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Educational Gender Segregation and Educational Mismatch

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Abstract
The increasing connection between higher education and the workforce may influence gender-based educational and occupational segregation. If men and women continue to gravitate toward fields historically dominated by their own gender, this segregation will persist. Furthermore, the chosen field of study carries implications for labor market mismatch, as certain majors are more prone to producing graduates who struggle to find positions aligned with their qualifications. Using a representative sample of employed graduates from the Spanish Labor Force Survey, this paper examines the relationship between gender, gender-dominated fields of study, and educational mismatch. Conditional on labor market participation, discrete choice models reveal that studying in a gender-dominated field is associated with lower vertical and horizontal mismatch (i.e., overeducation and field of study mismatch) —a finding supported by several robustness checks. This finding is especially pronounced in horizontal mismatch when gender and field-dominance coincide. Consequently, the higher risk of mismatch in gender-neutral fields may provide a rationale for the continued persistence of gender-segregated educational choices.

Keywords Educational segregation · Field of study · Horizontal mismatch · Overeducation

Introduction

The most recent decades have witnessed growth in the education level of the workforce (Marginson, 2016). Specifically, the proportion of young adults with tertiary qualifications in OECD countries has nearly doubled since the turn of the century, rising from 27% in 2000 to 48% in 2023 (OECD, 2024). Two significant unintended consequences of this may be the spread of both gender segregations in education, i.e., the unequal distribution of men and women across different fields of study (Charles & Bradley, 2002), and educational mis-

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match, i.e., the lack of correspondence between what is studied and/or the level of what is studied and the requirements for performing a particular job (McGuinness, 2006).

Increases in education may affect the levels of educational (and occupational) segregation if there are certain fields of study or professions that workers of a particular gender tend to pursue more frequently. Mastekaasa and Smeby (2008) point out that an increase in education and in participation rates, such as have been observed among women in recent decades, may add to the willingness of female students to pursue gender-typical fields, to the extent that higher education might reproduce the prevailing conceptions of gender-appropriate fields of knowledge and thus reinforce the phenomenon of educational gender segregation. Smyth and Steinmetz (2008) suggest that increasing the participation of women in male-dominated fields could also have an integrative effect, reducing educational segregation by lowering barriers to entry. Cross-country analyses (Blossfeld et al., 2015; Bradley, 2000; Charles & Bradley, 2009) reveal an imbalanced distribution of women and men across fields of study, despite pro-egalitarian cultural changes (Charles & Bradley, 2002).

Increases in educational level may also lead to vertical or horizontal mismatches. If firms' demands are not adequately covered by workers' qualifications, vertical and horizontal imbalances between what is required for a job and the abilities workers possess may arise (McGuinness et al., 2018). Vertical mismatch (overeducation and overqualification) occurs when worker's qualifications are above those required for performing the specific job of the worker, while horizontal mismatch reflects that the given occupation is weakly related (or completely unrelated) to the field of education studied. Mismatch in the workplace is often seen as a source of inefficiency and a waste of worker investments in education, since mismatched workers usually show lower rewards from the job, worse working conditions, and lower job satisfaction or occupational prestige (Garcia-Mainar et al., 2016; Leuven & Oosterbeek, 2011; McGuinnes, 2006; Nordin et al., 2010; Robst, 2008).

These two unintended consequences of increased educational attainment may be interrelated. This possibility has been habitually overlooked in literature. While some studies have examined educational and occupational segregation (Blossfeld et al., 2015; Charles & Bradley, 2002, 2009; England, 2010; Morgan et al., 2013; Smyth & Steinmetz, 2008) and others have examined educational mismatch (Barone & Ortiz, 2011; McGuinness & Sloane, 2011; Montt, 2017; Morgado et al., 2016; Nordin et al., 2010; Robst, 2008), the connections between the fields of study chosen by women and men and educational mismatch in the labor market have been explored less often. This is the main contribution of our study. Specifically, we focus first on analyzing the distribution of men and women across different fields of study. We then examine whether the risk of educational mismatch is higher in gender-dominated fields, i.e. in fields where either men or women are in a majority, or in integrated fields, i.e. fields where both genders are more evenly distributed.

Efforts to promote greater equality between men and women in the performance of work and family tasks, whether through cultural changes or policy measures, have not effectively reduced educational and occupational segregation (Blossfeld et al., 2015; England, 2020; Smyth & Steinmetz, 2008). Learning more about how men and women make different choices in their fields of study, as well as how these choices may result in a mismatch in the workplace, could help identify erroneous patterns and thus lead to a redesign of such policies.

We use data from the expanded 2019–2021–2022 subsamples of the Spanish Labor Force Survey (LFS), selecting respondents who graduated in the last 10 years and grouping the information into one-digit fields of study (11 fields) and two-digit occupations (38 occupations) from ISCO-08.[1] Discrete choice regression models are applied to investigate the role played by the individual's gender, and the character of the individual's field of study, on the likelihood of being job-mismatched. After controlling for the individual's participation in the labor market, our results suggest that graduating in gender-typical fields of study is associated with lower mismatch in the labor market. Those who are of the same gender as the one that predominates in their field of study are less likely to suffer from any type of labor mismatch.

We explore whether our results depend on regional, personal and job-related variables, as well as different measures of educational mismatch and sample selection. The final result remains mostly unaltered against alternative specifications and robustness checks: reducing inequality in the distribution of men and women across fields of study would not reduce job mismatch. This partially helps to explain the observed persistence in gender educational segregation and reveals no existing incentives for reducing such segregation.

The rest of the paper is organized as follows. In Section "Literature Review", we provide some background information, including a subsection focused on the case of Spain. In Section "Data, Sample and Descriptive Analysis", we present our data and measures. Sections "Methodology" and "Results" discuss the methodology and empirical results of the research, and Section "Discussion and Conclusions" concludes.

Literature Review

Gender Occupational Segregation

The process of gender occupational segregation decline seems to have stalled in recent decades (England, 2010, 2020; Moskos, 2020). Despite policies aimed at achieving more equality in job allocation, there still exist marked differences in the occupations filled mostly by men and those filled mostly by women.[2] This uneven distribution across occupations by gender is an important source of the disadvantages that women encounter in the labor market, such as lower wages, fewer possibilities for promotion, and lower occupational prestige (Bayard et al., 2003; Blau & Kahn, 2017; England et al., 2007; Shauman, 2006).

One reason for this gender occupational segregation persistence stems from the still-high segregation in higher education, despite the extraordinary increase in women's educational attainment in recent decades (Blossfeld et al., 2015; Bradley, 2000; Charles & Bradley,

[1] The Spanish National Occupation Classification in 2011 (NOC-11) follows that of the ISCO-08 (International Standard Classification of Occupations) but does not entirely coincide. At the one-digit level, this includes: 1. Managers, 2. Professionals, 3. Technicians and Associate Professionals, 4. Clerical Support Workers, 5. Services and Sales Workers, 6. Skilled Agricultural, Forestry, and Fishery Workers, 7. Craft and Related Trades Workers, 8. Plant and Machine Operators and Assemblers, and 9. Elementary Occupations. We have adapted the information provided by the 66 occupations of the NOC-11 to the 38 of the two-digit ISCO-08, following the Spanish National Statistics Institute guidelines available at https://www.ine.es/dyngs/INEbase/en/operacion.htm?c=Estadistica_C&cid=1254736177033&menu=ultiDatos&idp=1254735976614. Table A1 in the Appendix lists ISCO-08 occupations.

[2] For example, in Spain, the percentage of female in Personal service and care workers (code 51 in 2-digit ISCO-08 classification) or Customer services clerks (42) is over 75%, whereas it is less than 5% in the occupations of Metal, machinery and related trades workers (72) or Drivers and mobile plant operators (83). Data from 2019 Spanish Labor Force Survey.

2009; Smyth & Steinmetz, 2008). By countries, Mastekaasa and Smelby (2008) examined Norway, and Chesters (2022) examined Germany, providing evidence that strong occupational segregation is largely explained by educational segregation. Men continue to be overrepresented in STEM-related fields of study—such as engineering, information and communication technologies (ICT), computing, and some other sciences—which bring the most lucrative rewards in the labor market. By contrast, women are overrepresented in the fields of humanities, some social sciences (sociology, politics, and communication), teaching and health-related studies. Except for the latter, degrees in all these fields lead to occupations that are not particularly well-paid in the labor market (Barone and Assirelly, 2020; Barone & Ortiz, 2011; Reimer et al., 2008). If the wage gap between men and women is partly due to an unequal distribution of people across different occupations, and if this distribution is in turn due to an unequal choice of fields of study, then perhaps policy measures aimed at reducing educational segregation could help reduce the unequal distribution of people across different occupations, and ultimately, the wage differences between men and women.

Various arguments have been put forward to explain how people choose their field of study. Barone and Assirelli (2020) distill these arguments down to two main sources of specialization. Specialization may result from a rational choice process, in which individuals opt for studies that can bring greater rewards in the labor market, or from a disposition guided by preferences. As for the first possibility, several factors may influence students' behavior when choosing specific fields of study. A student may choose fields that are expected to lead to occupations that: i) are more productive and better paid (Barone & Ortiz, 2011); ii) provide rewards in other spheres of work (promotion, working conditions) or life, as in family-work (Polachek, 1981) or leisure-work (Hakim, 2006) balances; iii) signal higher acquired human capital (Ortiz & Kucel, 2008; Reimer et al., 2008); iv) show lower levels of competence or saturation (Montt, 2017; Verhaest et al., 2017); or v) are more occupationally oriented (Martinak, 2020; Reimer et al., 2008). As regards students' desires, individuals may decide the field they want to study based on their preferences for subjects or occupations, peer/family/ societal pressure, or because of decisions made while in high school (Barone & Assirelli, 2020; Montt, 2017; Morgan et al., 2013; see Somers et al., 2019 for a review).

While these arguments can shed light on why individuals choose each field of study, it is more difficult to explain why men more often choose STEM- or ICT-related fields and women tend to enter more general studies such as humanities, arts, or teaching. Blossfeld et al. (2015) summarizes contributions from economic and sociological views arguing that the increase in women's access to education would have driven them to make similar educational choices to those of men. Since men tend to study in fields leading to higher-paying occupations, women would rationally choose fields widely followed by men and avoid fields leading to lower-paying occupations, such as nursing, the humanities, and the arts. However, this is not the case. While women are increasingly entering the labor market, they continue to be overrepresented in traditionally feminine programs.

One might think that women's and men's motivations are very different when it comes to choosing occupations that offer better rewards in the labor market. In terms of preferences, the differences between men and women may be due to innate differences or different socialization. In this sense, the traditional essentialist view of gender—according to which men and women are innately and fundamentally different—is strongly challenged and complemented by sociological approaches that point to different socialization for men and women (Charles & Bradley, 2009; Chesters, 2022; Humlum et al., 2012). A purely biological argument emphasizes the fact that men may have greater abilities in mathematical and scientific fields in absolute or relative terms (Barone and Assirelly, 2020). However, when innate abilities are controlled for, these differences tend to disappear. Nevertheless, the belief persists that boys may have an advantage over girls in programs of study with strong mathematical content (Correll, 2001; Marini & Brinton, 1984).

Psychological factors can play a significant role in the decisions men and women make about the rewards they expect from their chosen studies. If men and women have different personality traits, they may be better suited to different roles. As Blossfeld et al. (2015) note, women may be more affected than men by the undervaluation of their work and lower self-esteem when deciding to pursue math-related studies. Garcia-Aracil et al. (2007) examined the relationship between students' personality traits and their choice of field of study in seven countries with different educational structures and institutional aspects. The authors found that each field of study has characteristics that appeal to people of different genders. For example, the humanities attract more women, while the natural sciences and engineering attract more men. Medical and social sciences are more neutral in this regard.

The relevant question is whether these differences in preference, which ultimately lead men and women to choose different fields of study, are intrinsic to individuals or the result of socialization. Several sociological theories help explain the persistence of gender segregation in higher education.[3] According to social reproduction theory, the educational choices of men and women tend to mirror and reproduce gender-differentiated societal patterns. Rigid gender-specific stereotypes and ideals constrain men's and women's choices according to what is seen as socially acceptable. These differences in skills, preferences, and beliefs are transmitted by parents, relatives, neighbors, peers, and society in general, which causes gender stereotypes to persist over time (Bielby & Bielby, 1988; Bradley, 2000; Carlana & Corno, 2021).[4] Thus, normative rules associate "female" values to humanities, nurturing or education, and "male" values to business and STEM.

From another perspective, according to identity theory, students' choice of field of study is influenced by a multitude of factors, leading them to choose what is appropriate for or inherent to their social group rather than what they prefer. Identity models (Akerlof & Kranton, 2000, 2002) may also explain why women and men choose different fields of specialization. Identity, or the pursuit of social categories (educational, occupational, etc.) that fit individuals, is an additional intrinsic motivation for educational and occupational choice. People categorize themselves and try to fit into their own category. Deviating from one's category leads to "disutility" and a loss of non-pecuniary compensation. Using 2004 PISA (Program for International Student Assessment) data from Denmark, Humlum et al. (2012) demonstrated that field and occupational choices are driven by what they refer to as "career-oriented" and "socially oriented" attitudinal factors. On average, women have much lower career-oriented factors than men, leading them to more frequently choose short- and

[3] See Bielby and Bielby (1988), Mastekaasa and Smeby (2008) and Weeden (2002). See Marini and Brinton (1984) in the context of sex-typing in occupational socialization.

[4] Earlier decisions (in high school) about which field to major in may well influence the choice of majors in higher education, reflecting the relevant role that socialization plays since students are children (Barone and Assirelli, 2020; Blossfeld et al., 2015). Mastekaasa and Smeby (2008), for example, conclude that girls are more sensitive to the influence of family and peers than boys in Norway.

medium-cycle studies, such as education and health, and less frequently choose business and other social sciences. Conversely, men tend to avoid education and humanities and are more likely to study business or law.

The gendered patterns in choice of study field are highly resistant to increased female participation as well as pro-egalitarian cultural change (Mastekaasa & Smeby, 2008). In her study, Bradley (2000) showed that more industrialized and developed countries have greater educational segregation than less developed countries. Similarly, Charles and Bradley (2009) examined gender segregation by field of study using data from 44 societies, finding that gender typification of curricular fields is stronger in more economically developed contexts. Stoet and Geary (2018) offer an explanation for this paradoxical result within the context of STEM studies. Using international data from the 2004 PISA, they demonstrated that schools prepare more girls to pursue STEM studies than obtain STEM degrees, even though girls perform similarly to or better than boys on generic STEM literacy tests. In less developed countries with less gender equality, girls are more likely to pursue STEM fields because fewer economic opportunities and greater economic risks make well-paid STEM occupations more attractive relative to other studies. Since economic and general life risks are lower in countries with gender equality, women have greater opportunities to pursue other academic paths. As a result, policies that provide more educational and empowerment opportunities do not necessarily lead to higher enrollment in STEM programs.

Educational Mismatch

With the spread of higher education in recent decades, vertical and horizontal imbalances have become much more common. However, in the new century, this trend has stabilized in many countries. In Spain, for example, Morgado et al. (2016) observed a sharp rise in overeducation rates until the late 1990s, followed by a stabilization at rates above 30%.[5] Regarding horizontal mismatch, the trend in Spain was downward until 2007 and has since shown a slight upward trend.

Several sources of educational mismatch have been discussed in the literature (see Leuven & Oosterbeek, 2011; McGuinness et al., 2018; Somers et al., 2019; Smyth & Steinmetz, 2008; Verhaest et al., 2017). Human capital, assignment, and job competition models are the most common approaches explaining educational mismatch. Regarding horizontal mismatch, these models provide arguments for both demand- and supply-driven causes. In the first case, imperfect information, bad luck, discrimination, or poorer skills than competitors lead some individuals to be horizontally mismatched. By contrast, supply characteristics, like preferences or some type of constraint on the part of individuals may also lead to horizontal mismatch (see Albert et al., 2025, for a recent survey).

Much of the research on educational mismatch has focused on analyzing the disadvantages experienced by mismatched workers compared to those who are not mismatched. Mismatch is typically associated with labor market inefficiency and negative consequences, including wage penalties, higher turnover rates, lower job satisfaction, and diminished professional prestige (McGuinness et al., 2018; Montt, 2017; Robst, 2008; Verhaest et al., 2017). Somers et al (2019) selected a set of 24 studies published between 1995 and 2015 with empirical evidence focused on horizontal mismatch. They analyze various aspects such

[5] Like other southern European countries, Spain shows over time consistently higher rates of overeducation than the rest of Europe (see also McGuinness et al., 2018).

as the measurement of horizontal mismatch, the prevalence of the phenomenon, and its determinants (variables related to the type of education, the labor market, the job position, and individual variables). They show that the main results associated with horizontal mismatch are the existence of wage penalties, increased job search, and a decline in prestige and job satisfaction.

Cross-country studies reach very similar conclusions when analyzing the relationship between the choice of field of study and the existence of vertical or horizontal mismatches. For example, degrees in fields such as the humanities, arts, services, and social sciences favor both types of mismatch. In contrast, the risk of mismatch is lower in fields such as engineering, mathematics, health and welfare, and ICT. Business, law, teaching, and certain natural sciences fall somewhere in between. Table 1 shows the results of a series of studies on the matter, some of them focusing on the Spanish case. A recent survey of the main results can be seen in Somers et al. (2019), who conclude that the level of transferability of skills, abilities, and knowledge of a particular field of study is relevant to the risk of mismatch. Students in fields that provide more specific skills are more difficult to allocate to occupations that require other, different skills and are less likely to suffer horizontal mismatches (e.g., health and welfare or ICT). Conversely, those who choose fields in which the acquired skills are more easily transferable to a broad set of occupations (social sciences, communication, or humanities) are more likely to suffer mismatches (a similar result for the US can be seen in Leighton & Speer, 2020).

Against this background, studies on the relationship between gender, the gender-typed nature of the field of study, and the likelihood of being mismatched are still quite rare. Rossen et al. (2019) is an exception. In their study, various indices of overeducation and horizontal mismatch were used to study the relationship between educational mismatch, field of study, and gender among people aged 20 to 35 with tertiary education from the 2016 LFS in 21 European Union countries. The authors identify six channels through which men and women may decide what study to pursue, although with little evidence of behaviors that differ by gender. The typed nature of the field of study is not considered, however. The aim of our study is to bridge this gap by studying these relationships for the case of Spain.

Spain as a Case Study

Bradley (2000) demonstrated a strong correlation between educational and occupational segregation across a variety of countries, with Spain ranking highest among those analyzed for both indicators. In their comparative study for 30 countries over the period 1993–2011, Morgado et al. (2016) found that Spain was among the countries that presented the highest levels of both horizontal mismatch and overeducation, with a 40% horizontal mismatch. Overeducation rates depend on the way they are measured, but studies consistently find the highest values within Europe in Spain (about 35%, Eurostat, 2025; McGuinness et al., 2018; Morgado et al., 2016). Observed growth in higher education has not been accompanied by a general increase at all levels; the structure of the Spanish workforce in terms of educational attainment has the shape of an hourglass, with almost 50% being highly educated, and about 25% with only compulsory education. In this context, many intermediate positions are often filled by workers with higher education, leading to a downgrading of qualifications.

In Spain, compulsory education is general and covers primary and lower secondary education, lasting 10 years, from age 6 to 16. Students who complete lower secondary school

Table 1 Studies on mismatch and field of study

Autor	Country	Year/Data	More overeducation	Less overeducation	Horizontal mismatch	Less mismatch	Double mismatch
Robst (2008)	US	1993 National Survey of College Graduates	Arts Agriculture	Health Law			
Leighton and Speer (2020)	US	2009–15 American Community Survey	Social Science Science	Nursing/ Health Education			
Somers et al. (2019)	Survey of studies	Survey of studies	Liberal Arts	Health Engineering			
Capsada-Munsech (2019)	Pool of 11 European countries + Japan	2005 REFLEX (graduated 2000) 2008 HEGESCO (graduated 2003)	Humanities, Social sciences, Business and law, Agri and Vet, Services	Health and Welfare			
Capsada-Munsech (2015)	Italy	2007 Italian Graduate Employment Survey	Humanities	Health Engineering			
Rosen et al. (2019)	21 EU countries	2016 EU LFS	Science Services	Health and welfare ICT, Engineering			
Rosen et al. (2019)	Spain	2016 EU LFS	–	Education ICT			
Ortiz and Kucel (2008)	Spain Germany	2003–05 EULFS	Social Science Services Humanities	Engineering Sciences Education			
Barone and Ortiz (2011)	8 EU countries (including Spain)	2005 REFLEX (graduated in 2000)	Humanities Arts Education	Sciences			
Boto-Garcia and Escalonilla (2022)	Spain	2014 Labour Insertion of University Graduates Survey (graduated in 2010)	Arts Humanities	Health and welfare (women) Engineering (men)			

Table 1 (continued)

Autor	Country	Year/Data	More overeducation	Less overeducation	Horizontal mismatch	Less mismatch	Double mismatch
Verhaest et al. (2017)	Pool of 12 European countries + Japan	2005 REFLEX (graduated 2000) 2008 HEGESCO (graduated 2003)	Engineering (TEC)	Education,	Services, Agri and Vet	Health and welfare	Humanities
Salas-Velasco (2021)	Spain	2014 Labour Insertion of University Graduates Survey (graduated in 2010)	Sports-Tourism Business-Management-Economics		History – Philosophy Politics-Sociology	Medicine Nursing Veterinary	Social Work Fine Arts Labor Relations Journalism

have two main options: baccalaureate (*bachillerato*) and vocational training (*formación profesional*). The former is designed as an entrée to university studies and the latter for direct access to the labor market. Each of these pathways comprises several curricula, which are often strongly gender-biased. Curricular pathways and teachers' recommendations are not fully binding but are influential in choosing subsequent studies. Parents also play an important role at this stage, given the young age of their children and the lack of standardized assessments of children's skills and abilities. In this respect, Spain resembles other continental European countries where curricular options are quite early, formalized, and restrictive (like, for instance, Italy; see Barone & Assirelli, 2020).

All upper secondary pathways and curricula are completed in two years and permit access to higher education programs. Entry into each field of study is determined, however, by entrance examinations and other factors, since demand and availability vary from field to field. Higher education in Spain comprises a large university sector and a small but growing sector of short-term, post-secondary vocational training programs. University education is divided into four-year bachelor's degree courses (the exceptions are architecture and medicine, which last five and six years, respectively) and one- or two-year master's degree courses. The choice of field of study occurs upon entry at the bachelor's degree level. Post-secondary vocational studies last two years and allow direct access to the labor market as a technical worker.

The analysis of the relationship between the field of study followed and the existence of horizontal and/or vertical mismatch has been the main objective of studies focused on the Spanish case (see Table 1). Although the periods considered and the statistical sources used differ, the results do not. Ortiz and Kucel (2008) use data from the LFSs in Germany and Spain for the period 2003–05, considering eight fields of study and finding that studying engineering, science, or health-related degrees has less risk of leading to overeducation, while the risk increases among workers who have studied social sciences, humanities, or services. Barone and Ortiz (2011) obtain a similar result for a set of eight countries, taking into account 12 fields of study and using data from the 2005 REFLEX (REsearch into employment and professional FLEXibility) database for students who graduated in the year 2000. These authors claim that Spain is the only country where the risk of overeducation is of concern, especially among graduates who have completed studies in the humanities (education, arts, psychology, etc.).

Rossen et al. (2019) examine the case of 21 countries with the 2016 EU-LFS for 11 fields of study, finding that, for the aggregate set of countries, studies in ICT, engineering, and health are associated with a lower risk of being overeducated, while studies in science and services are associated with a higher risk. In their cross-country study, these authors find, for Spain, that there is significant evidence that only studies in the fields of education and ICT reduce the risk of being overeducated. The authors also take into account the gender of the workers, finding that it has little influence on the risk of being overeducated, particularly in the Spanish case, where no differential behavior by gender is observed in any field of study. A recent study by Salas-Velasco (2021) uses data from the 2014–15 Spanish Survey on the Labor Insertion of University Graduates (SLIU) for graduates in academic year 2009–10, grouping information from 123 degrees into 27 categories. This author simultaneously studies vertical and horizontal mismatches to identify fields of study that may be related to a higher risk of resulting in one or both types of mismatches. He finds that health-related studies have the lowest risk of being in one of these types of mismatches.

In light of the evidence and literature, further research is warranted to examine the relationship between the gender type of a field of study (i.e., feminized, masculinized, or integrated), an individual's gender, and their educational mismatch in the labor market. Specifically, we aim to investigate whether studying in a "typical" or "atypical" field of one's gender is related to the presence of educational mismatch. Note that policies aimed at reducing educational segregation may impact educational mismatch in ways that need to be identified.

Data, Sample and Descriptive Analysis

Data and Sample

The Spanish LFS consists of a large-scale, nationally representative survey common to other EU countries**.** It was standardized and harmonized by Eurostat, first in 2005 and, more recently, in 2021. It provides quarterly, cross-sectional information on individual labor force participation and other aspects, such as the respondent's demographic background, labor status, employment characteristics, and educational attainment. The SpanishLFS covers approximately 200,000 people over the age of 15. Our analysis is based on the expanded 2019, 2021 and 2022 subsamples,[6] which includes additional information on educational fields of study.

As is common in prior studies (Reimer et al., 2008; Rossen et al., 2019; Smyth & Steinmetz, 2008), we restrict our sample to highly educated individuals, since the issue of overeducation is more relevant to this group and our primary interest is in the impact of the field

[6] We omitted the year 2020 due to the potential distortions it could cause in the data and its collection, as it was the year of the COVID-19 pandemic.

of study. Highly educated individuals are defined as people who have completed tertiary education, corresponding to educational levels 5, 6, 7, and 8 of the ISCED 2011 (International Standard Classification of Education) classification and includes university studies and other short-cycle tertiary education. The initial sample of 70,948 workers was thus reduced to 49,713 workers with higher education. This sample is further reduced since we only include individuals who finished their studies in the last 10 years, to mitigate age or cohort effects that might increase heterogeneity within fields.[7] After reducing the sample to 12,697 individuals—6,912 women and 5,785 men—we still have a sizeable sample at the individual level.

In empirical studies, overeducation can be measured through the expert evaluation of occupation-specific required education, the respondents' subjective assessments, or by means of statistical approaches (realized matches). Results often change depending on the measure used, but each measure has its pros and cons.[8] For our purposes, we adopt the variant of the realized matches approach because of data availability. Specifically, we apply our main analysis to the 80th percentile of the levels of education within each occupational group, as proposed by Ortiz and Kucel (2008). Since the survey records the educational level attained by each worker, we impute for each individual the number of years of education from the number of years required to reach each educational level. We then compute the 80th percentile value of the number of years for each of the 38 occupations at the two-digit ISCO-08 disaggregation level (considering all individuals in the whole sample). Accordingly, we consider a person in the sample as overeducated when their number of years of study exceeds the 80th percentile of the number of years within each occupational group. (In the robustness checks subsection, an alternative measure of overeducation is also considered).

The same three methods used to measure overeducation can be used to measure horizontal mismatch (see Sellami et al., 2018, for a comparison of different indicators). Although subjective measures are the norm in these studies (see Albert et al., 2025), their use has been challenged by some scholars. Thus, Nordin et al., (2010: 1048) argue that self-reported mismatch may be endogenous to the workplace because it may reflect the rationalization of a general feeling of disappointment. Eventually, the availability of data dictates the measure used.[9] We make use of LFS data and hence base our analysis on statistical realized matches criteria. Specifically, the modal value (the most frequent value) of the fields of study in each of the 38 occupations of ISCO-08 is taken as a reference for considering individuals as matched. Following the ISCED 2013-F classification scheme, we distinguish 10 categories of field of study: teacher training and education science (EDU); foreign languages, arts, and humanities (HUM); social sciences, journalism, and information (SJI); business, administration, and law (BAL); natural sciences and math (NAT); information and communica-

[7] It avoids the fact that workers could compensate deficits in skills and knowledge with on-the-job training and work experience. We have also replicated the estimates with workers who completed their studies in the last 5 and 15 years, see below.

[8] For recent surveys on measuring overeducation, see Leuven and Oosterbeek (2011) and McGuinnes et al. (2018). For a comparison between different measures, see Capsada-Munsech (2019).

[9] A subjective measure based on responses to the question of the extent to which workers consider their studies to be related to their current occupation is used in Barone and Ortiz (2011), Robst (2008) and Verhaest et al. (2017). Studies based on the EU-LFS like Reimer et al. (2008) and Rossen et al. (2019) employ objective/statistical definitions of horizontal mismatch.

tion technologies (ICT); engineering, manufacturing, and construction (TEC); agriculture, forestry, fisheries, and veterinary (AGR); health and welfare (HW), and services (SER).[10]

Many fields of study directly correspond to specific occupations. For example, 91% of health studies graduates work in health professions, while 75% of information and communication technology (ICT) graduates work as ICT professionals. These individuals are classified as "matched," as opposed to those who graduated from other programs and are considered "mismatched." However, there are cases in which different fields of study may appropriately match an occupation. In these cases, workers with the most common field of study are considered matched, while others are considered mismatched. For example, in the four managerial occupations, the most common field of study is business and law (BAL), and approximately half of the workers have a degree in this field. We consider workers who graduated from these programs to be matched, while the rest are considered mismatched.

While this strategy is applied in most cases, we have used objective criteria for cases in which the fields of education are broader and align with more than one occupation. In these cases, we select the two most important in quantitative terms or the ones that more accurately qualify combinations as matched. For example, 60% of workers in occupation 21, Science and Engineering Professionals, have a degree in engineering (TEC), while only 21% have a degree in science. Since working in this occupation fits with either type of study, we consider workers with a degree in either field to be matched and those without a degree in technology or natural sciences to be mismatched. Similar reasoning applies to teaching professionals (23), professionals and related associate professionals in legal, social, and cultural occupations (26 and 34, respectively), and market-oriented skilled agricultural workers (61). Table A1 in the Appendix outlines the scheme we use to classify matched versus mismatched education-occupation pairs at the two-digit disaggregation level (38 occupations). There, we explain our approach in more detail.

The feminized, masculinized, or integrated character of a field of study is inspired by Hakim (1993); so that when the percentage of women in a field is above 66%, then it is female-dominated (feminized), if it is below 33%, then it is male-dominated (masculinized), and if it is between 33%-66%, then it is considered to be integrated.

Descriptive analysis

Table 2 lists the fields of study and provides information for each about: i) their weight in total employment; ii) the share of women; and iii) the share of individuals who are horizontally and vertically mismatched, both as a whole and distinguishing by gender. According to the criteria mentioned above, we categorize fields of ICT and engineering as masculinized; education, social sciences, and health and welfare as feminized; and the rest as integrated. It can be seen that the percentage of people in the sample who are horizontally mismatched and the percentage of people who are overeducated are similar, both being around 35%.

There is great disparity in horizontal mismatch across fields of study, with Agriculture and related (AGR) showing a percentage of around 80%, compared with less than 20% in Health and Welfare. Variation is less marked in the case of overeducation, ranging from about 20% in Health and Welfare to 45% in the Sciences. Regarding gender, we can see clear differences across fields of study. For example, horizontal mismatch is generally higher for

[10] An eleventh category, "General," has been discarded since it corresponds to lower levels of educational attainment.

Table 2 Horizontal and vertical mismatch

Field	Weight	Women's share		Horizontal mismatch Overall	Men	Women	Overeducation Overall	Men	Women
Education (EDU)	13.55	74.46	Fem	43.07	48.28	41.29	31.79	35.93	30.38
Humanities (HUM)	6.43	56.53	Int	63.55	66.01	61.66	42.36	48.16	37.91
Social Sciences (SJI)	5.70	68.85	Fem	63.42	71.88	59.60	42.84	49.11	40.00
Bus-Adm-Law (BAL)	21.65	57.30	Int	22.72	25.79	20.43	34.10	36.85	32.06
Sciences (NAT)	5.47	52.39	Int	41.82	45.59	38.40	45.01	46.20	43.92
ICT	7.68	19.48	Mas	28.56	25.74	40.21	27.01	26.38	29.63
Eng-Man-Cons (TEC)	13.00	20.23	Mas	22.61	20.17	32.23	42.78	46.68	27.41
Primary Sector (AGR)	1.77	43.05	Int	79.82	74.80	86.46	39.91	48.03	29.17
Health and Welfare (HW)	18.51	74.50	Fem	18.49	23.83	16.66	22.42	27.52	20.68
Services (SER)	6.23	46.95	Int	62.72	58.51	67.48	44.15	47.96	39.84
Total	100	54.53		34.62	34.88	34.40	34,56	39.43	30.57
Total observations	12,623				5,740	6,883		5,740	6,883

Fem: feminized; Int: integrated; Mas: Masculinized

men than for women in most of the fields, except those which are more masculinized. Thus, in AGR, SER, TEC and ICT fields, the number of mismatched women is between 9 and 15 percentage points higher than that of men. The average rate of overeducation is clearly higher for men (39%) than for women (30%), but the differences are even bigger in some fields (the primary sector, and engineering, by about 20 percentage points). At first sight, there is no apparent relationship between the intensity of mismatch and the feminized or masculinized character of the field of study. Instead, it can be seen that the other fields of study we can consider integrated show values of horizontal mismatch and overeducation well above average, with the exception of Business and Law.

Methodology

In order to study which factors are related to horizontal and vertical mismatches, we carry out regression analyses in which we make being mismatched dependent on the field of study, controlling for a set of personal and job-related variables. We run several sets of regressions. First, attending to the dependent variable, we carry out two types of regression: one for the probability of a worker being horizontally mismatched and one for the probability of being overeducated. The dependent variable (Y) takes the value 1 if the respondent is mismatched, as previously defined, and 0 if the respondent is perfectly matched.

We perform the estimation by means of a probit model.

$$Y = \delta\, field + X'\beta + e$$

where *field* captures the category of the field of study in which the respondent obtained their degree, X is a vector of control variables including a constant term, e is the statistical disturbance, and δ and β's are parameters. Control variables are gender, age, the level of studies attained, whether he/she lives with a partner, foreign nationality, potential experience (computed as the difference between the current age and the age at which studies were completed), whether the individual works in the public or the private sector, whether he/she is a wage earner or self-employed, firm size, whether he/she works part- or full-time, sector of activity, year and dummies for regions (17 Autonomous Communities). Age and firm size variables are split into different ranges. Regarding the educational level, we distinguish between tertiary-non university studies (ISCED 5), lower-than-240-ECTs graduates (ISCED 6) and over-240-ECTs graduates and above (ISCED 7 and 8). The sector of activity is divided into agriculture, industry, construction, and services.

Regarding how the gender of the individual and the character of the field of study (masculinized, feminized, or integrated) are included in the estimation, we consider three different possibilities. In the baseline model (Model 1), in addition to the field of study, the variable identifying the gender of a person is included as an individual variable. In the second case (Model 2), instead of the field of study, we include a variable indicating whether the individual's field of study is gender-typed (i.e. whether it is either masculinized or feminized) against being integrated, while gender is included also as an individual variable. In the third case (Model 3), we drop the gender variable and interact the individual's gender with the field of study in which the individual graduated. Following this strategy produces six different sets of estimates.

The selection of workers from the population of highly educated individuals is non-random, potentially introducing selection bias. To address this, we employ Heckman's (1979) two-step procedure, which provides more consistent estimates than Ordinary Least Squares (OLS) by accounting for systematic differences between the observed sample and the underlying population. In the first stage, a probit model estimates the probability of being a worker as a function of personal characteristics and regional gender-specific employment rates. This yields the Inverse Mills Ratio (IMR)—or Heckman's Lambda— which is subsequently included in the second-stage educational mismatch equation. By treating Lambda as an additional regressor, we control for the correlation between the unobserved determinants of the selection process and the outcome of interest.

Results

We comment on the three sets of estimates for each of the indicators of mismatch considered, with reference to the marginal effects. Table 3 shows the results for the second-stage estimations corresponding to horizontal mismatch.[11] The results indicate that this is more likely among individuals who are older, who live together as a couple, are more experienced, work in the private sector, are wage earners, work in a small firm, work part-time, and work in the primary sector. Longer studies are associated with lower risk of being horizontally mismatched. The gender variable is significant in Model 1, indicating that men are more prone to being horizontally mismatched than women.

Focusing on the variables capturing the field of study, marginal effects are quantitatively more relevant than other personal or job variables. Results for Model 1 show that having studied in any field other than Agriculture is associated with a lower likelihood of horizontal mismatch. (The category of Agriculture is taken as reference because it has the highest rate

[11] The statistical significance of parameter lambda confirms the need to control for selection bias and the positive sign indicates that unobservable variables influencing participation also influence the risk of mismatch, in the same direction.

Table 3 Heckman's second stage of horizontal mismatch probability. Marginal effects

	Model 1: fields		Model 2: field feminized or masculinized		Model 3: field x gender	
	dy/dx	Std. Err	dy/dx	Std. Err	dy/dx	Std. Err
Gender (1 = man)	0.030***	0.010	0.011	0.010		
Age < 25 (ref.)						
Age 26–35	0.134***	0.029	0.101***	0.034	0.134***	0.028
Age > 35	0.156***	0.034	0.117***	0.038	0.155***	0.032
Non-university higher education (ref.)						
Univ. up to 240 credits	-0.107***	0.012	-0.097***	0.011	-0.117***	0.012
Univ. > 240 credits	-0.141***	0.017	-0.141***	0.016	-0.155***	0.017
Cohabits with a partner	0.055***	0.015	0.035**	0.017	0.057***	0.015
Non-native	0.019	0.028	0.042	0.029	0.020	0.027
Experience	0.009***	0.003	0.007***	0.003	0.009***	0.003
Public sector	-0.176***	0.010	-0.129***	0.011	-0.175***	0.010
Wage-earning	0.058***	0.015	0.048***	0.016	0.060***	0.015
Firm size < 10 workers (ref.)						
Firm size 11–49	-0.034***	0.010	-0.038***	0.011	-0.035***	0.010
Firm size 50–249	-0.047***	0.012	-0.049***	0.013	-0.047***	0.012
Firm size 250 +	0.016	0.013	-0.036***	0.014	0.017	0.013
Part-time	0.049***	0.010	0.117***	0.011	0.048***	0.010
Services (ref)						
Primary sector	0.142***	0.034	0.227***	0.036	0.154***	0.034
Industry	0.002	0.013	-0.030**	0.014	0.004	0.013
Construction	-0.054**	0.026	-0.135***	0.027	-0.054**	0.025
EDU	-0.346***	0.032				
HUM	-0.229***	0.040				
SJI	-0.152***	0.036				
BAL	-0.595***	0.030				
NAT	-0.388***	0.036				
ICT	-0.546***	0.033				
TEC	-0.591***	0.031				
AGR (ref.)						
HW	-0.546***	0.030				
SER	-0.248***	0.034				
Femin/masculinized			-0.055***	0.013		
EDUxman					-0.244***	0.043
HUMxman					-0.168***	0.048
SJIxman					-0.018	0.049
BALxman					-0.502***	0.037
NATxman					-0.319***	0.045
ICTxman					-0.530***	0.038
TECxman					-0.575***	0.037
AGRxman (ref.)						
HWxman					-0.475***	0.040
SERxman					-0.247***	0.042
EDUxwoman					-0.339***	0.038
HUMxwoman					-0.210***	0.048
SJIxwoman					-0.161***	0.043
BALxwoman					-0.601***	0.038

Table 3 (continued)

	Model 1: fields		Model 2: field feminized or masculinized		Model 3: field x gender	
	dy/dx	Std. Err	dy/dx	Std. Err	dy/dx	Std. Err
NATxwoman					-0.378***	0.045
ICTxwoman					-0.381***	0.049
TECxwoman					-0.431***	0.044
AGRxwoman					0.116***	0.060
HWxwoman					-0.528***	0.036
SERxwoman					-0.174***	0.043
Year dummies	x		x		x	
Regional dummies	x		x		x	
λ Heckman	0.424***	0.101	0.286**	0.118	0.425***	0.097
ρ	0.835		0.577		0.840	
σ	0.508		0.495		0.506	
Observations workers	12,697		12,697		12,697	

*$p<0.1$; **$p<0.05$; ***$p<0.01$

of horizontal mismatch). Specifically, the lowest values are attained for those who studied TEC, ICT, Health, and Business-Law. Whereas the first two fields are male dominated, the two latter fields are female-oriented. This result is reinforced by estimates of Model 2. The variable capturing whether a field of study is gender-typed (i.e., either masculinized or feminized) is statistically significant with a negative marginal effect, indicating that graduating in such a field is associated with a lower risk of horizontal mismatch. The results of Model 3 reveal that, although the reduction in the risk of horizontal mismatch in each of these fields of study is generally greater for women, this is qualified by the fact that the reduction is more pronounced for people of the predominant gender. In other words, a man's risk of horizontal mismatch in ICT or TEC is clearly lower than a woman's risk in the same fields. Conversely, a woman's risk of horizontal mismatch in health or education is much lower than a man's risk in those fields.

Table 4 shows the results of the relationship between field of study and various control variables on the probability of being overeducated. Some control variables show similar results to those observed in horizontal mismatch cases. These include public sector employment, salaried employment, company size, part-time work, and sector of activity. However, others do not. Short-cycle university education levels are associated with a lower probability of overeducation, while long-cycle education levels are associated with a higher probability. This is true with respect to the reference category of not having attended university. Additionally, age and experience are insignificant variables. Being an immigrant increases the probability of being overeducated and the gender variable is statistically significant, indicating greater overeducation among men. Regarding the field of study, the marginal effects in Model 1 are generally smaller than those in the case of horizontal mismatch. Thus, only workers who studied ICT or health have a lower risk of being overeducated than workers in agriculture. Workers in the social sciences (SJI), SER, HUM and NAT are more likely to be overeducated, while differences among the other fields are not statistically significant.

Results from Model 2 show that having studied in a gendered field of study is significantly associated with overeducation, and that the risk of being overeducated is higher for

Table 4 Heckman's second stage of overeducation mismatch probability. Statistical definition Marginal effects

	Model 1: fields		Model 2: field feminized or masculinized		Model 3: field x gender	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
Gender (1 = man)	0.063***	0.009	0.067***	0.010		
Age < 25 (ref.)						
Age 26–35	-0.005	0.030	0.000	0.033	-0.025	0.029
Age > 35	0.044	0.034	0.046	0.037	0.022	0.033
Non-university higher education (ref.)						
Univ. up to 240 credits	-0.139***	0.012	-0.132***	0.011	-0.138***	0.012
Univ. > 240 credits	0.101***	0.016	0.108***	0.015	0.097***	0.017
Cohabits with a partner	-0.009	0.015	-0.010	0.016	-0.017	0.015
Non-native	0.143***	0.027	0.142***	0.028	0.155***	0.027
Experience	-0.002	0.003	-0.001	0.003	-0.003	0.003
Public sector	-0.106***	0.011	-0.100***	0.011	-0.107***	0.011
Wage-earning	0.075***	0.016	0.072***	0.016	0.075***	0.016
Firm size < 10 workers (ref.)						
Firm size 11–49	-0.014	0.011	-0.014	0.011	-0.014	0.010
Firm size 50–249	-0.006	0.013	-0.005	0.013	-0.007	0.013
Firm size 250 +	0.033**	0.013	0.016	0.013	0.032**	0.013
Part-time	0.074***	0.011	0.090***	0.011	0.074***	0.011
Services (ref)						
Primary sector	0.352***	0.036	0.356***	0.036	0.347***	0.036
Industry	0.089***	0.014	0.107***	0.013	0.087***	0.014
Construction	0.093***	0.027	0.115***	0.026	0.093**	0.027
EDU	0.047	0.030				
HUM	0.110***	0.039				
SJI	0.123***	0.034				
BAL	0.004	0.029				
NAT	0.089***	0.034				
ICT	-0.066**	0.031				
TEC	0.041	0.029				
AGR (ref.)						
HW	-0.068**	0.029				
SER	0.108***	0.032				
Femin/masculinized			-0.044***	0.012		
EDUxman					0.006	0.041
HUMxman					0.112**	0.047
SJIxman					0.134***	0.047
BALxman					-0.038	0.036
NATxman					0.037	0.044
ICTxman					-0.117***	0.037
TECxman					0.030	0.035
AGRxman (ref.)						
HWxman					-0.109***	0.038
SERxman					0.089**	0.041
EDUxwoman					-0.036	0.037

Table 4 (continued)

	Model 1: fields		Model 2: field feminized or masculinized		Model 3: field x gender	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
HUMxwoman					0.020	0.047
SJIxwoman					0.021	0.041
BALxwoman					-0.075**	0.036
NATxwoman					0.033	0.044
ICTxwoman					-0.082*	0.047
TECxwoman					-0.141***	0.042
AGRxwoman					-0.175***	0.057
HWxwoman					-0.161***	0.035
SERxwoman					0.012	0.041
Year dummies	x		x		x	
Regional dummies	x		x		x	
λ Heckman	-0.061	0.105	-0.052	0.115	-0.138	0.101
ρ	-0.135		-0.115		-0.301	
σ	0.451		0.454		0.458	
Observations workers	12,697		12,697		12,697	

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

men.[12] From Model 3, when interacting gender and field of study, women have lower risk than the reference category (Agriculture for men) of being overeducated in several gender-typed fields of study such as health and welfare, technology and ICT, as well as in agriculture and business and law. For men, graduating in ICT and HW reduces the likelihood of overeducation, while graduating in social sciences (SJI) and humanities, which are predominantly female fields, increases it. The general assessment of overeducation is that studying in a field dominated by one sex reduces the risk, but unlike horizontal mismatch, this is not more evident when the dominant sex is the same as the individual's. In fact, working men who graduated in social sciences or humanities are at a higher risk of overeducation.

Robustness Checks

Our results show a clear pattern, but we need to verify that they withstand various robustness tests. First, we want to investigate whether some of the results are due to how overeducation is measured. The realized matches measure is commonly used with graduate samples only because it reduces variability within occupational groups (Ortiz & Kucel, 2008). Now, we compare the results in Table 4 with those obtained using an objective measure of overeducation. This measure assumes that graduate workers must be employed in one of the first three ISCO-11 categories: Managers, Professionals, and Technicians. Any worker employed in a different category is considered overeducated (see Eurostat, 2025). According to this definition, the percentage of overeducated workers is 34,56%.[13]

[12] We estimated the same model for men and women separately (see below).

[13] This figure is very similar to the one obtained with the first definition of overeducation; however, the individuals are not entirely the same. In fact, according to this objective measure, one third of those considered

Results in Table 5 show that the gender variable is not significant. Thus, when expressed in this manner, we cannot confirm that overeducation is predominantly a male phenomenon. The other estimated coefficients are like those in Table 4, save for the age and education coefficients, cohabitation with a partner and experience. In the case of age, it now shows more overeducation in those over 25, especially in the 26–35 age group. This suggests that older individuals working in occupations 4 through 9 are more likely to be overeducated. Regarding educational attainment, long university courses were found to reduce the risk of overeducation, which was not observed with the initial measure. With the initial measure, studying long courses increased the possibility of overeducation compared to those without a university education. The variable indicating cohabitation with a partner is now insignificant, and experience becomes positive, i.e., there is greater overeducation with more years of experience.

Regarding the influence of the subjects studied, graduates in ICT and HW are still the least likely to be overeducated. However, studying other subjects (TEC, NAT) also reduces the risk of mismatch more than the reference category (see Model 1). Similarly to the case in Table 4, graduating in social sciences and services is associated with a higher likelihood of overeducation. Results from estimating Model 2 reveal again that studying in a gender-typed field is an effective antidote to overeducation. When the gender and field of study variables interact (see Model 3), the estimates reinforce the idea that studying ICT and Health are the most helpful in reducing overeducation, but also Sciences, TEC, and AGR, the latter only for women. Results reinforce the finding that studying in a gender-typed field helps reduce the risk of overeducation, except for the case of men who graduated in social sciences, SJI.

The second robustness exercise that we present investigates whether the results obtained are driven by considering that workers with non-university higher studies are highly educated. Montt (2017) found differences between those who studied vocational training and those who graduated. The former tends to suffer less mismatch. To explore this, we estimate our probit models by removing people with non-university higher education from the sample. In other words, we estimate the three models for each type of mismatch only for university graduates, thus distinguishing between short and long university studies. Results are shown in Tables A2.A and A2.B in the Appendix.

Although the results of the horizontal mismatch are virtually unchanged from those in Table 3, there are some differences with respect to Table 4 in the case of overeducation. Thus, the likelihood of overeducation is lower for those studying short cycles vs. those who studied longer cycles. Among fields of study, only graduating in technology, engineering, and construction (TEC) and health and welfare (HW) avoids the risk of overeducation compared to the reference category of agriculture. However, most of the qualitative results, particularly those related to our variables of interest, do not differ from those observed in Table 4: men are at a higher risk of overeducation than women, the probability of being overeducated is higher among older individuals, and studying in gender-typical fields reduces the risk of overeducation. Finally, the predominant gender in each field of study does not appear to influence the risk of overeducation.

To conclude, additional robustness analyses have been performed. In these analyses, two different samples were taken from workers who had completed their studies less than 5, and

overeducated would not be considered so according to the measure of realized matches used in Table 4. We believe this discrepancy is significant enough to make the robustness analysis informative.

Table 5 Heckman's second stage of objective overeducation probability. Objective definition Marginal effects

	Model 1: fields		Model 2: field feminized or masculinized		Model 3: field x gender	
	dy/dx	Std. Error	dy/dx	Std. Err.	dy/dx	Std. Err.
Gender (1 = man)	-0.010	0.008	-0.026	0.019		
Age < 25 (ref.)						
Age 26–35	0.071***	0.027	0.101***	0.030	0.056**	0.026
Age > 35	0.061**	0.031	0.096***	0.034	0.043	0.029
Non-university higher education (ref.)						
Univ. up to 240 credits	-0.321***	0.011	-0.308***	0.010	-0.319***	0.010
Univ. > 240 credits	-0.438***	0.015	-0.422***	0.014	-0.439***	0.015
Cohabits with a partner	0.006	0.014	0.017	0.015	0.001	0.013
Non-native	0.100***	0.025	0.088***	0.026	0.107***	0.024
Experience	0.007***	0.002	0.010***	0.003	0.006***	0.002
Public sector	-0.111***	0.010	-0.111***	0.010	-0.111***	0.010
Wage-earning	0.156***	0.014	0.152***	0.014	0.156***	0.014
Firm size < 10 workers (ref.)						
Firm size 11–49	-0.049***	0.009	-0.051***	0.009	-0.048***	0.009
Firm size 50–249	-0.052***	0.012	-0.061***	0.012	-0.051***	0.012
Firm size 250 +	-0.037***	0.012	-0.054***	0.012	-0.036***	0.012
Part-time	0.065***	0.010	0.077***	0.010	0.066***	0.010
Services (ref)						
Primary sector	0.292***	0.032	0.273***	0.032	0.285***	0.032
Industry	0.064***	0.012	0.066***	0.012	0.063***	0.012
Construction	0.081***	0.024	0.086***	0.024	0.083***	0.024
EDU	-0.021	0.028				
HUM	-0.008	0.036				
SJI	0.082***	0.031				
BAL	0.121***	0.026				
NAT	-0.096***	0.031				
ICT	-0.240***	0.028				
TEC	-0.055**	0.027				
AGR (ref.)						
HW	-0.106***	0.026				
SER	0.103***	0.029				
Femin/masculinized			-0.130***	0.012		
EDUxman					-0.061*	0.037
HUMxman					-0.033	0.042
SJIxman					0.109***	0.042
BALxman					0.059*	0.032
NATxman					-0.109***	0.039
ICTxman					-0.298***	0.033
TECxman					-0.077**	0.032
AGRxman (ref.)						
HWxman					-0.129***	0.034
SERxman					0.004	0.036
EDUxwoman					-0.047	0.033
HUMxwoman					-0.030	0.042

Table 5 (continued)

	Model 1: fields		Model 2: field feminized or masculinized		Model 3: field x gender	
	dy/dx	Std. Error	dy/dx	Std. Err.	dy/dx	Std. Err.
SJIxwoman					0.028	0.037
BALxwoman					0.111***	0.032
NATxwoman					-0.140***	0.039
ICTxwoman					-0.202***	0.042
TECxwoman					-0.168***	0.038
AGRxwoman					-0.108**	0.051
HWxwoman					-0.144***	0.031
SERxwoman					0.148***	0.037
Year dummies	x		x		x	
Regional dummies	x		x		x	
λ Heckman	0.209**	0.094	0.299***	0.105	0.155*	0.090
ρ	0.494		0.660		0.377	
σ	0.423		0.453		0.411	
Observations workers	12,697		12,697		12,697	

*$p<0.1$; **$p<0.05$; ***$p<0.01$

less than 15 years ago, respectively, in order to verify whether the main results hold true. Estimates of Models 1 and 2 were also made for separate samples of men and women. In all cases, the estimates show robust results, albeit with some nuances. We found that studying in a typed field reduces the risk of overeducation for women, but not for men. The opposite results were obtained for horizontal mismatch: studying in a typed field reduces the risk of horizontal mismatch for men, but not women. The whole set of results are not presented here but they are available upon request from the authors.

Discussion and Conclusions

Main Findings

The educational levels of the population have increased considerably in recent decades. When conceptualized as an investment, people will choose studies that lead to higher-wage occupations, better jobs, more opportunities for promotion, less risk of unemployment, and a better work-life balance (Hakim, 2006; Polachek, 1981). However, if education is viewed primarily as a consumer good, individuals' preferences are believed to dictate their choices about the type and extent of schooling pursued to achieve personal preferences.

However, the question remains as to whether final choices result solely from personal tastes, desires, and concerns, or whether the socialization process that everyone experiences by living in society also plays a significant role. Evidence found thus far, including this paper, confirms that men's and women's decisions about what to study differ, and these differences do not diminish over time. Thus, literature has widely shown that women's participation in STEM and ICT studies has hardly increased, whereas their presence in education and health studies continues to grow. Similarly, men are hardly increasing their participation in predominantly female studies. According to data from Spain, currently less than 20% of ICT graduates are women, and this figure is even lower than in the 1980s, when it was 30%, and has been falling ever since. The proportion of women with engineering degrees increased from 20% in the mid-1980s to less than 30% in the 2000s and has hardly changed in the last 25 years. In contrast, the percentage of women with degrees in education or health and welfare has remained consistently above 70% from the last century to the present day, and in education the percentage has even increased slightly. This behavior persists despite cultural changes and the widespread implementation of policies aimed at achieving greater gender equality in various spheres of life. In short, the increase in educational attainment has not been accompanied by a clear reduction in educational segregation.

Moreover, the increase in educational attainment may have led to educational mismatch, meaning that individuals are working in jobs that require a lower level of education or in a field other than the one they studied. Until now, the literature on this topic has not examined the possible relationship between educational segregation and mismatch risk in the labor market. Our study aimed to address this gap by analyzing which fields of study are more closely related to the existence of education-job mismatch. This primary objective is twofold. First, we investigate whether the gender composition of a field of study—classified as masculinized, feminized, or integrated—is associated with the risk of educational mismatch. Second, we examine whether belonging to the majority gender within a typified field qualifies the relationship between the field of study and mismatch risk. Our analysis drew on the expanded 2019–2021-2022 subsamples of the Spanish Labor Force Survey, which includes data on labor force characteristics and the individual's field of study.

As shown in Table 2, the descriptive analysis revealed that fields of study with a greater gender balance tended to have higher levels of horizontal and vertical educational mismatch. Conversely, the lowest levels of mismatch were observed in fields with greater gender typification. The econometric analysis confirms this: fields related to ICT, engineering, and health and welfare are less prone to educational mismatch. The estimates also show that, while many factors included in the regressions (age, gender, nationality, etc.) are associated with the probability of mismatch, the field of education is the most relevant predictor.

Although the results indicate less horizontal mismatch in gender-dominated fields, the probability of mismatch decreases further when the individual is the same gender as the predominant gender in the field. Studying engineering or ICT helps reduce the risk of horizontal mismatch for both men and women, though this is more evident in the case of men. Similarly, studying business, administration, or health reduces the risk of horizontal mismatch for everyone, though this is more evident for women. We find that the qualitative results regarding horizontal mismatch remain unchanged, after removing individuals with non-university education from the sample. A first main result is clear: more gender-balanced fields of study are associated with higher levels of horizontal mismatch. Note that these fields correspond to humanities, services, and sciences, and that these provide skills, abilities, and knowledge that are more easily transferable to a broad set of occupations, which are shown to be more likely to suffer mismatches (Leighton & Speer, 2020; Somers et al., 2019).

In the case of vertical mismatch, graduating from a gender-specific field of study is associated with a lower risk of being overeducated in the workplace. The only exception is men who studied social sciences. While the relationship between a person's sex, the gender that predominates in the chosen field of study, and the risk of being overeducated is less clear than in the case of horizontal mismatch, graduating in a gendered field of study generally alleviates the risk of overeducation for women. This is the second relevant result of our research. Robustness analysis reveals minor variations in certain fields of study when employing an objective measure of overeducation or excluding non-university graduates, though most outcomes remain consistent.

Taking all these results together, our main conclusion is that studying in a gender-balanced field seems to be associated with a higher risk of labor market mismatch. Since mismatch is an undesirable situation for the individual, it would be rational to opt for more "genderized" fields of study. Our results also show that the risk of mismatch is lower when a student's gender aligns with the gender that dominates their field of study. This may account for the persistent gender segregation across fields of study and the lack of convergence in these trends, as some disciplines remain starkly feminized while others are predominantly masculinized.

However, this is not the only factor explaining the educational segregation observed, as processes of social reproduction and identity carry great weight. The relevance of the gender variable highlights the role of socialization in choosing a field of study. Without ruling out the possibility that men and women have different life goals, psychological traits, skills, or abilities—facts on which essentialism is based—the role of socialization in shaping individual preferences seems very important. Thus, men and women perpetuate societal gender norms, which limit people's choices and link them to what is considered socially acceptable for their gender or social group. Deviating from these norms or the ideal category can result in a loss of social acceptance, which is not always offset by the potential benefits of choosing a field of study that does not conform to what is expected according to those social norms (Humlum et al., 2012).

The most serious consequence of this situation is that educational segregation would be transferred almost entirely to occupational segregation. Occupational segregation is a well-known source of differences in economic outcomes between men and women, such as wages and job satisfaction (Blau & Kahn, 2017; England, 2020). Additionally, individuals' attempts to avoid mismatches in the workplace could be explained by the pursuit of greater rewards, such as higher wages, greater job satisfaction, and lower job turnover, among matched workers compared to mismatched workers (McGuinness et al., 2018).

Policy Implications

In recent decades, advertising campaigns have been launched to reduce gender inequality in the choice of subjects. These campaigns have been aimed particularly at women, encouraging them to study subjects traditionally associated with men, such as ICT and technology. However, such campaigns have had limited success, since the proportion of women studying ICT and technology remains lower than it was 20 or 30 years ago (Carlana & Corno, 2021). Our results provide a plausible additional explanation for this fact: studying in a segregated field reduces the probability of labor market mismatch, especially in fields where one's own gender predominates. Therefore, men and women tend to prefer studying in traditionally male- or female-dominated fields. This argument must be viewed in the context of the changes experienced by the Spanish economy, particularly the labor market, over the last 50 years. There was a shift from a post-dictatorship scenario in which female labor participation was low and concentrated in occupations that replicated household tasks, such as care, nursing, and education, to a situation in which women began opening up to areas where they could earn substantially more (scientific, legal, medical, and financial professions, among others) during the last quarter of the twentieth century (Garcia-Mainar et al., 2015; 2025). While women's labor force participation increased during this period, educational segregation has remained constant since 2000. This could be explained by greater gender equality in European and western countries, as well as women's greater freedom to choose their fields of study compared to the situation in Spain last century and in other countries with lower levels of equality (Charles & Bradley, 2009; Stoet & Geary, 2018).

The evident persistence of gender-based inequality in field of study choices and the results of our study suggest that reducing educational mismatch should be the first step in reducing this inequality. When choosing a job, socialization can play a role similar to that in choosing a field of study. However, this can be exacerbated by demand if employers believe that certain occupations are more appropriate for men or women. This can lead to discriminatory behaviors due to prejudice, statistical discrimination, or labor segmentation. Under these conditions, gender equality policies should be maintained, even if some perpetuate gender differences in field of study choice. However, we believe that greater efforts should be devoted to equalizing supply by ensuring that skills and abilities closely match those required in the workplace. This would reduce the risk of mismatch and avoid differences between men and women. The ultimate reason for our preference for policies that affect worker qualifications is that Spain stands out for its high levels of educational mismatch, both horizontal and vertical.

Consequently, the results obtained in this article highlight the need to improve the adjustment in several of the fields studied, especially those we have defined as integrated. In order to make the labor market more flexible and enable people to move to jobs where mismatch is not an issue, it is important to facilitate continuous training and retraining opportunities to improve the skills required for certain jobs. More programs to retain highly qualified talent and better planning of professional profiles would also be useful. As an example of measures aimed at reducing skill mismatch, professional retraining in technology should be promoted for people currently working in labor-intensive occupations that generate little added value, such as hospitality, catering, tourism, retail, construction, etc. Another necessary and complementary measure is an improvement in public employment services to enable efficient job placement. Similarly, to improve geographical mobility and matching, aid for interregional mobility would be useful, which in Spain is difficult for many reasons, including access to housing.

In addition, to mitigate the incentive to study in fields where people of the same sex predominate, it would be advisable to promote mixed degrees combining integrated and segregated subjects. These degrees would allow for high labor market integration. Examples include degrees in economics and data analysis, biomedical engineering, and education and sciences. Starting in secondary school, career guidance services should be improved so that adolescents can make informed decisions about their future careers. Providing transparent information on job opportunities, salaries, and employability would improve the efficiency of the labor market. Our analysis suggests that successful measures should pursue ensuring that people studying in integrated fields or in fields where they are a minority do not have a worse future in the workplace than those in the majority. As long as there is a perception that it is difficult to enter a field not dominated by one's own gender, people will have no incentive to make that extra effort (Lundberg, 2022). Eventually, measures must be taken to reduce educational segregation to make better use of society's resources (Hsieh et al., 2019).

Limitations and Future Research

Our results cannot be generalized to other countries because Spain's national context is very specific. The country shows high levels of overeducation and horizontal mismatch across Europe (Morgado et al., 2016; Verhaest et al., 2017). The levels of occupational specificity, standardization, and stratification are medium, which is much lower than in conservative and social-democratic countries, but higher than in liberal ones (see Barone and Asirelli, 2020; Blossfeld et al., 2015). In this respect, as well as in the degree of women's participation in the labor market and gender culture, Spain is more similar to other southern Mediterranean countries, such as Italy (Barone and Asirelli, 2020). However, Spain's mismatch figures are much higher (Verhaest et al., 2017). It should be noted that fields of study with the highest risk of mismatch tend to be integrated and have skills that are easily transferable to different occupations. Thus, the question arises as to whether to maintain the status quo, which may result in workers being mismatched, though this could also lead to greater flexibility in job placement, or to ensure that studies provide more occupation-specific skills and thus guarantee a clearer career path. In Spain, the risk of unemployment and of having a temporary contract is much higher than in other European countries. A more generic education or the choice of more accessible fields may result in a lower probability of unemployment or holding a temporary or part-time position. In other words, the incentives to be overqualified or to pursue more generic studies are greater in Spain than in other countries in the region (Garcia-Mainar & Montuenga, 2019; Garcia-Mainar et al., 2015; Ortiz, 2010).

For future lines of research, first, it would be useful to have more disaggregated levels of education and occupations. In agriculture, forestry, fisheries, and veterinary medicine, for example, there are highly masculinized careers, such as agricultural engineering, as well as more feminized ones, such as veterinary medicine. Similarly, physics and geology are male-dominated fields of science, while environmental sciences and biology-related fields are female-dominated. For the time being, the necessary anonymization of the collected information prevents this. Second, while we did not delve into individual decision-making processes, our findings suggest that opting for non-gender-typical disciplines may heighten the risk of mismatch. In this context, adhering to traditional gender roles in education can be seen as a strategic, rational move. Nevertheless, the strong influence of the gender variable reveals how deeply socialization shapes the educational stage. Whether this is due to identity or social reproduction remains to be determined. Future research should clarify whether these academic paths are chosen in pursuit of economic returns or are a byproduct of social conditioning.

Third, empirical evidence (e.g., Moody et al., 2019) indicates that a significant share of employees in Western economies hold positions that differ greatly from their academic specializations. This underscores the critical role of technical and vocational education and training (TVET) alongside workplace learning. The potential mismatch between vocational training and job-specific requirements often arises from factors external to the chosen field of study, such as demand-side constraints—including barriers to entry and job characteristics—or institutional frameworks. Consequently, a future line of action would be the development of more nuanced measures of horizontal mismatch to enhance the robustness of our findings. Finally, it would be interesting to study the relationship between educational segregation, job mismatch, and occupational segregation; however, this is beyond the scope of this article.

Appendix

Table A1 lists 38 occupations according to the ISCO-08 classification and shows the percentage of employees in each occupation who graduated in its most frequent field of study (the modal value). Those who graduated in the field of study shown in Table A1 are considered matched, while those who graduated in fields not included in the table are considered mismatched. For instance, 67% of ICT Technicians (occupation 35) graduated in ICT. Those who studied ICT will be considered matched, while those who studied a different field will be considered mismatched.

It should be noted that, while the field of study is more clearly defined for occupations in groups 1 (Managers), 2 (Professionals), and 3 (Technicians), the relationship between the field of study and the occupation is less clear in the other groups, given that no specific degree is required for employment. Nevertheless, some fields are more dominant than others. For instance, business administration graduates (BAL) predominate in the clerical workers group (4); services graduates (SER) predominate in the services and sales workers group (5); and engineering graduates (TEC) predominate in the semi-skilled in primary and secondary sectors groups (6, 7, and 8). As indicated in the text, Group 21 considers science (NAT) and engineering (TEC) graduates to be well-matched and graduates in other fields to be mismatched. Since group 23 includes different types of teaching, teaching (EDU) and humanities graduates (HUM) are considered well-matched. Group 26 includes legal, social, and cultural activities. More than 95% of legal professionals are law graduates (BAL), whereas 80% of workers in social sciences (e.g., politics and sociology) and cultural occupations (e.g., writers and journalists) have degrees in the humanities (HUM) or social sciences (SJI). Therefore, all graduates in these fields are considered a good fit. Similar reasoning applies to groups 34 and 61.

Table A1. Share of individuals' field-occupation matched.

		% of employed who graduated in field of study
1	*Managers*	
11	Chief Executives, Senior Officials, and Legislators	BAL 50%
12	Administrative and Commercial Managers	BAL 53%
13	Production and Specialized Services Managers	BAL 45%
14	Hospitality, Retail, and Other Services Managers	BAL 48%
2	*Professionals*	
21	Science and Engineering Professionals	TEC (60%) NAT (17%)
22	Health Professionals	HW (91%)

		% of employed who graduated in field of study
23	Teaching Professionals	EDU (50%) HUM (23%)
24	Business and Administration Professionals	BAL (58%)
25	Information and Communications Technology Professionals	ICT (75%)
26	Legal, Social, and Cultural Professionals	BAL (60%), SJI (20%), HUM (20%)
3	*Technicians and Associate Professionals*	
31	Science and Engineering Associate Professionals	TEC (60%)
32	Health Associate Professionals	HW (64%)
33	Business and Administration Associate Professionals	BAL (60%)
34	Legal, Social, Cultural, and Related Associate Professionals	BAL (22%). SER (22%)
35	Information and Communications Technicians	ICT (67%)
4	*Clerical Support Workers*	
41	General and Keyboard Clerks	BAL (67%)
42	Customer Services Clerks	BAL (33%)
43	Numerical and Material Recording Clerks	BAL (52%)
44	Other Clerical Support Workers	SJI (23%)
5	*Services and Sales Workers*	
51	Personal Services Workers	SER (41%)
52	Sales Workers	BAL (33%)
53	Personal Care Workers	HW (52%)
54	Protective Services Workers	SER (23%)
6	*Skilled Agricultural, Forestry, and Fishery Workers*	
61	Market-oriented Skilled Agricultural Workers	AGR (25%), TEC (25%)
62	Market-oriented Skilled Forestry, Fishery, and Hunting Workers	AGR (57%)
7	*Craft and Related Trades Workers*	
71	Building and Related Trades Workers (excluding electricians)	TEC (65%)
72	Metal, Machinery, and Related Trades Workers	TEC (87%)
73	Handicraft and Printing Workers	TEC (42%)
74	Electrical and Electronic Trades Workers	TEC (88%)
75	Food Processing, Woodworking, Garment, and Other Craft and Related Trades Workers	TEC (30%)
8	*Plant and Machine Operators and Assemblers*	
81	Stationary Plant and Machine Operators	TEC (50%)
82	Assemblers	TEC (48%)
83	Drivers and Mobile Plant Operators	TEC (49%)
9	*Elementary Occupations*	
91	Cleaners and Helpers	
92	Agricultural, Forestry, and Fishery Laborers	AGR (25%)
93	Laborers in Mining, Construction, Manufacturing, and Transport	TEC (30%)
94	Food Preparation Assistants, Street and Related Sales, Refuse, Services, and Other Elementary Workers	
0	*Armed Forces Occupations*	

AAA (X%) means that X% of employees that graduated in the field of study AAA work in that occupation

Table A2.A. Heckman's second stage of horizontal mismatch probability. Estimation with a sample of university graduates. Marginal effects.

	Model 1: fields		Model 2: field feminized or masculinized		Model 3: field x gender	
	dy/dx	Std. Err	dy/dx	Std. Err	dy/dx	Std. Err
Gender (1 = man)	0.032***	0.010	0.023**	0.011		
Age < 25 (ref.)						
Age 26–35	0.119***	0.035	0.114***	0.044	0.126***	0.035
Age > 35	0.145***	0.041	0.140***	0.051	0.154***	0.040
Univ. up to 240 credits (ref.)						
Univ. > 240 credits	-0.045***	0.012	-0.045***	0.014	-0.046***	0.012
Cohabits with a partner	0.051***	0.016	0.040**	0.019	0.055***	0.016
Non-native	0.039	0.032	0.051	0.038	0.034	0.032
Experience	0.007***	0.003	0.007**	0.003	0.007***	0.003
Public sector	-0.193***	0.011	-0.158***	0.012	-0.194***	0.011
Wage-earning	0.091***	0.016	0.087***	0.018	0.092***	0.016
Firm size < 10 workers (ref.)						
Firm size 11–49	-0.063***	0.011	-0.062***	0.013	-0.063***	0.011
Firm size 50–249	-0.085***	0.014	-0.082***	0.015	-0.085***	0.014
Firm size 250 +	0.000	0.014	-0.055***	0.016	0.000	0.014
Part-time	0.028***	0.012	0.094***	0.013	0.027**	0.012
Services (ref)						
Primary sector	0.131***	0.045	0.289***	0.048	0.137***	0.045
Industry	0.031*	0.016	0.010	0.017	0.030*	0.016
Construction	-0.071**	0.031	-0.126***	0.033	-0.073***	0.031
EDU	-0.454***	0.036				
HUM	-0.319***	0.044				
SJI	-0.239***	0.039				
BAL	-0.685***	0.035				
NAT	-0.511***	0.040				
ICT	-0.638***	0.039				
TEC	-0.624***	0.037				
AGR (ref.)						
HW	-0.633***	0.036				
SER	-0.207***	0.042				
Femin/masculinized			-0.025**	0.010		
EDUxman					-0.346***	0.051
HUMxman					-0.281***	0.056
SJIxman					-0.116**	0.055
BALxman					-0.611***	0.047
NATxman					-0.480***	0.054
ICTxman					-0.661***	0.051
TECxman					-0.613***	0.048
AGRxman (ref.)						
HWxman					-0.576***	0.050
SERxman					-0.239***	0.056

	Model 1: fields		Model 2: field feminized or masculinized		Model 3: field x gender	
	dy/dx	Std. Err	dy/dx	Std. Err	dy/dx	Std. Err
EDUxwoman					-0.467***	0.048
HUMxwoman					-0.309***	0.055
SJIxwoman					-0.265***	0.051
BALxwoman					-0.696***	0.047
NATxwoman					-0.489***	0.053
ICTxwoman					-0.414***	0.059
TECxwoman					-0.525***	0.052
AGRxwoman					0.064	0.066
HWxwoman					-0.621***	0.047
SERxwoman					-0.106***	0.058
Year dummies	x		x		x	
Regional dummies	x		x		x	
λ Heckman	0.329***	0.105	0.280**	0.133	0.355***	0.102
ρ	0.722		0.586		0.768	
σ	0.457		0.479		0.462	
Observations workers	9,175	9,175	9,175			

*$p<0.1$; **$p<0.05$; ***$p<0.01$

Table A2.B. Heckman's second stage of overeducation mismatch probability. Estimation with a sample of university graduates. Marginal effects.

	Model 1: fields		Model 2: field feminized or masculinized		Model 3: field x gender	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
Gender (1 = man)	0,045***	0,011	0,051***	0,011	0,103***	0,037
Age < 25 (ref.)						
Age 26–35	0,109***	0,038	0,091**	0,044	0,185***	0,043
Age > 35	0,191***	0,044	0,169***	0,050	0,266***	0,013
Univ. up to 240 credits (ref.)						
Univ. > 240 credits	0,267***	0,013	0,258***	0,014	0,043***	0,016
Cohabits with a partner	0,044***	0,017	0,035*	0,019	0,090***	0,034
Non-native	0,084**	0,034	0,100***	0,037	0,004	0,003
Experience	0,005*	0,003	0,003	0,003	-0,112***	0,012
Public sector	-0,110***	0,012	-0,113***	0,012	0,101***	0,018
Wage-earning	0,101***	0,018	0,110***	0,018	-0,034***	0,012
Firm size < 10 workers (ref.)						
Firm size 11–49	-0,035***	0,012	-0,031***	0,013	-0,032**	0,015
Firm size 50–249	-0,032**	0,015	-0,024	0,015	0,012	0,015
Firm size 250 +	0,010	0,016	-0,014	0,015	0,123***	0,013
Part-time	0,124***	0,013	0,145***	0,013	0,271***	0,049
Services (ref)						
Primary sector	0,274***	0,048	0,242***	0,048	-0,006	0,017
Industry	-0,007	0,017	-0,015	0,017	0,004	0,033
Construction	0,004	0,033	-0,023	0,033		

	Model 1: fields		Model 2: field feminized or masculinized		Model 3: field x gender	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
EDU	0,101***	0,038				
HUM	0,110**	0,046				
SJI	0,147***	0,041				
BAL	0,114***	0,037				
NAT	0,131***	0,042				
ICT	0,105***	0,041				
TEC	0,019	0,039				
AGR (ref.)						
HW	-0,017	0,038				
SER	0,266***	0,044				
Femin/masculinized			-0,078***	0,016		
EDUxman					0,064	0,053
HUMxman					0,120**	0,059
SJIxman					0,186***	0,058
BALxman					0,076	0,050
NATxman					0,046	0,057
ICTxman					0,065	0,053
TECxman					-0,031	0,051
AGRxman (ref.)						
HWxman					-0,063	0,052
SERxman					0,266***	0,059
EDUxwoman					0,025	0,050
HUMxwoman					0,006	0,058
SJIxwoman					0,036	0,053
BALxwoman					0,039	0,050
NATxwoman					0,097*	0,055
ICTxwoman					0,041	0,062
TECxwoman					-0,027	0,055
AGRxwoman					-0,126*	0,069
HWxwoman					-0,094*	0,050
SERxwoman					0,150**	0,060
Year dummies	x		x		x	
Regional dummies	x		x		x	
λ Heckman	0,320***	0,113	0,240*	0,132	0,302***	0,110
ρ	0,665		0,513		0,634	
σ	0,482		0,468		0,476	
Observations workers	9,175		9,175		9,175	

*$p<0.1$; **$p<0.05$; ***$p<0.01$.

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