0.0171)	(0.0173)	(0.0180)
Overskilling									-0.133***	-0.138***	-0.137***	-0.139***
									(0.0126)	(0.0128)	(0.0130)	(0.0134)
Controls:												
Individual		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Academic			Yes	Yes			Yes	Yes			Yes	Yes
Employment				Yes				Yes				Yes
Observations	1,210	1,210	1,210	1,210	1,210	1,210	1,210	1,210	1,210	1,210	1,210	1,210
Pseudo R^2	0.0092	0.0108	0.0206	0.0627	0.0330	0.0350	0.0445	0.0826	0.0391	0.0432	0.0492	0.0948

Notes: Robust standard errors are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. The dependent variable is job satisfaction, measured on an ordered scale from 1 to 5, with higher values indicating greater satisfaction. Columns (1), (5) and (9) include only the respective mismatch measures. Columns (2), (6) and (10) add individual controls; columns (3), (7) and (11) additionally include academic controls; and columns (4), (8) and (12) further include employment controls. Individual controls include age and sex; academic controls include degree level, field of study and international experience; employment controls include firm size, sector of activity, public-sector employment, full-time employment, occupation, contract type and country of work.