

# Gendered Wage Penalties for the Overeducated: The Experiences of Young Men and Women in Ten European Countries

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## Abstract

In this study, we examine the impact of overeducation on wages and wage penalties among 19,000 young men and women aged 18–35 in ten European countries. Using data from the Cultural Pathways to Economic Self-sufficiency and Entrepreneurship (CUPESE) project and controlling for some endogeneity from omitted ability variables and employment selection, we find that women's wages and wage penalties align with job search theory, while men's observed wage offers are consistent with job competition theory. However, once selection is accounted for, wage penalties incurred by young men do not follow the predictions from this theory. Despite lower baseline wages, women in many countries face larger overeducation penalties than men, a pattern shaped by institutional regime type and gender norms. We offer possible explanations for this disparity and conclude with policy recommendations to address overeducation penalties.

**Keywords:** overeducation, wage penalty, selection model, job search theory, job competition theory

**JEL:** I0, I2, J0, J1, J3

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## Introduction

Young adults entering the labor market today face significant challenges that reflect broader changes in labor market structures, educational attainment levels, and employment practices. A growing body of evidence documents a mismatch between the educational qualifications of young workers and the demands of the jobs they occupy. This mismatch is especially acute for young people with tertiary degrees who are unable to secure employment that fully utilizes their level of education, a condition commonly referred to as overeducation. While overeducation has been extensively studied, relatively less is known about its gendered consequences – specifically, whether young women face larger wage penalties than young men when overeducated. Addressing this question is critical to understanding how gender inequalities are reproduced in contemporary labor markets, particularly during the critical early years of employment.

In this paper, we attempt to extend the research on the wage penalties associated with overeducation in three ways, viz., by (a) identifying how wage penalties fit into the human capital, job search, and job competition theories and other related theories of labor force attachment; (b) demonstrating the dependence of overeducation penalties on gender and on country-specific macro level factors that affect how human capital is absorbed into the labor market; and (c) addressing the contribution that individual ability makes in the assessment of wage penalties through the introduction of “soft skills” and work values such as grit, risk-taking, motivation, etc., in participation and earnings models (Carneiro and Heckman 2003; Chevalier 2003; Duckworth and Yeager 2015; Galloway et al. 2017; Stewart 2018; Palczyńska 2021).

The data we use to meet these research objectives originate from the Cultural Pathways to Economic Self-sufficiency and Entrepreneurship (CUPESSSE) database, which contains the survey responses of 20,008 young adults aged 18 to 35 from 11 European countries. This 2017–2018 survey, funded by the European Commission, asked respondents from Austria, Czechia, Denmark, Germany, Greece, Hungary, Italy, Spain, Switzerland, Turkey, and the United Kingdom a wide variety of questions concerning labor force participation, work values and skills, and labor market conditions. More information on CUPESSSE research goals and methodology can be found in Tosun et al. (2019) and Kraaykamp, Cemalcilar, and Tosun (2019).

Our empirical findings reveal that: (1) consistent with job search theory, women in a large majority of our study countries exhibit observed wages in OLS regressions that are greater than offered wages. Moreover, when earnings models are adjusted for women not observed in the labor market, these women are less likely to be overeducated and hence, less likely to incur wage penalties; (2) men in our country-specific samples appear to have observed wages that are less than those offered, an indication of job competition theory. However, contrary to job competition predictions, when above-average credentialed men, who are more likely to be overeducated, are accounted for, wage penalties *do not* increase as would be expected; and (3) one possible explanation for this second result is the significant display of “grit” or perseverance by men in our sample, which may serve as a productivity signal to employers and as a prophylactic against wage erosion.

The rest of the paper is organized as follows: Section 2 provides the theoretical framework for our empirical work and discusses the endogeneity problem and the potential role of soft

skills in controlling for endogeneity (at least partially) in the selection and wage equations; Section 3 reviews the relevant literature on wage penalty and its gendered nature; Section 4 details data sources, sample, measures and analytical methods used in this study; Section 5 reviews our empirical findings; and Section 6 discusses our findings and provides conclusions and policy suggestions.

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## Theoretical Framework

### Overeducation and Economic Theory

Several labor market theories explain how overeducation affects employment and earnings, each offering distinct mechanisms for understanding why individuals may work in jobs below their educational level and how this affects earnings.

#### Human Capital

Human capital theory (HCT) posits that education enhances worker productivity and wages, implying that surplus education still generates positive returns, albeit at a lower marginal rate than education aligned with job requirements. From this perspective, overeducation represents a transitional or frictional state, as market adjustments eventually align supply and demand for skills (Becker 1964; 1993; Mincer 1974; Duncan and Hoffman 1981; Card 1999). The compensation model suggests that overeducation offsets lower abilities, and wage penalties should vanish when controlling for skills (Chevalier 2003). Yet, persistent wage penalties challenge this view (Sicherman 1991; Büchel 2002; McGuinness 2003; Korpi and Tählin 2009; Kampelmann and Rycx 2012; Kleibrink 2016), perhaps due to inadequate skill measures on verbal ability or math proficiency. Two theories of labor force participation, namely, job search theory and career mobility theory, tend to support HCT by offering extenuating market demand circumstances for HCT's often less than perfect predictions of employment and earnings. A third, job competition theory, does not support an HCT explanation. Together, HCT and the job search, job mobility, and job competition models provide a foundation for understanding how educational attainment affects wages; this foundation is further enriched by Assignment Theory and Search and Matching Theory, which consider how workers are allocated to positions and how frictions in the matching process influence wage outcomes for the overeducated.

#### Job Search

This model argues workers accept jobs only above their reservation wage, implying higher earning potential correlates with employment (Baldwin and Johnson 1992; Nicaise 2001; Caroleo and Pastore 2016; 2018). Consequently, OLS may overstate wage penalties. Studies of younger women in the Netherlands and Belgium (Hartog and Oosterbeek 1988; Nicaise 2001) illustrate that overeducated women still require returns to education to justify labor force participation. Heckman's (1979) selection model suggests that a positive  $\lambda$  indicates wage penalties may shrink when accounting for unobserved traits like motivation (Baldwin and Johnson 1992; Ermisch and Wright 1994; Nicaise 2001).

### Job Mobility

Sicherman (1991) finds that overeducated workers often accept lower initial wages but use these jobs for advancement (Sicherman and Galor 1990). Over time, wage penalties diminish due to job mobility and on-the-job training (OJT) (Büchel 2002; Korpi and Tåhlin 2009; Kampelmann and Rycx 2012), though the “genuinely overeducated” continue to suffer penalties (Chevalier 2003; Chevalier and Lindley 2009). While U.S. labor markets support mobility and OJT, other systems may not (Zimmerman et al. 2013; Caroleo and Pastore 2018; Marques, Suleman, and Costa 2022).

### Job Competition

Thurow’s model (Kalamazoo and Thurow 1979) offers a demand-side perspective and depicts rigid labor markets where educated individuals take lower-level jobs, leading to wage penalties, especially in slow-growth economies (López Fogués 2017; Caroleo and Pastore 2018; Marques, Suleman and Costa 2022). Unlike job search theory, it predicts more penalties as motivated individuals accept suboptimal jobs. In sample selection models, this is reflected in a negative lambda ( $\lambda$ –), indicating unobserved traits increase employment probability, but reduce wages (Heckman 1979; Ermisch and Wright 1994).

### Assignment Theory

This theory complements Thurow’s thinking while emphasizing the roles of job constraints *and* individual capital (Sattinger 1993; McGuinness 2006; Kleibrink 2016; Caroleo and Pastore 2018). Overeducation leads to productivity losses because workers’ skills are underutilized, and employers do not fully compensate for unused human capital. This model predicts persistent penalties if mismatches reflect structural labor market rigidities rather than temporary frictions.

### Search and Matching Models

These models (Mortensen and Pissarides 1994) highlight that mismatches can result from imperfect information and frictions in job search. Overeducation in this framework reflects suboptimal matching rather than pure surplus supply. These models predict that penalties may be mitigated when labor markets are dynamic, and workers can transition more easily to better-matched jobs.

Together, these perspectives suggest that the incidence and penalty of overeducation will vary depending on whether mismatches are transitional (as in HCT and search models), structural (as in assignment theory), or employer-driven (as in job competition models). This study interprets its findings through these theoretical lenses, acknowledging that institutional features – such as vocational training systems, wage-setting mechanisms, gender norms and job mobility opportunities – will shape which mechanisms dominate in different contexts.

### Overeducation and Knowledge, Skills, Ability (KSA) Bias

Leuven and Oosterbeek (2011) note that wage penalties linked to overeducation may stem from endogeneity due to the correlation of measured overeducation with the error term and unobserved

heterogeneity in wage models. There, of course, is an additional source of potential endogeneity due to sample selection, affecting both labor force participation and earnings.

### Omitted Variables in Wage Equations

Common methods to address endogeneity include fixed effects, instrumental variables (IVs), and direct KSA measures. IVs, such as family background or early-life factors (Korpi and Tåhlin 2009; Kleibrink 2016; Caroleo and Pastore 2018), or baseline earnings at first job (Chevalier 2003) often fail to meet exclusion criteria. Including KSA measures such as numeracy and literacy has had minimal success in explaining wage variation in samples from OECD countries, Poland, Spain and Northern Ireland (McGuinness 2003; Kankaraš et al. 2016; Nieto and Ramos 2017; Palczyńska 2021). While soft skills – perseverance or grit, dependability, trustworthiness, and agreeability – may be more relevant (Heckman, Stixrud, and Urzua 2006; Heckman and Masterov 2007; Rosso, Dekas, and Wrzesniewski 2010; Duckworth and Yeager 2015; Hauff and Kircher 2015; Stewart 2018; Gesthuizen, Kovarek, and Rapp 2019; Camasso and Jagannathan 2021), they are largely absent from overeducation studies, with the exception being Palczyńska (2021).

### Omitted Variables in Participation Equations

Accounting for both workers and nonparticipants is essential, as models like job search and job competition highlight selection dynamics. When specifying sample selection models, choosing which KSAs and other factors should be included in the participation model and which should appear in the wage (earnings) equation is fundamental. Following Heckman (1979) and Killingsworth (1984), employment depends on income–leisure trade-offs, while wages reflect productivity. If we consider overeducation primarily as a labor market mismatch and not an individual characteristic, it only belongs in the wage equation. It has also been shown that including irrelevant KSAs in the wage equation may misstate selection effects (Dolton and Makepeace 1986; Caroleo and Pastore 2018).

Our approach in this paper addresses the issue of overeducation endogeneity at least to some extent by directly including often omitted KSAs in our wage equations and by including additional KSAs in our selection equations that we believe have an indirect impact on wages through their influence on the decision to seek employment. However, we acknowledge that a substantial portion of endogeneity may remain due to unobserved factors, including cognitive and non-cognitive skills, motivation, or other individual-level characteristics that influence both participation and wage outcomes. We also refine our analyses of wage penalties experienced by young adults by conducting a series of country- and gender-specific analyses.

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## Background Literature

In the empirical literature, two main approaches dominate the analysis of wage effects stemming from educational mismatch. The first is the ORU (Over-Required-Under education) specification (Hartog 2000), which decomposes total schooling into three additive components: required schooling, overeducation, and undereducation. Studies employing this framework consistently



find that overeducation yields positive but lower returns than required education, and higher returns than undereducation – highlighting a hierarchy of educational match in shaping wages. The second widely used method, developed by Verdugo and Verdugo (1989), treats overeducation as a dummy variable while controlling for actual education. In this approach, the wage penalty for overeducation is interpreted as the loss incurred by individuals who are mismatched, relative to similarly educated but adequately matched peers. The distinction between these approaches is not merely methodological; it affects the interpretation of wage effects. While the ORU model assesses the relative productivity of excess education, the Verdugo model captures the penalty associated with mismatch status itself. This study follows the latter approach, which is particularly suited for large-scale, cross-national data where direct job-education alignment measures are limited.

In one of the earliest discussions of overeducation in the social science literature, Duncan and Hoffman (1981) described the phenomenon of overeducation as the simple difference between attained years of schooling and years of schooling required to “discharge job responsibilities.” Since that work, other researchers have reported one of two general findings: (1) overeducation yields positive returns to schooling; however, each year of “surplus” education does not have as much economic value as an additional year of required education (Duncan and Hoffman 1981; Sicherman 1991; Cohn and Khan 1995; Büchel 2002; Leuven and Oosterbeek 2011; Kampelmann and Rycx 2012); and (2) overeducation is responsible for substantial wage penalties which may or may not persist indefinitely (Verdugo and Verdugo 1992; Korpi and Tåhlin 2009; McGuinness, Pouliakas, and Redmond 2017; Caroleo and Pastore 2018; McGuinness, Bergin, and Whelan 2018). Of course, these two findings need not be mutually exclusive, as Cohn and Khan (1995) and Sicherman (1991) clearly point out.

The accumulated research on the economic impact of overeducation has refined our understanding of this mismatch, particularly in cross-national contexts. Leuven and Oosterbeek (2011) and McGuinness (2006) found that wage penalties vary widely across countries depending on measurement method and institutional context. Meanwhile, Caroleo and Pastore (2016) demonstrated that wage penalties can even vary considerably within a country. Studies using the vertical mismatch perspective (Barone and Ortiz 2011; Levels, van der Velden, and Allen 2014) suggest that institutional factors such as vocational tracking, employment protection, and educational expansion shape both the incidence and impact of overeducation.

Gender has become an increasingly central dimension in overeducation research, which shows that gender differences in wage penalties are the rule rather than the exception (Duncan and Hoffman 1981; McGoldrick and Robst 1996; Blau and Khan 2003; McGuinness, Bergin, and Whelan 2018; European Commission 2021). Women are more likely to be overeducated than men, especially in countries with weaker family support policies or stronger occupational gender segregation (Boll et al. 2016). More recent studies confirm this trend and show that the wage penalty for overeducation tends to be steeper for women (Robst 2007; Boto-García and Escalonilla 2022). This reflects not only labor market discrimination but also institutional constraints limiting women’s occupational mobility, especially post-childbirth (Budig and England 2001; Cha and Weeden 2014).

Recent contributions have also examined how labor market institutions interact with gender to structure overeducation outcomes. For example, Reisel, Østbakken, and Attewell (2019) found that the gender gap in overeducation is narrower in countries with strong public sector employment and generous parental leave, whereas it is exacerbated in dualized labor markets with precarious service-sector jobs. Similarly, findings from Fernandez-Macias and Hurley (2020) suggest that technological change and polarization disproportionately affect women's job-matching prospects in certain occupations.

Despite the depth of prior work, few studies adopt a multi-country comparative design that simultaneously considers institutional regimes and gendered outcomes of overeducation. This study addresses that gap by using harmonized data across ten European countries and evaluating how gender shapes the wage penalties of overeducation in different labor market contexts.

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## Data, Measures, and Methods

### Selection of Study Countries

The data used to examine the impact of overeducation on labor force participation and wages were generated from the youth sample (ages 18–35 years) of the Cultural Pathways to Economic Self-sufficiency and Entrepreneurship (CUPESSSE) survey research project. Young people from 11 countries<sup>1</sup> were queried from 2017 to 2018 on a broad range of issues, including labor force attachment, school-to-work transitions, perceptions of skill levels and work values. The choice of the ten countries studied here is not only driven by data availability but is anchored in comparative labor market and welfare regime theory, which helps explain the institutional roots of overeducation and its gendered wage penalties. We draw on comparative frameworks such as Esping-Andersen's (1990) welfare regime typology, and its extensions (Estevez-Abe, Iversen, and Soskice 2001; Emmenegger et al. 2012), which explain cross-national variations in education systems, labor market regulations, and social protection. These institutional arrangements have direct implications for how education credentials are matched to jobs, the prevalence of overeducation, and the extent to which gendered norms moderate penalties.

The ten countries represent a range of regimes along three key institutional dimensions discussed in the recent literature on overeducation:

1. Education–Employment Linkages: In Coordinated Market Economies (CMEs) like Germany and Austria, strong vocational education and training (VET) systems and close school-to-work pathways should reduce the likelihood of overeducation (Shavit and Müller, 2000). These countries provide clear occupational signaling to employers, which facilitates better matching. In contrast, Liberal Market Economies (LMEs) like the United Kingdom feature generalized higher education and looser credentialing norms, which should increase educational mismatch due to weak institutional alignment between education and labor market demand (Hall and Soskice 2001).

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<sup>1</sup> Switzerland was excluded from our analyses due to low levels of variation in both participation and wages.

2. **Labor Market Regulation and Segmentation:** In Mediterranean countries such as Spain and Italy, labor markets are characterized by high levels of segmentation, with stable, regulated employment in the public sector and insecure, flexible contracts in the private sector (Barbieri and Scherer 2009). This dualism should increase the overeducation risk, particularly for young and female workers entering precarious sectors. In post-socialist economies (e.g., Hungary and Czechia), educational systems are relatively standardized, but labor markets are transitioning, often with liberalized hiring and weaker employment protections. This may simultaneously increase mismatch and diminish the wage returns to education.
3. **Gender Norms and Care Responsibilities:** Countries also differ significantly in gender role expectations and care infrastructure, both of which influence women's educational and occupational trajectories. In countries like Denmark, public childcare and generous leave policies support maternal employment and reduce occupational downgrading. Conversely, in countries like Italy and Spain, traditional gender norms and weak state support for caregiving often restrict women to a narrower set of jobs, heightening their risk of being overeducated and increasing the wage penalties they incur (Mandel and Semyonov 2005; Boll et al. 2016).

To clarify our rationale for including these ten countries, we draw on comparative political economy frameworks that emphasize how institutional variation shapes education–employment linkages, labor market segmentation, and gender norms. Table 1 provides a summary classification of the study countries along these three dimensions, drawing on Esping-Andersen's (1990; 2002) welfare regime typology and Hall and Soskice's (2001) varieties of capitalism, as well as subsequent comparative research (Gallie 2007; Iversen and Stephens 2008). As shown, our sample captures diversity across coordinated and liberal market economies, Mediterranean regimes, post-socialist contexts, and a Nordic comparator, with Turkey serving as a hybrid/transitional case. This classification demonstrates the theoretical breadth of our country selection and highlights how institutional contexts condition both the incidence of overeducation and the magnitude of its wage penalties.

**Table 1.** Institutional classification of study countries by education–employment linkages, labor market segmentation, and gender norms

Country	Education–Employment Linkages	Labor Market Regulation/ Segmentation	Gender Norms & Care Responsibilities	Welfare/Market Regime
Austria	Strong vocational orientation (VET system)	Coordinated wage bargaining, moderate segmentation	Conservative family model, limited childcare support	Coordinated Market Economy, Conservative regime
Germany	Strong VET, high school-to-work linkages	Coordinated labor markets, insider–outsider divide	Conservative family model, part-time female employment common	Coordinated Market Economy, Conservative regime
United Kingdom	Weak linkages between education and jobs	Deregulated, flexible labor markets, low employment protection	Dual-earner model but limited family policy supports	Liberal Market Economy
Italy	Weak school-to-work transitions	Rigid labor markets, high segmentation	Traditional gender norms, weak childcare provision	Mediterranean regime
Spain	Weak transitions, high graduate underemployment	Rigid labor markets, high youth unemployment	Strong male-breadwinner legacy, limited family supports	Mediterranean regime



Country	Education-Employment Linkages	Labor Market Regulation/ Segmentation	Gender Norms & Care Responsibilities	Welfare/Market Regime
Greece	Weak transitions, clientelistic hiring	Highly segmented, rigid markets	Strong traditional norms, weak childcare infrastructure	Mediterranean regime
Czechia	Moderate transitions, less developed VET	Transitional labor markets, some segmentation	Legacy of dual-earner norm, but care burden on women	Post-socialist economy
Hungary	Moderate transitions, limited VET expansion	Transitional labor market, insider-outsider divide	Dual-earner legacy but weak family supports	Post-socialist economy
Turkey	Weak education-to-work linkages; high graduate underemployment	Highly segmented labor market; large informal sector	Strongly traditional gender roles; low female labor force participation	Hybrid/Transitional; often grouped with Southern/Mediterranean regimes
Denmark	Strong linkages via active labor market policy	Flexible security ("flexicurity"), low segmentation	Strong gender equality supports, extensive childcare	Nordic coordinated market economy

Source: adapted from Esping-Andersen 1990; Hall and Soskice 2001; Gallie 2007; Iversen and Stephens 2008.

Each of the participating countries was required to interview at least 1,000 respondents who represented the (age-adjusted) employed, unemployed and in-school segments of their populations. Country samples were stratified to ensure regional labor market representation that was consistent with NUTS 1 (Nomenclature of Territorial Units for Statistics) and NUTS 2 (in the cases of Czechia and Denmark) 2017 classification. Most of these interviews were conducted using computer-assisted telephone interviewing (CATI) or computer-assisted personal interviewing (CAPI) techniques, with Turkey relying on traditional paper and pencil methodology. As shown in Table 2, each country was able to meet the sample size minimum, with Germany, Turkey and the United Kingdom far surpassing 1,000. Funding for CUPESSE was provided by the European Commission from February 2014 through January 2018 (Tosun et al. 2019).

**Table 2.** General Description of the CUPESSE Young Adults Database

Country	Number of observations	Gender (%)	
		Male	Female
Austria	1,684	44	56
Czechia	1,214	43	57
Denmark	1,142	56	44
Germany	3,279	49	51
Greece	1,538	40	60
Hungary	1,295	45	55
Italy	1,008	54	46
Spain	1,826	49	51
Switzerland	1,002	40	60
Turkey	3,016	50	50
UK	3,004	49	51
<b>Total</b>	<b>20,008</b>	<b>47</b>	<b>53</b>

Source: Tosun et al. 2019.

## Study Variables

We provide descriptions of the study variables in Table 3. The measurement and coding of the earnings, education, and work experience variables follow the stylized manner of Mincer returns-to-education equations (Mincer 1974; Verdugo and Verdugo 1989; Card 1999). Overeducation is the Yes (= 1) or No (= 0) response to the questions: (a) “Do you think your present job is a good match with your overall qualifications?” (if employed) and (b) “Do you think your previous job(s) were a good match?” (if currently not working).

The literature on overeducation uses three main measurement approaches: (1) Individual Self-Assessment (ISA), (2) Job Analysis (JA), and (3) Statistical Approach (SA). In the ISA method (Alba-Ramirez 1993; Hartog 2000; Chevalier 2003; Boto-Garcia and Escalonilla 2022), the respondent is directly asked whether their current job requires a lower level of education than they possess. JA (Rumberger 1987; Baert, Cockx, and Verhaest 2013) compares the respondent’s actual education to benchmarks devised by expert ratings or occupation-specific guidelines, such as ISCO codes, to determine overeducation. SA (Verdugo and Verdugo 1989) uses the statistical mode or median of education levels within occupations to define required education; individuals who exceed this occupational average are considered overeducated.

Each approach has its advantages and disadvantages. The ISA method, used in this study, is the simplest and most widely used in large-scale surveys (e.g., European Social Survey (ESS) and the Programme for the International Assessment of Adult Competencies (PIAAC)). However, it is quite vulnerable to subjective distortions and reporting biases, including:

- Perception bias: individuals may misjudge job requirements based on career aspirations, job satisfaction or cultural expectations (Hartog 2000).
- Gender bias: men are more likely to report mismatch, possibly inflating perceived overeducation, while women may normalize underemployment due to constrained labor market opportunities or caregiving obligations (Robst 2007; Bender and Heywood 2011).
- Cross-national comparability issues: interpretations of what constitutes “required education” may differ across national and occupational contexts, making standardization difficult.

While more objective than ISA, both JA and SA have their own difficulties, such as the cost involved and the difficulty of measurement across multiple countries with varying job classification systems (JA) or the sensitivity to outliers and educational inflation within occupations and the heterogeneity in job complexity or skill use (SA). Given the cross-national scope of this study and the structure of the CUPESSE dataset, where occupational codes or even broad industry sectors are missing for a high proportion of the observations, ISA is the most feasible and internally consistent option.

While acknowledging its weaknesses, we believe that the ISA method allows for comparability across diverse labor market contexts and captures the subjective experience of mismatch, which is particularly relevant when analyzing gendered labor market outcomes. Moreover, recent studies have shown that subjective and objective measures of overeducation tend to converge at the macro level (Mavromaras et al. 2013) and that self-perceived mismatch is a strong predictor of job dissatisfaction

and wage penalties (Green and Zhu 2010; Pecoraro 2014). The use of ISA, therefore, while imperfect, provides meaningful insight into how workers experience and report educational mismatch – especially across countries with different job classification systems, wage structures, and gender norms.

Specific items used to construct “soft skills” and “work values” scales are also included in Table 3, along with Cronbach alphas used to assess internal consistency reliability. Inasmuch as many of these values/skills items have not typically been measured in the employment literature (Heckman 2000; Carneiro and Heckman 2003; Heckman, Stixrud, and Urzua 2006), it is not possible to state if the distributions of these variables are either typical or uncharacteristic of country norms. Data collected by Camasso and Jagannathan (2021) would suggest that risk-taking levels in the CUPESE sample are lower, on average, than they are for youth (18–34 years) in the United States. The measure of “grit”, i.e., perseverance, is based on the work of Duckworth and Yeager (2015), while the indicators of intrinsic vs. extrinsic values, work centrality, and motivation follow from the work done by Hauff and Kirschner (2015), Gesthuizen, Kovarek, and Rapp (2019), and Kraaykamp, Cemalcilar, and Tosun (2019).

All demographic variables, except age, were collected as yes/no questions and were coded as dummy variables. In addition to these variables, NUTS regions were used to control for regional and territorial differences within countries, thus serving as a labor market proxy. NUTS 1 level controls were utilized in all countries excepting Denmark and Czechia, which have only one NUTS level 1 designation. In these two countries, NUTS 2 level controls were used.

Table 3. Description of Study Variables

Variable Description	Detailed Description
<b>Employment / Earnings</b>	
The logarithm of standardized hourly wages	The CUPESE survey asked for personal monthly income. If employed, monthly income was divided by 148 hours. <sup>2,3</sup>
Currently Employed	In paid work in the last month as either an employee or self-employed.
<b>Education / Experience</b>	
Formal Education	CUPESE survey coded the highest level of education using ES-ISCED Categories I, II, III, IV, V, and V2. Converted into years using UNESCO Country Specific Comparison Charts (2011).
Work Experience	Measured as Potential Experience (age – years of schooling – 6) following the Mincer definition. EXPERIENCE squared variable is included, again following the Mincer definition
Currently / Recently Overeducated	The CUPESE survey asked, “Do you think your job is a good match with your overall qualifications?” Response options: Yes – Good Match / No – I am overqualified / No – I am underqualified.

2 We calculate a *standardized hourly wage* by dividing monthly earnings by a constant of 148 hours, the assumed average monthly workload. This allows for comparability across respondents but does not capture variation in actual hours worked.

3 Wages were not CPI-deflated following established practice in cross-European mismatch/wage studies (e.g., McGuinness and Pouliakas 2016; Cultrera et al. 2022). The CUPESE survey was conducted in 2017–2018, a period of low and stable inflation across Europe, making real wage erosion negligible. Moreover, since our analysis emphasizes relative wage penalties rather than absolute wage levels, and the ranking of high-wage (e.g., Denmark, Germany) and low-wage (e.g., Hungary, Greece, Turkey) contexts is preserved, the absence of deflation does not bias the substantive conclusions.

Variable Description	Detailed Description
<b>Soft Skills/Work Values</b> Motivation: Willingness to change jobs	Willingness to change or start new jobs: Summed score over four questions, coded 1 = No, 2 = Maybe, 3 = Yes. Cronbach's alpha = 0.63. Items include: a) I would be willing to move within the country. b) I would be willing to move to a different country. c) I would be willing to learn new skills, such as a new language or computer programs. d) I would be willing to learn completely new skills or retrain to get a job.
Value-centrality of work on life	Mean value calculated over five questions, coded 1 = Strongly Disagree, 2 = Somewhat Disagree, 3 = Somewhat Agree, 4 = Strongly Agree. Cronbach's alpha = 0.67. Items include: a) To fully develop your talents, you need to have a job. b) It's humiliating to receive money without having to work. c) If welfare benefits are too high, there is no incentive to work. d) Work is a duty towards society. e) Work should always come first, even if it means less spare time.
Grit (Perseverance)	Mean value calculated over nine items - Coded 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree. Cronbach's alpha = 0.69. Items include: a) I often set a goal but later choose to pursue a different one. b) I have difficulty maintaining my focus on projects that take more than a few months to complete. c) New ideas and projects sometimes distract me from previous ones. d) I always finish whatever I begin. e) Setbacks discourage me. f) I am hard working. g) I am confident that I can deal efficiently with unexpected events. h) Usually, I do more than I am asked to do. i) My life is determined by my own actions.
Aversion to Risk	Coded on a scale of 0 (I tend to avoid risks) to 10 (I am fully prepared to take risks).
Intrinsic and Extrinsic Motivation	Mean value calculated over nine items, coded 1 = Very Unimportant, 2 = Rather Unimportant, 3 = Rather Important, 4 = Very Important. Cronbach's alpha = 0.78. Items include the importance of: a) ...a job that is secure. b) ...a high income. c) ...a job that allows me to help other people. d) ...a job that allows me to work independently. e) ...a job that allows me to learn new things. f) ...a job that leaves me enough time for leisure activities. g) ...a job that allows me to develop my creativity. h) ...a job that allows me to meet and interact with people. i) ...a job that gives me a feeling of self-worth.
<b>Demographics</b>	
Age	CUPESE question - How old are you? (Years).
Marital status	Coded 1 = Married, 0 = Single/separated/widowed.
Has children	Coded 1 if respondent had one or more children, 0 otherwise.
Caring responsibilities	Coded 1 if respondent had caregiving responsibilities, 0 otherwise.
Permanent contract	Coded 1 if respondent had a permanent contract, 0 otherwise.
Works full-time	Coded 1 if respondent worked full-time, 0 otherwise.
Religiosity	Respondent identifies as belonging to a particular religion. Coded 1 = Yes, 0 = No.
Immigrant status	Respondent identifies as belonging to a minority ethnic group. Coded 1 = Yes, 0 = No.

Source: Tosun, Hörisch, Schuck 2018.

## Description of Study Sample

Table 4 provides information on the variable distributions for young men and women in each of the 10 countries we examine. These data include comparative information on employment status, self-reported overeducation, attained education, experience, standardized hourly earnings, full-time work and permanent contract status. It also shows gender-specific distributions on five measures of soft skills and work values, and six additional demographic variables, including caring responsibilities.

The table shows a substantial gender gap in wages among the 10 countries. This gap ranges from €9.26 (females) to €12.11 (males) in Germany, the highest wage country, to €1.72 to €2.64 in Turkey. Furthermore, in all ten countries, the average standardized hourly wages (computed) are lower for women. Comparative information on measures of age, immigrant status, education level and experience does not reveal much insight.

Men are more likely to hold permanent work contracts in all sample countries. The levels of such contracts in Italy, Greece, Spain and Turkey for both men and women are much lower when contrasted with Austria, Germany, and the UK. The Turkish respondents are, by far, the most religious, with the Czech sample the most secular.

With respect to soft skills and work values, men and women in Spain and Italy were most likely to state their willingness to make geographic and job sector moves, while Turkish and Czech respondents were the most likely to take risks. Levels of intrinsic/extrinsic work motivation, grit, and work centrality were very similar across countries, trending toward the view that these are all positive values/traits to possess.

Self-reported overeducation levels ranged from lows of 10% (males) and 6.5% (females) in Turkey to highs of 26% (males) and 27% (females) in the UK. In five countries (Austria, Czechia, Germany, Italy and the UK), women reported higher levels of overeducation than men, with the opposite being true in Denmark, Greece, Hungary, Spain and Turkey. Women in all countries more often reported having caring responsibilities, with children accounting for a good deal of those responsibilities.

Table 4. Sample Characteristics for Males and Females in the Ten Study Countries

Country characteristics	Austria		Czechia		Denmark		Germany		Greece	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Number of Cases	745	939	521	693	636	506	1603	1696	612	926
Employment / Earnings										
Standardized <sup>4</sup> Wages (Euro)	9.40 (9.75)	6.92 (8.43)	4.01 (2.82)	2.66 (2.04)	11.43 (13.24)	8.09 (10.91)	12.11 (10.04)	9.26 (9.88)	3.85 (4.66)	3.03 (4.13)
Employed (1 = Yes)	0.567 (0.50)	0.460 (0.50)	0.698 (0.46)	0.477 (0.50)	0.541 (0.50)	0.421 (0.49)	0.758 (0.43)	0.606 (0.49)	0.604 (0.49)	0.462 (0.50)
Education / Experience										
Education (Years)	14.81 (2.78)	15.46 (2.46)	13.92 (2.54)	14.43 (2.74)	14.70 (2.84)	15.06 (2.78)	15.08 (2.59)	14.92 (2.61)	16.09 (2.14)	16.33 (1.91)
Experience (Years)	5.94 (5.09)	5.15 (4.90)	8.09 (4.65)	8.07 (4.63)	7.81 (4.25)	7.37 (4.26)	7.38 (5.00)	6.79 (5.16)	7.65 (4.71)	6.93 (4.60)
Overeducation (1 = Yes)	0.205 (0.40)	0.266 (0.44)	0.199 (0.40)	0.233 (0.42)	0.227 (0.42)	0.208 (0.41)	0.191 (0.39)	0.202 (0.40)	0.399 (0.49)	0.371 (0.48)
Soft Skills / Work Values										
Motivation – Willingness to Change Jobs	9.55 (1.73)	9.38 (1.72)	9.36 (0.459)	8.95 (1.54)	9.61 (1.64)	9.45 (1.52)	9.31 (1.83)	9.26 (1.78)	9.94 (1.65)	9.86 (1.64)
Work Centrality	2.74 (0.59)	2.72 (0.59)	3.10 (0.42)	2.72 (0.51)	2.77 (0.59)	2.71 (0.54)	2.86 (0.60)	2.87 (0.55)	2.75 (0.56)	2.65 (0.51)

4 Male-female wage difference within each country is statistically significant in all countries.



Country characteristics	Austria		Czechia		Denmark		Germany		Greece	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Grit	2.93 (0.42)	2.94 (0.40)	2.84 (0.39)	2.87 (0.37)	2.86 (0.35)	2.94 (0.34)	2.86 (0.40)	2.89 (0.40)	2.95 (0.40)	3.01 (0.39)
Risk-Taking	5.66 (2.15)	4.97 (2.28)	5.78 (2.44)	4.93 (2.34)	5.03 (2.32)	4.69 (2.22)	5.09 (2.15)	4.46 (2.17)	5.43 (2.55)	5.21 (2.44)
Motivation – Intrinsic and Extrinsic	3.23 (0.44)	3.30 (0.37)	3.10 (0.42)	3.15 (0.39)	3.06 (0.37)	3.18 (0.32)	3.12 (0.40)	3.21 (0.38)	3.45 (0.42)	3.52 (0.41)
Demographics										
Age (Years)	26.00 (4.99)	25.76 (5.00)	27.13 (4.98)	27.39 (5.06)	27.32 (4.84)	26.48 (4.97)	27.75 (4.08)	26.93 (4.85)	28.56 (4.76)	27.95 (4.79)
Married (1 = Yes)	0.244 (0.43)	0.193 (0.40)	0.224 (0.42)	0.343 (0.48)	0.320 (0.47)	0.414 (0.49)	0.304 (0.46)	0.283 (0.45)	0.254 (0.44)	0.325 (0.50)
Has Children (1 = Yes)	0.166 (0.37)	0.180 (0.38)	0.227 (0.42)	0.411 (0.50)	0.209 (0.41)	0.227 (0.42)	0.189 (0.39)	0.242 (0.43)	0.150 (0.36)	0.233 (0.42)
Has Caring Responsibilities (1 = Yes)	0.167 (0.37)	0.237 (0.43)	0.234 (0.42)	0.447 (0.50)	0.226 (0.42)	0.255 (0.44)	0.197 (0.40)	0.254 (0.44)	0.278 (0.45)	0.357 (0.48)
Has Permanent Contract (1 = Yes)	0.707 (0.46)	0.691 (0.46)	0.601 (0.49)	0.543 (0.50)	0.692 (0.46)	0.673 (0.47)	0.746 (0.44)	0.715 (0.45)	0.629 (0.48)	0.613 (0.49)
Works Full-time (1 = Yes)	0.673 (0.47)	0.456 (0.50)	0.818 (0.39)	0.692 (0.46)	0.692 (0.462)	0.514 (0.500)	0.814 (0.39)	0.626 (0.48)	0.748 (0.43)	0.645 (0.48)
Religious (1 = Yes)	0.417 (0.49)	0.455 (0.50)	0.176 (0.38)	0.147 (0.35)	0.275 (0.45)	0.400 (0.49)	0.375 (0.48)	0.403 (0.49)	0.554 (0.50)	0.587 (2.44)
Immigrant (1 = Yes)	0.128 (0.33)	0.132 (0.34)	0.032 (0.18)	0.020 (0.14)	0.030 (0.12)	0.031 (0.12)	0.074 (0.26)	0.090 (0.29)	0.037 (0.19)	0.011 (0.26)
Country characteristics	Hungary		Italy		Spain		Turkey		United Kingdom	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Number of Cases	582	713	510	498	893	933	1,497	1,519	1,479	1,525
Employment / Earnings										
Standardized Wages (Euro)	2.25 (1.03)	1.91 (1.01)	3.37 (2.76)	2.55 (2.37)	3.62 (4.62)	3.28 (3.79)	2.64 (3.60)	1.72 (2.44)	11.11 (10.27)	8.35 (7.05)
Employed (1 = Yes)	0.722 (0.45)	0.576 (0.50)	0.563 (0.50)	0.432 (0.50)	0.444 (0.50)	0.430 (0.50)	0.652 (0.48)	0.295 (0.46)	0.745 (0.44)	0.691 (0.46)
Education / Experience										
Education (Years)	12.93 (3.16)	13.12 (3.07)	15.46 (2.27)	15.74 (2.15)	14.62 (3.75)	15.06 (3.65)	12.44 (3.32)	13.18 (3.19)	14.66 (2.85)	14.42 (2.81)
Experience (Years)	7.94 (6.11)	8.57 (5.92)	6.55 (4.28)	6.45 (4.14)	7.73 (5.78)	7.63 (5.57)	8.92 (5.76)	10.31 (7.39)	7.07 (5.62)	6.66 (5.69)
Overeducation (1 = Yes)	0.122 (0.33)	0.107 (0.31)	0.107 (0.31)	0.118 (0.32)	0.233 (0.42)	0.202 (0.40)	0.100 (0.30)	0.065 (0.25)	0.258 (0.44)	0.273 (0.45)
Soft Skills / Work Values										
Motivation – Willingness to Change Jobs	9.36 (2.08)	8.98 (2.21)	10.09 (1.43)	9.91 (1.44)	10.27 (1.61)	10.06 (1.70)	8.10 (2.61)	7.71 (2.56)	9.47 (1.87)	9.33 (1.81)
Work Centrality	2.92 (0.50)	2.86 (0.50)	2.96 (0.50)	2.94 (0.51)	2.72 (0.544)	2.65 (0.57)	3.30 (0.48)	3.26 (0.47)	2.87 (0.56)	2.86 (0.52)
Grit	2.96 (0.43)	2.92 (0.44)	2.79 (0.39)	2.84 (0.41)	2.92 (0.446)	3.03 (0.43)	3.07 (0.48)	3.03 (0.47)	2.82 (0.39)	2.83 (0.38)
Risk-Taking	5.58 (2.46)	4.62 (2.60)	5.53 (2.44)	5.49 (2.60)	5.56 (2.44)	5.52 (2.57)	6.56 (2.42)	5.63 (2.72)	5.41 (2.18)	5.15 (2.15)
Motivation – Intrinsic and Extrinsic	3.39 (0.46)	3.41 (0.43)	3.20 (0.45)	3.31 (0.44)	3.27 (0.43)	3.39 (0.40)	3.55 (0.39)	3.54 (0.38)	3.19 (0.43)	3.22 (0.42)

Country characteristics	Hungary		Italy		Spain		Turkey		United Kingdom	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Demographics										
Age (Years)	26.51 (5.17)	27.11 (5.00)	27.36 (4.54)	27.33 (4.40)	27.39 (4.97)	27.70 (5.04)	25.57 (5.20)	25.97 (5.45)	27.01 (5.17)	26.37 (4.98)
Married (1 = Yes)	0.240 (0.43)	0.391 (0.49)	0.174 (0.38)	0.181 (0.39)	0.191 (0.35)	0.381 (0.45)	0.347 (0.48)	0.389 (0.50)	0.277 (0.48)	0.262 (0.44)
Has Children (1 = Yes)	0.196 (0.40)	0.408 (0.39)	0.119 (0.33)	0.153 (0.36)	0.133 (0.34)	0.236 (0.43)	0.80 (0.40)	0.947 (0.22)	0.234 (0.42)	0.248 (0.43)
Has Caring Responsibilities (1 = Yes)	0.206 (0.40)	0.407 (0.49)	0.202 (0.40)	0.383 (0.45)	0.288 (0.45)	0.371 (0.48)	0.363 (0.48)	0.450 (0.50)	0.237 (0.43)	0.277 (0.45)
Has Permanent Contract (1 = Yes)	0.751 (0.43)	0.727 (0.45)	0.492 (0.50)	0.396 (0.49)	0.426 (0.50)	0.475 (0.50)	0.377 (0.48)	0.396 (0.50)	0.791 (0.41)	0.760 (0.43)
Works Full-time (1 = Yes)	0.946 (0.19)	0.928 (0.26)	0.644 (0.49)	0.522 (0.50)	0.577 (0.49)	0.542 (0.509)	0.950 (0.22)	0.906 (0.29)	0.668 (0.47)	0.482 (0.49)
Religious (1 = Yes)	0.356 (0.48)	0.408 (0.49)	0.521 (0.50)	0.540 (0.50)	0.228 (0.42)	0.298 (0.45)	0.966 (0.18)	0.965 (0.19)	0.255 (0.44)	0.257 (0.44)
Immigrant (1 = Yes)	0.015 (0.12)	0.022 (0.15)	0.036 (0.19)	0.022 (0.15)	0.057 (0.23)	0.071 (0.26)	0.004 (0.06)	0.007 (0.098)	0.091 (0.299)	0.026 (0.33)

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

## Analytic Model

For each of the ten countries and separately for men and women<sup>5</sup>, we estimated log-linear wage equations of the form:

$$\text{Log}(W_i) = B'x_i + w\lambda_i + e_i. \quad (1)$$

Here,  $B'$  represents the effect of a set of explanatory variables  $x_i$ , which include education, experience, possession of a permanent work contract, works full time, possession of the soft skill of grit and the values of work centrality, and the focal independent variable, overeducation.  $x_i$  also includes controls for NUTS labor market regions. In addition, a specific independent variable can exert an indirect influence on  $\text{Log}(W_i)$  through:

$$Z_i^* = \gamma' w_i + u_i, \quad (2)$$

where  $Z_i^*$  is the likelihood a case is observed in equation (1) and  $\gamma'$  is a set of variables that influence wages through their impact on the decision to participate in the labor force.  $\gamma'$  includes education, experience, marital status, having children, having caring

<sup>5</sup> Prior to conducting gender- and country-specific analyses, we estimated two regression models using the pooled data across all ten countries. The first model included a gender dummy variable, coded as 1 = Male, interacted with overeducation to test if gender moderates the wage penalty. The second model tested whether wage penalty significantly differed across countries by including country fixed effects and their interaction with the overeducation dummy. The first model produced an interaction coefficient that was significant at the 5% level (coefficient: 0.07, standard error: 0.03, p-value 0.047). The second model produced significant coefficients at the 1% or 5% level for virtually every country x overeducation interaction term. Given these results, we proceeded to estimate models that were specific to each gender and country. The results from both regressions are available from the authors upon request.

responsibilities, possessing KSAs of risk taking, willingness to change jobs, grit, centrality of work, and intrinsic and/or extrinsic motivation, immigrant status, religiosity, and controls for NUTS regions.

If the probability of  $Z_i^*$  is positive, it is hypothesized to influence  $\text{Log}(W_i)$  through its presence in  $\lambda_i$ , i.e., the probability an individual chooses employment over the cumulative probability of the individual's decision  $[\phi(Z_i^* \gamma') / \Phi((Z_i^* \gamma'))]$ . The term  $\lambda_i$  in equation (1) controls that component of the error term wherein the decision to work influences the wage earned.

Our choice of which variables are included in equations (1) and (2) is based on whether they are hypothesized to affect wages exclusively or through the decision to seek employment (instrumental variables). Of our five soft skills and values items, three – willingness to change jobs, risk taking, and intrinsic/extrinsic motivation – met the exclusion criterion. Grit and work centrality were hypothesized to exert both direct and indirect effects on wages. Following Dolton and Makepeace (1986), we include religion, childcare, and other caring responsibilities only in the participation models, while marital and immigration statuses are included in both equations. The principal independent variable, overeducation, is excluded from the selection equation since it is considered more a labor market mismatch characteristic than a personal one.

## Results

The results from our analyses of labor force participation, controlling for both omitted variables (soft skills) and sample selection, are presented as marginal effects in Table 5a for young men and Table 5b for young women<sup>6</sup>.

Table 5a shows that formal education significantly increases employment probability by 2–3 percentage points for males in half of our sample countries; exceptions are Austria, Greece, Hungary, Italy and Turkey. Except for Hungary, Italy and Turkey, experience significantly increases the probability of labor force participation by 1–3 percentage points. Being married increases this probability by 10–17 percentage points in most countries. Caring responsibilities, however, do not appear to exert a significant influence on employment probability in any country. Among our soft skills and work values questions, only work centrality demonstrates a consistent positive effect across countries. This effect is statistically significant in Germany and the UK at the 5% level or lower, and is marginally significant in Czechia, Greece and Turkey.

For women (Table 5b), education significantly increases the probability of labor force participation by 2–4 percentage points in most countries; the exceptions are Hungary and Italy. Work experience exerts an increase of 1–4 percentage points everywhere except for Hungary, Italy, Spain, and Turkey. Young married women are about 13–15 percentage points less likely to participate in the labor market in Greece and Hungary, but 7–9 percentage points more likely to be employed in the UK and Austria. Having children significantly lowers this probability in Austria, Czechia, Hungary, and Turkey, ranging from 8.4 percentage points (Austria) to 56 percentage

<sup>6</sup> Table of coefficients and standard errors for the full selection models appear in the Appendix as Table A1 for males and Table A2 for females.

points (Hungary). Caring responsibilities lower employment probability by 9 and 18 percentage points in Germany and Italy, respectively. Work centrality generally exerts a positive effect of about 8–10 percentage points; this is statistically significant in Austria, Germany, Hungary, and the UK.

**Table 5a.** Marginal Effects from Probit Sample Selection Equations for Male Labor Force Participation in Ten Countries

Variable	Austria	Czechia	Denmark	Germany	Greece	Hungary	Italy	Spain	Turkey	UK
Education	0.003	0.028 <sup>c</sup>	0.032 <sup>c</sup>	0.019 <sup>c</sup>	0.017	–0.002	0.014	0.027 <sup>c</sup>	0.005	0.019 <sup>c</sup>
Experience	0.015 <sup>c</sup>	0.025 <sup>c</sup>	0.017 <sup>c</sup>	0.009 <sup>c</sup>	0.025 <sup>c</sup>	–0.005	0.008	0.010 <sup>a</sup>	–0.005	0.013 <sup>c</sup>
Married	0.151 <sup>c</sup>	0.100 <sup>a</sup>	0.164 <sup>b</sup>	0.093 <sup>c</sup>	0.050	0.020	0.167 <sup>b</sup>	0.031	0.092 <sup>a</sup>	0.105 <sup>c</sup>
Immigrant	–0.045	–0.088	–0.157	0.015	0.295	0.125	0.166	–0.304 <sup>c</sup>	0.941 <sup>c</sup>	0.000
Has child(ren)	0.188 <sup>b</sup>	0.049	–0.068	–0.049	0.152 <sup>a</sup>	0.080	0.046	0.199 <sup>b</sup>	–0.109 <sup>b</sup>	–0.016
Has caring responsibilities	–0.080	–0.116	0.055	–0.000	–0.068	–0.048	–0.107	0.033	0.001	0.042
Work Centrality	0.065	0.070 <sup>a</sup>	0.066	0.071 <sup>c</sup>	0.077 <sup>a</sup>	0.030	0.012	0.052	0.075 <sup>a</sup>	0.086 <sup>c</sup>
Grit	0.140 <sup>c</sup>	–0.021	0.086	–0.024	0.061	–0.068	0.011	–0.005	–0.026	0.004
Risk-Taking	–0.017	–0.001	0.001	–0.003	–0.002	–0.003	–0.014	0.006	0.004	0.005
Willingness to change jobs	–0.014	0.008	–0.000	0.000	–0.000	–0.025 <sup>b</sup>	0.045 <sup>b</sup>	0.015	–0.006	0.012 <sup>a</sup>
Job Importance	–0.064	0.017	0.178 <sup>b</sup>	0.018	0.001	–0.069	0.072	0.029	0.059	0.022
Religious	–0.041	–0.049	0.104 <sup>b</sup>	0.001	0.060	–0.085 <sup>a</sup>	–0.045	0.013	0.120 <sup>a</sup>	–0.059 <sup>b</sup>
NUTS regions	Not Sig	Sig	Not Sig	Sig	Not sig	Not Sig	Sig	Not Sig	Sig	Not Sig

<sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

**Table 5b.** Marginal Effects from Probit Sample Selection Equations for Female Labor Force Participation in Ten Countries

Variable	Austria	Czechia	Denmark	Germany	Greece	Hungary	Italy	Spain	Turkey	UK
Education	0.028 <sup>c</sup>	0.025 <sup>c</sup>	0.043 <sup>c</sup>	0.016 <sup>c</sup>	0.038 <sup>c</sup>	–0.012	0.016	0.027 <sup>c</sup>	0.019 <sup>a</sup>	0.032 <sup>c</sup>
Experience	0.018 <sup>c</sup>	0.037 <sup>c</sup>	0.017 <sup>b</sup>	0.013 <sup>c</sup>	0.011 <sup>a</sup>	0.004	0.008	–0.002	0.011	0.019 <sup>c</sup>
Married	0.091 <sup>b</sup>	–0.047	–0.010	0.010	–0.149 <sup>b</sup>	–0.132 <sup>c</sup>	–0.023	–0.009	–0.093	0.071 <sup>b</sup>
Immigrant	–0.091	0.070	–0.198	0.108 <sup>b</sup>	–0.108	0.014	–0.050	0.074	–0.173	0.010
Has child(ren)	–0.084 <sup>b</sup>	–0.492 <sup>c</sup>	–0.126	–0.025	–0.047	–0.557 <sup>c</sup>	0.061	–0.065	–0.327 <sup>b</sup>	–0.085
Has caring responsibilities	–0.013	–0.030	0.034	–0.087 <sup>b</sup>	–0.105	0.231 <sup>a</sup>	–0.183 <sup>b</sup>	–0.065	0.001	0.031
Work Centrality	0.081 <sup>c</sup>	0.047	0.063	0.094 <sup>c</sup>	0.007	0.094 <sup>a</sup>	0.064	0.052	–0.010	0.105 <sup>c</sup>
Grit	0.109 <sup>b</sup>	0.007	0.180 <sup>a</sup>	0.010	0.088	0.021	0.105	–0.008	0.072	–0.038
Risk-Taking	0.007	0.007	0.002	–0.001	–0.007	–0.018 <sup>b</sup>	0.007	0.004	0.001	–0.002

Variable	Austria	Czechia	Denmark	Germany	Greece	Hungary	Italy	Spain	Turkey	UK
Will- ingness to change jobs	0.007	0.009	-0.024	0.002	-0.000	-0.014	-0.029	-0.001	0.008	0.012 <sup>a</sup>
Job Impor- tance	0.010	-0.058	0.009	0.033	-0.142 <sup>b</sup>	-0.261 <sup>c</sup>	0.160 <sup>b</sup>	0.083	0.077	-0.029
Religious	-0.016	0.011	0.001	-0.023	0.008	0.036	0.020	0.026	-0.097	-0.021
NUTS regions	Not Sig	Not Sig	Not Sig	Not Sig	Not sig	Not Sig	Not Sig	Not Sig	Not Sig	Not Sig

<sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

Tables 6a (males) and 6b (females) present abbreviated estimation results that show only the key variables returns to education and experience, and wage penalty in the earning equations from both the OLS and selection-corrected estimations. Full estimation results are provided in Appendix Tables A3 for males and A4 for females. There is also a graphical description of the selection-corrected wage distribution of those who are over- and not overeducated by gender for each country in Appendix Figure A1.

Table 6a shows that for males, returns to education and experience are positive in both the OLS and selection-corrected models for all countries, but these effects are typically smaller in the latter. Overeducation is found to reduce earnings consistently across sample countries, and the effect is statistically significant everywhere except Austria and Italy. These wage penalties range from 6% in Hungary to 56% in Spain. While the general pattern of negative lambdas ( $\lambda$ -) signals that our OLS models overstate the wage magnitude (i.e., observed wage < offered wage), consistent with crowding theory, the prediction that wage penalties from overeducation should be higher in the selection models does not hold. In fact, the wage penalties in these models are lower in all country samples except Greece, where OLS and selection-adjusted wage penalties are equal, and Turkey, where the selection-adjusted penalties are about four percentage points higher. Finally, we highlight the magnitude of explained variance ( $R^2$ ) in our country-specific models. Adjusted  $R^2$ s are quite large for employment studies with self-reported data, especially those lacking occupational data<sup>7</sup>.

The more complete Table A3 shows that possessing a permanent work contract and/or a full-time job increases earnings in most countries. Notably, the “soft skill” grit positively impacts earnings in all country samples except Denmark, Hungary, Turkey and the UK. In the selection-adjusted regressions, the impact ranges from approximately 13% in Austria, Germany, and Spain to 27% in Greece. Work centrality, however, a factor of some consequence in our participation models, proves to be significant only in Denmark, Germany, and the UK.

<sup>7</sup> Data on occupations were missing in 54% of the cases in our overall sample, preventing the use of this important variable in the analyses. In addition, where available, these data were so inconsistently coded as to render them unusable for analyses. The available data also show that of those responses that were coded correctly, only about 6% were classified as professionals and/or managers, preventing the possibility of employing the professional/managerial–non-professional/non-managerial contrast often used with sparse occupation data (Borjas 2008; Blau and Kahn 2017).



Table 6b presents abbreviated results from our OLS and selection-adjusted earnings regressions for women. As in the case of men, returns to education and experience are positive and significant in most countries, except for Italy and Greece, where returns to education are not significant. As hypothesized, overeducation among women negatively affects earnings, with wage penalties generally smaller in the selection-adjusted models in all the countries where this effect was significant, the one exception being Italy, where the effect is only significant in the selection-adjusted model. The wage penalties range from 7% in Hungary to 44% in Denmark.

For women, we find a pattern of positive lambdas ( $\lambda_+$ ), which indicates that our OLS tends to understate the wage magnitudes in nine of the ten countries; in Austria, Germany, Spain, and the UK, those effects are statistically significant. This suggests that observed wages > offered wages, a symptom of markets where job search is predominant. The expectation that wage penalties should be lower in selection-adjusted models is also consistent with job search theory.

Finally, the adjusted R<sup>2</sup>s for the country-specific wage regressions in Table 6b are smaller, except in Hungary and Italy. This indicates that additional, omitted variables that distinguish the job experiences of men and women are at play.

The more complete Table A4 shows that, as with men, having a full-time job exerts a large, significant impact on wages. However, unlike our regression models for men, we find a reverse pattern of “soft skill” impact on wages for women. Grit is significant only in Austria and Hungary, and only marginally so in Germany. The value of work centrality has a stronger impact, however, achieving statistical significance in Austria, Germany, Greece, Hungary, Italy (marginally), and the UK.

**Table 6a.** Returns to Education, Experience and Wage Penalty from OLS and Selection-Corrected Regressions – Males Coefficients and (Std. Errors)

Country	Education		Experience		Overeducation		Lambda (Selection)	Adj. R <sup>2</sup> (OLS)
	OLS	Selection- Corrected	OLS	Selection- Corrected	OLS	Selection- Corrected		
Austria	0.042 <sup>b</sup> (0.192)	0.013 (0.009)	0.024 (0.025)	0.021 <sup>a</sup> (0.012)	-0.293 <sup>b</sup> (0.019)	-0.040 (0.060)	-0.011 (0.112)	0.42
Czechia	0.059 <sup>c</sup> (0.010)	0.036 <sup>c</sup> (0.011)	0.101 <sup>c</sup> (0.023)	0.021 (0.019)	-0.154 <sup>c</sup> (0.055)	-0.136 <sup>c</sup> (0.039)	-0.164 (0.171)	0.43
Denmark	0.107 <sup>c</sup> (0.023)	0.088 <sup>c</sup> (0.016)	0.115 <sup>b</sup> (0.052)	0.048 <sup>a</sup> (0.025)	-0.507 <sup>b</sup> (0.133)	-0.269 <sup>c</sup> (0.066)	-0.269 (0.217)	0.46
Germany	0.046 <sup>c</sup> (0.008)	0.048 <sup>c</sup> (0.007)	0.017 (0.011)	0.014 <sup>a</sup> (0.007)	-0.159 <sup>c</sup> (0.048)	-0.102 <sup>c</sup> (0.031)	-0.468 <sup>c</sup> (0.017)	0.19
Greece	0.086 <sup>c</sup> (0.031)	0.079 <sup>c</sup> (0.031)	-0.000 (0.041)	-0.068 (0.053)	-0.267 <sup>b</sup> (0.117)	-0.267 <sup>b</sup> (0.110)	0.063 (0.543)	0.18
Hungary	0.005 (0.006)	0.011 <sup>b</sup> (0.005)	0.028 <sup>c</sup> (0.009)	0.006 (0.008)	-0.072 <sup>a</sup> (0.039)	-0.055 <sup>b</sup> (0.032)	-0.129 <sup>c</sup> (0.028)	0.16
Italy	0.018 (0.020)	0.028 <sup>a</sup> (0.015)	0.036 (0.036)	-0.002 (0.025)	-0.007 (0.103)	-0.023 (0.069)	-0.226 (0.213)	0.04
Spain	0.075 <sup>c</sup> (0.016)	0.025 (0.019)	0.092 <sup>c</sup> (0.023)	-0.001 (0.021)	-0.564 <sup>c</sup> (0.090)	-0.262 <sup>c</sup> (0.072)	-0.442 <sup>b</sup> (0.194)	0.43

	Education		Experience		Overeducation		Lambda (Selection)	Adj. R2 (OLS)
Country	OLS	Selection- Corrected	OLS	Selection- Corrected	OLS	Selection- Corrected		
Turkey	0.044 <sup>c</sup> (0.009)	0.055 <sup>c</sup> (0.013)	0.014 (0.013)	0.015 (0.022)	-0.255 <sup>c</sup> (0.065)	-0.304 <sup>c</sup> (0.094)	-0.223 (0.337)	0.24
UK	0.050 <sup>c</sup> (0.009)	0.039 <sup>c</sup> (0.006)	0.073 <sup>c</sup> (0.011)	0.012 (0.008)	-0.311 <sup>c</sup> (0.048)	-0.236 <sup>c</sup> (0.032)	-0.073 <sup>a</sup> (0.039)	0.31

Standard errors in parentheses.

<sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

**Table 6b.** Returns to Education, Experience and Wage Penalty from OLS and Selection-Corrected Regressions – Females Coefficients and (Std. Errors)

	Education		Experience		Overeducation		Lambda (Selection)	Adj. R2 (OLS)
Country	OLS	Selection- Corrected	OLS	Selection- Corrected	OLS	Selection- Corrected		
Austria	0.098 <sup>c</sup> (0.023)	0.055 <sup>c</sup> (0.012)	0.085 <sup>c</sup> (0.025)	0.021 <sup>b</sup> (0.010)	-0.0148 (0.113)	-0.120 <sup>c</sup> (0.038)	0.543 <sup>c</sup> (0.037)	0.34
Czechia	0.053 <sup>c</sup> (0.012)	0.022 <sup>c</sup> (0.006)	0.062 <sup>b</sup> (0.028)	0.015 (0.013)	-0.313 <sup>c</sup> (0.065)	-0.112 <sup>c</sup> (0.032)	-0.032 (0.039)	0.29
Denmark	0.105 <sup>c</sup> (0.034)	0.088 <sup>c</sup> (0.031)	0.102 (0.074)	0.031 (0.030)	-0.540 <sup>c</sup> (0.194)	-0.435 <sup>c</sup> (0.082)	0.333 (0.427)	0.34
Germany	0.063 <sup>c</sup> (0.012)	0.058 <sup>c</sup> (0.008)	0.003 (0.016)	0.021 <sup>b</sup> (0.008)	-0.264 <sup>c</sup> (0.065)	-0.097 <sup>c</sup> (0.032)	0.578 <sup>c</sup> (0.021)	0.17
Greece	0.050 (0.035)	0.059 (0.040)	0.103 <sup>b</sup> (0.041)	0.048 (0.044)	-0.165 (0.111)	-0.150 (0.106)	0.256 (0.350)	0.09
Hungary	0.012 <sup>c</sup> (0.004)	0.011 <sup>c</sup> (0.003)	0.024 <sup>c</sup> (0.005)	0.013 <sup>c</sup> (0.004)	-0.068 <sup>c</sup> (0.027)	-0.072 <sup>b</sup> (0.020)	0.018 (0.019)	0.29
Italy	0.002 (0.033)	0.021 (0.020)	0.092 <sup>a</sup> (0.051)	0.038 (0.027)	-0.028 (0.142)	-0.127 <sup>a</sup> (0.074)	0.354 (0.202)	0.07
Spain	0.060 <sup>c</sup> (0.019)	0.054 <sup>c</sup> (0.018)	0.066 <sup>c</sup> (0.025)	0.037 <sup>b</sup> (0.017)	-0.427 <sup>c</sup> (0.095)	-0.331 <sup>c</sup> (0.063)	0.326 <sup>a</sup> (0.181)	0.27
Turkey	0.041 <sup>c</sup> (0.015)	0.069 <sup>b</sup> (0.027)	0.050 <sup>c</sup> (0.017)	0.029 (0.046)	-0.135 (0.091)	-0.119 (0.184)	0.494 (0.356)	0.20
UK	0.037 <sup>c</sup> (0.011)	0.043 <sup>c</sup> (0.005)	0.103 <sup>c</sup> (0.011)	0.030 <sup>c</sup> (0.005)	-0.187 <sup>c</sup> (0.053)	-0.146 <sup>c</sup> (0.024)	0.294 <sup>c</sup> (0.014)	0.32

Standard errors in parentheses.

<sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

To guard against the possibility that our OLS results might mask any differential effects of overeducation among low- versus high-wage earners, we also estimated quantile regressions, assessing overeducation effects at the first, second, and third quartiles of the wage distribution for each gender and country. These results, along with the OLS and selection-adjusted results, are presented in Appendix Table A5 for men and Table A6 for women. Table A5 shows that the coefficients across the quartiles are not significantly different according to the Wald test in eight out of the ten countries, the exceptions being Czechia (significant at 1%) and Denmark (significant

at 10%). For females, Table A6 shows that nine out of the ten countries do not show that the effect of overeducation varies significantly across quartiles, except for Turkey.

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## Discussion and Conclusions

The results of this study, based on data from 19,000 young adults across ten European countries, underscore the importance of understanding overeducation and its wage penalties not only as individual outcomes but as phenomena embedded in distinct institutional and welfare contexts. By examining countries that span Coordinated Market Economies (Austria, Germany), a Liberal Market Economy (United Kingdom), Mediterranean regimes (Italy, Spain, Greece), post-socialist economies (Czechia, Hungary), and Denmark as a Nordic comparator, we ground our analysis in the institutional diversity emphasized by Esping-Andersen (1990) and subsequent comparative labor market research. These regimes differ systematically in their education–employment linkages, labor market segmentation, and gender role norms, all factors that our theoretical framework – spanning human capital theory, job search theory, job competition theory, assignment theory, and search and matching models – predict will shape both the incidence and magnitude of overeducation penalties. Our findings should thus be read through this dual lens of theoretical mechanisms and institutional variation.

We can draw seven key conclusions from our cross-national examination of wage penalties due to overeducation:

1. **Observed wages for women often exceed offered wages.** This pattern aligns with job search theory, especially in liberal and Nordic regimes like the UK and Denmark, where flexible labor markets and strong family policy infrastructures allow women to reject below-average wage offers and accept only those above their reservation wage.
2. **Selection-adjusted models reduce wage penalties for women.** This reflects job search dynamics where women who participate in employment likely possess unobserved traits (e.g., motivation or family support) associated with higher wages. Once selection is accounted for, penalties decline, although they remain higher than men's, suggesting persistent structural or discriminatory barriers.
3. **Observed wages for men fall below offered wages.** Consistent with job competition theory, especially in Mediterranean and post-socialist countries (e.g., Italy, Spain, Hungary, Turkey), many men accept below-average wage offers, with labor market rigidities and seniority-based systems limiting reward for higher qualifications.
4. **Selection-adjusted models reduce penalties for men as well.** Contrary to job competition theory's prediction of increasing penalties when higher-ability individuals are included, selection corrections yield smaller penalties, pointing to the moderating role of perseverance or work values in actual wage outcomes.

5. **Work centrality among women correlates with higher wages.** In half of the countries analyzed, women who assign greater importance to work earn significantly more, aligning with assignment theory and search and matching dynamics, which posit that valuing work influences the quality of job matches and wage outcomes.
6. **Grit reduces wage penalties, especially for men.** In nearly all selection-adjusted models, the soft skill of grit (perseverance) emerges as a significant wage enhancer. This is consistent with growing empirical evidence on the value of non-cognitive traits in labor market outcomes (Heckman, Stixrud, and Urzua 2006; Gutman and Schoon 2013; Duckworth and Yeager 2015; Bryan, Choi, and Karlan 2021).
7. **Wage penalties are typically higher for women than for men, with notable country variation.** Despite lower baseline wages, women face larger penalties for overeducation in most contexts. This gender gap is especially wide in countries like Denmark (Nordic, coordinated market economy: 44% for women vs. 27% for men), Spain (Mediterranean: 33% vs. 26%), and Italy (13% vs. 2%, not significant). These disparities are shaped by differences in institutional context, gender norms, and labor market segmentation. For example, Denmark's surprising results suggest that egalitarian systems may still harbor occupational sorting or undervaluation of female qualifications, while Spain and Italy reflect more traditional barriers associated with rigid labor markets and care burdens. Austria, another coordinated economy with a conservative welfare regime, shows a significant gap (12% for women vs. 4% for men), likely due to traditional family models. Hungary, a post-socialist coordinated economy, has smaller but still gendered penalties (7.2% vs. 6%), suggesting the persistence of inequality despite wage compression legacies.

The consistent pattern described in (7) begs the question: Why are women more heavily penalized for overeducation? One potential explanation lies in occupational sorting. As Blau and Kahn (2017), McGuinness, Bergin, and Whelan (2018), and Barroso and Brown (2021) note, women may be overrepresented in lower-paying sectors or roles where overeducation is more common or less rewarded. Unfortunately, the lack of harmonized and consistently coded occupational data across the full sample precludes a direct test of this hypothesis. Moreover, occupational data where available are often incomplete or non-random, risking selection bias. For these reasons, we chose not to include occupational codes, though future work using rich task- or skill-based data could yield more refined insights.

Another explanation invokes the argument that women are less productive than men due to shorter or more discontinuous work histories, often linked to caregiving responsibilities. If this were true, one might expect smaller wage penalties for women, given expectations of weaker labor force attachment and concentration in lower-risk jobs. However, our findings suggest the opposite.

A third explanation, and one supported by accumulating evidence, is that women face prejudice-based discrimination. Numerous studies (Blau and Kahn 2017; Barroso and Brown 2021; European Commission 2021; Jagannathan, Camasso, and LeFleur 2024) have found that employers may undervalue women's qualifications or avoid hiring women unless a wage discount compensates for perceived costs. Our findings suggest that overeducation penalties may

represent a second layer of gender discrimination beyond baseline wage gaps what might be considered a “piling on” effect.

From a policy perspective, addressing overeducation penalties requires a dual strategy tailored to different institutional contexts. For employers, greater recognition of non-cognitive skills – particularly persistence and centrality of work can help ensure that overeducated workers are not systematically undervalued. For governments, policies that strengthen anti-discrimination frameworks, expand affordable childcare, and support active labor market programs are especially crucial in regimes where structural barriers weigh most heavily on women (OECD 2020; European Commission 2021). Addressing overeducation penalties is not solely a matter of improving individual attributes or aligning education with jobs; it requires interventions that confront the institutional and cultural conditions shaping how education is rewarded.

Another implication is the value of publishing overeducation penalties by occupation and sector, much like pay scales. Providing workers with data on potential earnings gains alongside expected losses would give job seekers a “balance sheet” framework for shaping job search, on-the-job training, and mobility strategies. Publicizing such information could also prompt wage-setting institutions to act when gender disparities emerge, leading to reforms in professional licensure, apprenticeship programs, collective bargaining, and minimum wage policies.

This study faces several limitations beyond the lack of occupational data. Its cross-sectional design precludes testing hypotheses about job mobility or the long-term effects of overeducation. Self-reported data bring risks of recall error, survey fatigue, dissembling, and comprehension issues. Moreover, perceptions of overeducation may be distorted or amplified by volatile labor markets and rapidly changing technological conditions, which shape young workers’ expectations and experiences. Finally, we recognize that we have not eliminated all sources of endogeneity through our modeling and that a good deal that emanates from omitted ability and skills could remain. This may bias estimated penalties; future research employing longitudinal or instrumental variable approaches could address this limitation more robustly.

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## References

- Alba-Ramirez, A. (1993), *Mismatch in the Spanish Labor Market: Overeducation?*, “Journal of Human Resources”, 28 (2), pp. 259–278, <https://doi.org/10.2307/146203>
- Baert, S., Cockx, B., Verhaest, D. (2013), *Overeducation at the start of the career: Stepping stone or trap?*, “Labour Economics”, 25, pp. 123–140, <https://doi.org/10.1016/j.labeco.2013.04.013>
- Baldwin, M., Johnson, W.G. (1992), *Estimating the Employment Effects of Wage Discrimination*, “The Review of Economics and Statistics”, 74 (3), pp. 446–455, <https://doi.org/10.2307/2109489>
- Barbieri, P., Scherer, S. (2009), *Labour Market Flexibilization and its Consequences in Italy*, “European Sociological Review”, 25 (6), pp. 677–692, <https://doi.org/10.1093/esr/jcp009>
- Barone, C., Ortiz, L. (2011), *Overeducation among European University Graduates: a comparative analysis of its incidence and the importance of higher education differentiation*, “Higher Education”, 61, pp. 325–337, <https://doi.org/10.1007/s10734-010-9380-0>



- Barroso, A., Brown, A. (2021), *Gender pay gap in US held steady in 2020*, Pew Research Center, Washington.
- Becker, G.S. (1964), *Human capital: A theoretical and empirical analysis, with special reference to education*, University of Chicago Press, Chicago.
- Becker, G.S. (1993), *Human Capital: A Theoretical and Empirical Analysis, with Special Reference To Education*, University of Chicago Press, Chicago, <https://doi.org/10.7208/chicago/9780226041223.001.0001>
- Bender, K.A., Heywood, J.S. (2011), *Educational mismatch and the careers of scientists*, “Education Economics”, 19 (3), pp. 253–274, <https://doi.org/10.1080/09645292.2011.577555>
- Blau, F.D., Kahn, L.M. (2003), *Understanding International Differences in the Gender Pay Gap*, “Journal of Labor Economics”, 21 (1), <https://doi.org/10.1086/344125>
- Blau, F.D., Kahn, L.M. (2017), *The Gender Wage Gap: Extent, Trends, and Explanations*, “Journal of Economic Literature”, 55 (3), pp. 789–865, <https://doi.org/10.1257/jel.20160995>
- Boll, C., Leppin, J., Rossen, A., Wolf, A. (2016), *Magnitude and impact factors of the gender pay gap in EU countries*, “European Commission Discussion Paper”.
- Borjas, G.J. (2008), *Labor Economics*, McGraw-Hill Education, New York.
- Boto-García, D., Escalonilla, M. (2022), *University education, mismatched jobs: are there gender differences in the drivers of overeducation?*, “Economia Politica: Journal of Analytical and Institutional Economics”, 39 (3), pp. 861–902, <https://doi.org/10.1007/s40888-022-00270-y>
- Bryan, G., Choi, J.J., Karlan, D. (2021), *Randomizing Religion: the Impact of Protestant Evangelism on Economic Outcomes*, “The Quarterly Journal of Economics”, 136 (1), pp. 293–380, <https://doi.org/10.1093/qje/qjaa023>
- Budig, M.J., England, P. (2001), *The Wage Penalty for Motherhood*, “American Sociological Review”, 66 (2), <https://doi.org/10.1177/000312240106600203>
- Büchel, F. (2002), *The effects of overeducation on productivity in Germany – the firms’ viewpoint*, “Economics of Education Review”, 21 (3), pp. 263–275, [https://doi.org/10.1016/S0272-7757\(01\)00020-6](https://doi.org/10.1016/S0272-7757(01)00020-6)
- Camasso, M.J., Jagannathan, R. (2021), *Caught in the Cultural Preference Net: Three Generations of Employment Choices in Six Capitalist Democracies*, Oxford University Press, Oxford, <https://doi.org/10.1093/oso/9780190672782.001.0001>
- Card, D. (1999), *The causal effect of education on earnings*, [in:] O.C. Ashenfelter, D. Card (eds.), *Handbook of Labor Economics*, Vol. 3, Elsevier, Amsterdam, pp. 1801–1863.
- Carneiro, P.M., Heckman, J.J. (2003), *Human Capital Policy*, “IZA Discussion Paper”, 821, <https://doi.org/10.2139/ssrn.434544>
- Caroleo, F.E., Pastore, F. (2016), *Overeducation: A Disease of the School-to-Work Transition System*, “IZA Discussion Paper”, 9049, <https://doi.org/10.2139/ssrn.2606902>
- Caroleo, F.E., Pastore, F. (2018), *Overeducation at a Glance. Determinants and Wage Effects of the Educational Mismatch Based on AlmaLaurea Data*, “Social Indicators Research”, 137, pp. 999–1032, <https://doi.org/10.1007/s11205-017-1641-1>
- Cha, Y., Weeden, K.A. (2014), *Overwork and the Slow Convergence in the Gender Gap in Wages*, “American Sociological Review”, 79 (3), <https://doi.org/10.1177/0003122414528936>
- Chevalier, A. (2003), *Measuring Over-education*, “Economica”, 70 (279), pp. 509–531, <https://doi.org/10.1111/1468-0335.t01-1-00296>

- Chevalier, A., Lindley, J. (2009), *Overeducation and the Skills of UK Graduates*, "Journal of the Royal Statistical Society Series A: Statistics in Society", 172 (2), pp. 307–337, <https://doi.org/10.1111/j.1467-985X.2008.00578.x>
- Cohn, E., Khan, S.P. (1995), *The wage effects of overschooling revisited*, "Labour Economics", 2 (1), pp. 67–76, [https://doi.org/10.1016/0927-5371\(95\)80008-L](https://doi.org/10.1016/0927-5371(95)80008-L)
- Cultrera, L., Mahy, B., Rycx, F., Vermeylen, G. (2022), *Educational and Skills Mismatches: Unravelling Their Effects on Wages across Europe*, "IZA Discussion Papers", 15108.
- Dolton, P.J., Makepeace, G.H. (1986), *Sample selection and male-female earnings differentials in the graduate labour market*, "Oxford Economic Papers", 38 (2), pp. 317–341, <https://doi.org/10.1093/oxford-journals.oep.a041743>
- Duckworth, A.L., Yeager, D.S. (2015), *Measurement Matters: Assessing Personal Qualities Other Than Cognitive Ability for Educational Purposes*, "Educational Researcher", 44 (4), <https://doi.org/10.3102/0013189X15584327>
- Duncan, G.J., Hoffman, S.D. (1981), *The incidence and wage effects of overeducation*, "Economics of Education Review", 1 (1), pp. 75–86, [https://doi.org/10.1016/0272-7757\(81\)90028-5](https://doi.org/10.1016/0272-7757(81)90028-5)
- Emmenegger, P., Häusermann, S., Palier, B., Seeleib-Kaiser, M. (eds.) (2012), *The Age of Dualization: The Changing Face of Inequality in Deindustrializing Societies*, Oxford University Press, Oxford–New York, <https://doi.org/10.1093/acprof:oso/9780199797899.001.0001>
- Ermisch, J.F., Wright, R.E. (1994), *Interpretation of negative sample selection effects in wage offer equations*, "Applied Economics Letters", 1 (11), pp. 187–189, <https://doi.org/10.1080/135048594357844>
- Esping-Andersen, G. (1990), *The three worlds of welfare capitalism*, Princeton University Press, Princeton.
- Esping-Andersen, G. (2002), *Why we need a new welfare state*, Oxford University Press, Oxford.
- Estevez-Abe, M., Iversen, T., Soskice, D. (2001), *Social Protection and the Formation of Skills: A Reinterpretation of the Welfare State*, [in:] P.A. Hall, D. Soskice (eds.), *Varieties of Capitalism: The Institutional Foundations of Comparative Advantage*, Oxford University Press, Oxford, pp. 145–183, <https://doi.org/10.1093/0199247757.003.0004>
- European Commission (2021), *The gender pay gap situation in the EU*, Brussels, [https://commission.europa.eu/strategy-and-policy/policies/justice-and-fundamental-rights/gender-equality/equal-pay/gender-pay-gap-situation-eu\\_en](https://commission.europa.eu/strategy-and-policy/policies/justice-and-fundamental-rights/gender-equality/equal-pay/gender-pay-gap-situation-eu_en) (accessed:12.02.2024).
- Fernandez-Macias, E., Hurley, J. (2017), *Routine-biased technical change and job polarization in Europe*, "Socio-Economic Review", 15 (3), pp. 563–585, <https://doi.org/10.1093/ser/mww016>
- Gallie, D. (eds.) (2007), *Employment Regimes and the Quality of Work*, Oxford University Press, Oxford, <https://doi.org/10.1093/acprof:oso/9780199230105.001.0001>
- Galloway, T., Lippman, L., Burke, H., Diener, O., Gates, S. (2017), *Measuring soft skills and life skills in international youth development programs: A review and inventory of tools*, USAID Youth Power Implementation IDIQ, Washington.
- Gesthuizen, M., Kovarek, D., Rapp, C. (2019), *Extrinsic and Intrinsic Work Values: Findings on Equivalence in Different Cultural Contexts*, "The ANNALS of the American Academy of Political and Social Science", 682 (1), <https://doi.org/10.1177/0002716219829016>
- Green, F., Zhu, Y. (2010), *Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education*, "Oxford Economic Papers", 62 (4), pp. 740–763, <https://doi.org/10.1093/oep/gpq002>

- Gutman, L.M., Schoon, I. (2013), *The impact of non-cognitive skills on outcomes for young people: A literature review*, Institute of Education, University of London, London.
- Hall, P.A., Soskice, D. (eds.) (2001), *Varieties of Capitalism. The Institutional Foundations of Comparative Advantage*, Oxford University Press, Oxford, <https://doi.org/10.1093/0199247757.001.0001>
- Hartog, J. (2000), *Over-education and earnings: where are we, where should we go?*, “Economics of Education Review”, 19 (2), pp. 131–147, [https://doi.org/10.1016/S0272-7757\(99\)00050-3](https://doi.org/10.1016/S0272-7757(99)00050-3)
- Hartog, J., Oosterbeek, H. (1988), *Education, allocation and earnings in the Netherlands: Overschooling?*, “Economics of Education Review”, 7 (2), pp. 185–194, [https://doi.org/10.1016/0272-7757\(88\)90043-X](https://doi.org/10.1016/0272-7757(88)90043-X)
- Hauff, S., Kirchner, S. (2015), *Identifying work value patterns: cross-national comparison and historical dynamics*, “International Journal of Manpower”, 36 (2), pp. 151–168, <https://doi.org/10.1108/IJM-05-2013-0101>
- Heckman, J.J. (1979), *Sample Selection Bias as a Specification Error*, “Econometrica: Journal of the Econometric Society”, 47 (1), pp. 153–161, <https://doi.org/10.2307/1912352>
- Heckman, J.J. (2000), *Policies to foster human capital*, “Research in Economics”, 54 (1), pp. 3–56, <https://doi.org/10.1006/reec.1999.0225>
- Heckman, J.J., Masterov, D.V. (2007), *The Productivity Argument for Investing in Young Children*, “NBER Working Papers”, 13016, National Bureau of Economic Research, Cambridge, <https://www.nber.org/papers/w13016> (accessed: 24.11.2024).
- Heckman, J.J., Stixrud, J., Urzua, S. (2006), *The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior*, “Journal of Labor Economics”, 24 (3), <https://doi.org/10.1086/504455>
- Iversen, T., Stephens, J. (2008), *Partisan Politics, the Welfare State, and the Three Worlds of Human Capital Formation*, “Comparative Political Studies”, 41 (4–5), <https://doi.org/10.1177/0010414007313117>
- Jagannathan, R., Camasso, M.J., LeFleur, J. (2024), *Gender pay gaps in the young adult labor force: prejudice-based discrimination or misreading of the observed-to-offered wage relationship?*, “Oxford Economic Papers”, 76 (4), pp. 1168–1188, <https://doi.org/10.1093/oep/gpae009>
- Kampelmann, S., Rycx, F. (2012), *The impact of educational mismatch on firm productivity: Evidence from linked panel data*, “Economics of Education Review”, 31 (6), pp. 918–931, <https://doi.org/10.1016/j.econedurev.2012.07.003>
- Kankaraš, M., Montt, G., Paccagnella, M., Quintini, G., Thorn, W. (2016), *Skills Matter: Further Results from the Survey of Adult Skills*, OECD Skills Studies, OECD Publishing, Paris.
- Killingsworth, M.R. (1984), *Labor supply*, Cambridge University Press, New York, <https://doi.org/10.1017/CBO9780511572104>
- Kleibrink, J. (2016), *Inept or Badly Matched? – Effects of Educational Mismatch in the Labor Market*, “Labour”, 30 (1), pp. 88–108, <https://doi.org/10.1111/labr.12065>
- Korpi, T., Tählin, M. (2009), *Educational mismatch, wages, and wage growth: Overeducation in Sweden, 1974–2000*, “Labour Economics”, 16 (2), pp. 183–193, <https://doi.org/10.1016/j.labeco.2008.08.004>
- Kraaykamp, G., Cemalcilar, Z., Tosun, J. (2019), *Transmission of Work Attitudes and Values: Comparisons, Consequences, and Implications*, “The ANNALS of the American Academy of Political and Social Science”, 682 (1), <https://doi.org/10.1177/0002716219831947>
- Leuven, E., Oosterbeek, H. (2011), *Overeducation and Mismatch in the Labor Market*, [in:] E.A. Hanushek, S. Machin, L. Woessmann (eds.), *Handbook of the Economics of Education*, Vol. 4, Elsevier, Amsterdam, pp. 283–326, <https://doi.org/10.1016/B978-0-444-53444-6.00003-1>

- Levels, M., Velden, R. van der, Allen, J. (2014), *Educational mismatches and skills: new empirical tests of old hypotheses*, "Oxford Economic Papers", 66 (4), pp. 959–982, <https://doi.org/10.1093/oep/gpu024>
- López Fogués, A. (2017), *Addressing Mismatch in Spain: A Concern and Proposal Beyond the Economic Sphere*, [in:] M. Pilz (ed.), *Vocational Education and Training in Times of Economic Crisis*, Springer, Cham, pp. 355–368, [https://doi.org/10.1007/978-3-319-47856-2\\_19](https://doi.org/10.1007/978-3-319-47856-2_19)
- Mandel, H., Semyonov, M. (2005), *Family Policies, Wage Structures, and Gender Gaps: Sources of Earnings Inequality in 20 Countries*, "American Sociological Review", 70 (6), <https://doi.org/10.1177/000312240507000604>
- Marques, P., Suleman, F., Costa, J.M. (2022), *Moving beyond supply-side arguments to explain over-qualification: The ability to absorb graduates in different models of capitalism*, "European Journal of Education", 57 (2), pp. 342–360, <https://doi.org/10.1111/ejed.12500>
- Mavromaras, K., McGuinness, S., O’Leary, N., Sloane, P., Wei, Z. (2013), *Job Mismatches and Labour Market Outcomes: Panel Evidence on University Graduates*, "Economic Record", 89 (286), pp. 382–395, <https://doi.org/10.1111/1475-4932.12054>
- McGoldrick, K., Robst, J. (1996), *Gender Differences in Overeducation: A Test of the Theory of Differential Overqualification*, "The American Economic Review", 86 (2), pp. 280–284, <https://www.jstor.org/stable/2118137>
- McGuinness, S. (2003), *Graduate overeducation as a sheepskin effect: evidence from Northern Ireland*, "Applied Economics", 35 (5), pp. 597–608, <https://doi.org/10.1080/0003684022000029284>
- McGuinness, S. (2006), *Overeducation in the Labour Market*, "Journal of Economic Surveys", 20 (3), pp. 387–418, <https://doi.org/10.1111/j.0950-0804.2006.00284.x>
- McGuinness, S., Pouliakas, K. (2016), *Deconstructing Theories of Overeducation in Europe: A Wage Decomposition Approach*, "IZA Discussion Papers", 9698, <https://doi.org/10.2139/ssrn.2731961>
- McGuinness, S., Bergin, A., Whelan, A. (2018), *Overeducation in Europe: trends, convergence, and drivers*, "Oxford Economic Papers", 70 (4), pp. 994–1015, <https://doi.org/10.1093/oep/gpy022>
- McGuinness, S., Pouliakas, K., Redmond, P. (2017), *How Useful is the Concept of Skills Mismatch?*, "IZA Discussion Paper", 10786, <https://doi.org/10.2139/ssrn.2979934>
- Mincer, J. (1974), *Schooling, Experience, and Earnings*, National Bureau of Economic Research, New York.
- Mortensen, D.T., Pissarides, C.A. (1994), *Job Creation and Job Destruction in the Theory of Unemployment*, "The Review of Economic Studies", 61 (3), pp. 397–415, <https://doi.org/10.2307/2297896>
- Nicaise, I. (2001), *Human capital, reservation wages and job competition: Heckman’s lambda re-interpreted*, "Applied Economics", 33 (3), pp. 309–315, <https://doi.org/10.1080/00036840121810>
- Nieto, S., Ramos, R. (2017), *Overeducation, Skills and Wage Penalty: Evidence for Spain Using PIAAC Data*, "Social Indicators Research", 134, pp. 219–236, <https://doi.org/10.1007/s11205-016-1423-1>
- OECD (2020), *Tackling discriminatory social institutions to pave the way towards women’s full inclusion and gender equality in G20 countries*, OECD Publishing, Paris, [https://www.oecd.org/content/dam/oecd/en/publications/reports/2020/11/tackling-discriminatory-social-institutions-to-pave-the-way-towards-women-s-full-inclusion-and-gender-equality-in-g20-countries\\_adddd61a5/87c9ef24-en.pdf](https://www.oecd.org/content/dam/oecd/en/publications/reports/2020/11/tackling-discriminatory-social-institutions-to-pave-the-way-towards-women-s-full-inclusion-and-gender-equality-in-g20-countries_adddd61a5/87c9ef24-en.pdf) (accessed: 7.02.2025).
- Palczyńska, M. (2021), *Overeducation and wages: the role of cognitive skills and personality traits*, "Baltic Journal of Economics", 21 (1), pp. 85–111, <https://doi.org/10.1080/1406099X.2021.1950388>



- Pecoraro, M. (2014), *Is There Still a Wage Penalty for Being Overeducated but Well-Matched in Skills? A Panel Data Analysis of a Swiss Graduate Cohort*, "Labour", 28 (3), pp. 309–337, <https://doi.org/10.1111/labr.12031>
- Reisel, L., Østbakken, K.M., Attewell, P. (2019), *Dynamics of Claims Making and Gender Wage Gaps in the United States and Norway*, "Social Politics: International Studies in Gender, State & Society", 26 (1), pp. 87–115, <https://doi.org/10.1093/sp/jxy019>
- Robst, J. (2007), *Education and job match: The relatedness of college major and work*, "Economics of Education Review", 26 (4), pp. 397–407, <https://doi.org/10.1016/j.econedurev.2006.08.003>
- Rosso, B.D., Dekas, K.H., Wrzesniewski, A. (2010), *On the meaning of work: A theoretical integration and review*, "Research in Organizational Behavior", 30, pp. 91–127, <https://doi.org/10.1016/j.riob.2010.09.001>
- Rumberger, R.W. (1987), *The Impact of Surplus Schooling on Productivity and Earnings*, "Journal of Human Resources", 22 (1), pp. 24–50, <https://doi.org/10.2307/145865>
- Sattinger, M. (1993), *Assignment Models of the Distribution of Earnings*, "Journal of Economic Literature", 31 (2), pp. 831–880, <https://www.jstor.org/stable/2728516> (accessed: 10.10.2024).
- Shavit, Y., Müller, W. (2000), *Vocational secondary education: Where diversion and where safety net?*, "European Societies", 2 (1), pp. 29–50, <https://doi.org/10.1080/146166900360710>
- Sicherman, N. (1991), *"Overeducation" in the Labor Market*, "Journal of Labor Economics", 9 (2), <https://doi.org/10.1086/298261>
- Sicherman, N., Galor, O. (1990), *A Theory of Career Mobility*, "Journal of Political Economy", 98 (1), <https://doi.org/10.1086/261674>
- Stewart, F. (2018), *The STEM Dilemma: Skills That Matter to Regions*, WE Upjohn Institute for Employment Research, Kalamazoo.
- Thurow, L.C. (1979), *A job competition model*, [in:] M.J. Piore (ed.), *Unemployment and Inflation: Institutional and Structuralist Views*, Routledge, London, pp. 17–32.
- Tosun, J., Hörisch, F., Schuck, B. (2018), *CUPESSE: Cultural Pathways to Economic Self-Sufficiency and Entrepreneurship*, [https://search.gesis.org/research\\_data/ZA7475](https://search.gesis.org/research_data/ZA7475) (accessed: 6.11.2023).
- Tosun, J., Arco-Tirado, J.L., Caserta, M., Cemalcilar, Z., Freitag, M., Hörisch, F., Jensen, C., Kittel, B., Littvay, L., Lukeš, M., Maloney, W.A. (2019), *Perceived economic self-sufficiency: A country- and generation-comparative approach*, "European Political Science", 18, pp. 510–531, <https://doi.org/10.1057/s41304-018-0186-3>
- Verdugo, R.R., Verdugo, N.T. (1989), *The Impact of Surplus Schooling on Earnings: Some Additional Findings*, "Journal of Human Resources", 24 (4), pp. 629–643, <https://doi.org/10.2307/145998>
- Verdugo, R.R., Verdugo, N.T. (1992), *Surplus Schooling and Earnings: Reply to Cohn and to Gill and Solberg*, "Journal of Human Resources", 27 (4), pp. 690–695, <https://doi.org/10.2307/146083>
- Zimmermann, K.F., Biavaschi, C., Eichhorst, W., Giulietti, C., Kendzia, M.J., Muravyev, A., Schmidl, R. (2013), *Youth unemployment and vocational training*, "Foundations and Trends® in Microeconomic", 1–2.



## APPENDIX

Table A1. Sample Selection Equations for Male Labor Force Participation in Ten Countries

Variable	Austria	Czechia	Denmark	Germany	Greece	Hungary	Italy	Spain	Turkey	UK
Education	0.008 (0.025)	0.139 <sup>c</sup> (0.040)	0.101 <sup>c</sup> (0.028)	0.065 <sup>c</sup> (0.016)	0.054 (0.038)	-0.006 (0.025)	0.041 (0.037)	0.075 <sup>c</sup> (0.023)	0.029 (0.033)	0.069 <sup>c</sup> (0.018)
Experience	0.043 <sup>c</sup> (0.015)	0.122 <sup>c</sup> (0.024)	0.055 <sup>c</sup> (0.019)	0.032 <sup>c</sup> (0.009)	0.078 <sup>c</sup> (0.019)	-0.016 (0.016)	0.025 (0.021)	0.029 <sup>a</sup> (0.016)	-0.025 (0.024)	0.048 <sup>c</sup> (0.010)
Married	0.446 <sup>c</sup> (0.153)	0.484 <sup>a</sup> (0.289)	0.513 <sup>b</sup> (0.206)	0.326 <sup>c</sup> (0.089)	0.160 (0.218)	0.060 (0.199)	0.502 <sup>b</sup> (0.227)	0.088 (0.197)	0.485 <sup>a</sup> (0.289)	0.377 <sup>c</sup> (0.122)
Immigrant	-0.133 (0.196)	-0.430 (0.550)	-0.493 (0.419)	0.054 (0.140)	0.937 (0.597)	0.375 (0.584)	0.498 (0.515)	-0.848 <sup>c</sup> (0.307)	0.542 (0.451)	0.000 (0.169)
Has child(ren)	0.557 <sup>b</sup> (0.278)	0.238 (0.421)	-0.212 (0.360)	-0.170 (0.114)	0.480 <sup>a</sup> (0.286)	0.239 (0.288)	0.138 (0.288)	0.556 <sup>b</sup> (0.268)	-0.576 <sup>b</sup> (0.284)	-0.056 (0.225)
Has caring responsibility	-0.235 (0.256)	-0.562 (0.347)	0.173 (0.322)	0.000 (0.106)	-0.216 (0.216)	-0.143 (0.251)	-0.321 (0.232)	0.092 (0.184)	0.000 (0.101)	0.152 (0.212)
Work Centrality	0.192 <sup>a</sup> (0.113)	0.340 <sup>a</sup> (0.190)	0.206 (0.133)	0.249 <sup>c</sup> (0.064)	0.244 <sup>a</sup> (0.130)	0.091 (0.151)	-0.035 (0.181)	0.144 (0.123)	0.394 <sup>a</sup> (0.208)	0.307 <sup>c</sup> (0.083)
Grit	0.415 <sup>c</sup> (0.160)	-0.103 (0.256)	0.269 (0.211)	-0.085 (0.100)	0.193 (0.201)	-0.204 (0.182)	0.034 (0.229)	-0.013 (0.152)	-0.135 (0.191)	0.016 (0.122)
Risk-Taking	-0.050 (0.031)	-0.004 (0.040)	0.004 (0.033)	-0.012 (0.014)	-0.006 (0.030)	-0.009 (0.028)	-0.042 (0.036)	0.016 (0.027)	0.022 (0.037)	0.017 (0.022)
Willingness to change jobs	-0.040 (0.038)	0.040 (0.057)	-0.001 (0.047)	0.002 (0.016)	-0.001 (0.050)	-0.074 <sup>b</sup> (0.034)	0.136 <sup>b</sup> (0.061)	0.042 (0.040)	-0.032 (0.036)	0.043 <sup>a</sup> (0.026)
Job Importance	-0.190 (0.151)	0.082 (0.222)	0.559 <sup>b</sup> (0.222)	0.064 (0.071)	0.002 (0.183)	-0.208 (0.169)	0.217 (0.201)	0.080 (0.169)	0.312 (0.235)	0.077 (0.116)
Religious	-0.122 (0.126)	-0.237 (0.238)	0.327 <sup>b</sup> (0.172)	0.002 (0.060)	0.191 (0.150)	-0.253 <sup>a</sup> (0.132)	-0.136 (0.166)	0.036 (0.161)	1.056 <sup>a</sup> (0.578)	-0.211 <sup>b</sup> (0.104)
NUTS regions	Not Sig	Sig	Not Sig	Sig	Not sig	Not Sig	Sig	Not Sig	Sig	Not Sig

Standard errors in parenthesis. <sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

Table A2. Sample Selection Equations for Female Labor Force Participation in Ten Countries

Variable	Austria	Czechia	Denmark	Germany	Greece	Hungary	Italy	Spain	Turkey	UK
Education	0.073 <sup>c</sup> (0.021)	0.077 <sup>c</sup> (0.026)	0.123 <sup>c</sup> (0.035)	0.044 <sup>c</sup> (0.015)	0.106 <sup>c</sup> (0.034)	-0.036 (0.027)	0.045 (0.044)	0.074 <sup>c</sup> (0.022)	0.067 <sup>a</sup> (0.040)	0.097 <sup>c</sup> (0.017)
Experience	0.047 <sup>c</sup> (0.011)	0.114 <sup>c</sup> (0.020)	0.049 <sup>b</sup> (0.024)	0.036 <sup>c</sup> (0.008)	0.030 <sup>a</sup> (0.016)	0.013 (0.018)	0.021 (0.025)	-0.006 (0.016)	0.039 (0.028)	0.057 <sup>c</sup> (0.009)
Married	0.242 <sup>b</sup> (0.122)	-0.146 (0.149)	-0.029 (0.210)	0.027 (0.085)	-0.411 <sup>b</sup> (0.167)	-0.41 <sup>c</sup> (0.151)	-0.064 (0.274)	-0.024 (0.159)	-0.323 (0.324)	0.212 <sup>b</sup> (0.101)
Immigrant	-0.240 (0.153)	0.217 (0.426)	-0.596 (0.718)	0.304 <sup>b</sup> (0.126)	-0.297 (0.239)	0.042 (0.447)	-0.137 (0.619)	0.203 (0.251)	-0.597 (0.718)	0.029 (0.126)
Has child(ren)	-0.224 <sup>b</sup> (0.114)	-1.525 <sup>c</sup> (0.305)	-0.357 (0.482)	-0.071 (0.107)	-0.128 (0.228)	-1.71 <sup>c</sup> (0.404)	0.167 (0.338)	-0.177 (0.229)	-1.13 <sup>c</sup> (0.427)	-0.255 (0.185)
Has caring responsibility	-0.034 (0.112)	-0.094 (0.273)	0.097 (0.447)	-0.244 <sup>b</sup> (0.097)	-0.290 <sup>a</sup> (0.178)	0.711 <sup>a</sup> (0.382)	-0.502 <sup>b</sup> (0.263)	-0.178 (0.199)	0.000 (0.012)	0.092 (0.176)

Variable	Austria	Czechia	Denmark	Germany	Greece	Hungary	Italy	Spain	Turkey	UK
Work Centrality	0.216 <sup>c</sup> (0.081)	0.144 (0.127)	0.178 (0.171)	0.264 <sup>c</sup> (0.066)	0.019 (0.113)	0.290 <sup>a</sup> (0.156)	0.175 (0.178)	0.143 (0.106)	-0.036 (0.273)	0.315 <sup>c</sup> (0.079)
Grit	0.289 <sup>b</sup> (0.124)	0.022 (0.028)	0.513 <sup>a</sup> (0.291)	0.027 (0.093)	0.241 (0.168)	0.066 (0.181)	0.288 (0.231)	-0.021 (0.148)	0.250 (0.284)	-0.114 (0.110)
Risk-Taking	0.018 (0.014)	0.022 (0.028)	0.007 (0.041)	-0.002 (0.010)	-0.018 (0.024)	-0.056 <sup>b</sup> (0.027)	0.019 (0.036)	0.012 (0.025)	0.005 (0.044)	-0.006 (0.016)
Willingness to change jobs	0.019 (0.019)	0.027 (0.044)	-0.067 (0.064)	0.006 (0.013)	0.000 (0.036)	-0.043 (0.034)	-0.079 (0.063)	-0.003 (0.039)	0.027 (0.049)	0.036 <sup>a</sup> (0.019)
Job Importance	0.026 (0.082)	-0.179 (0.167)	0.025 (0.295)	0.093 (0.063)	-0.392 <sup>b</sup> (0.163)	-0.80 <sup>c</sup> (0.186)	0.440 <sup>b</sup> (0.218)	0.227 (0.165)	0.267 (0.339)	-0.087 (0.079)
Religious	-0.042 (0.062)	0.033 (0.179)	0.003 (0.177)	-0.066 (0.050)	0.023 (0.122)	0.110 (0.138)	0.054 (0.183)	0.070 (0.132)	-0.336 (0.721)	-0.062 (0.074)
NUTS regions	Not Sig	Not Sig	Not Sig	Not Sig	Not sig	Not Sig	Not Sig	Not Sig	Not Sig	Not Sig

Standard errors in parenthesis. <sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

**Table A3. Earnings Equations for Males – OLS (Left Columns) and Selection Corrected (Right Columns) for each of the Ten Countries**

Variable	Austria		Czechia		Denmark		Germany		Greece	
	OLS	Selection	OLS	Selection	OLS	Selection	OLS	Selection	OLS	Selection
Education	0.042 <sup>b</sup>	0.013	0.059 <sup>c</sup>	0.036 <sup>c</sup>	0.107 <sup>c</sup>	0.088 <sup>c</sup>	0.046 <sup>c</sup>	0.048 <sup>c</sup>	0.086 <sup>c</sup>	0.079 <sup>b</sup>
	(0.192)	(0.009)	(0.010)	(0.011)	(0.023)	(0.016)	(0.008)	(0.007)	(0.031)	(0.031)
Overeducation	-0.293 <sup>b</sup>	-0.040	-0.154 <sup>c</sup>	-0.136 <sup>c</sup>	-0.507 <sup>c</sup>	-0.269 <sup>c</sup>	-0.159 <sup>c</sup>	-0.102 <sup>c</sup>	-0.267 <sup>b</sup>	-0.267 <sup>b</sup>
	(0.121)	(0.060)	(0.055)	(0.039)	(0.133)	(0.066)	(0.048)	(0.031)	(0.117)	(0.110)
Experience	0.024	0.021 <sup>a</sup>	0.101 <sup>c</sup>	0.021	0.115 <sup>b</sup>	0.048 <sup>a</sup>	0.017	0.014 <sup>a</sup>	-0.000	-0.068
	(0.025)	(0.012)	(0.023)	(0.019)	(0.052)	(0.025)	(0.011)	(0.007)	(0.041)	(0.053)
Experience	-0.001	0.001	-0.004 <sup>c</sup>	0.000	-0.003	-0.001	0.000	0.000	0.003	0.005 <sup>b</sup>
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)
Perm. Contract	0.501 <sup>c</sup>	0.058	0.094 <sup>a</sup>	0.040	0.297 <sup>b</sup>	0.189 <sup>c</sup>	0.190 <sup>c</sup>	0.148 <sup>c</sup>	0.129	0.008
	(0.115)	(0.058)	(0.049)	(0.034)	(0.120)	(0.059)	(0.045)	(0.027)	(0.100)	(0.096)
Full-time Job	1.176 <sup>c</sup>	0.154 <sup>b</sup>	0.494 <sup>c</sup>	0.067	0.984 <sup>c</sup>	0.150 <sup>b</sup>	0.313 <sup>c</sup>	0.118 <sup>c</sup>	0.405 <sup>c</sup>	0.331 <sup>c</sup>
	(0.117)	(0.061)	(0.064)	(0.052)	(0.132)	(0.071)	(0.050)	(0.031)	(0.109)	(0.105)
Married	0.238 <sup>b</sup>	0.127 <sup>b</sup>	0.068	0.145 <sup>c</sup>	0.343 <sup>c</sup>	0.147 <sup>a</sup>	0.218 <sup>c</sup>	0.268 <sup>c</sup>	0.158	0.168
	(0.105)	(0.053)	(0.054)	(0.041)	(0.116)	(0.077)	(0.039)	(0.032)	(0.103)	(0.120)
Immigrant	0.018	-0.158 <sup>b</sup>	-0.031	0.085	-0.028	-0.169	0.029	0.052	-0.036	-0.122
	(0.152)	(0.071)	(0.126)	(0.091)	(0.334)	(0.169)	(0.067)	(0.055)	(0.232)	(0.287)
Work centrality	-0.062	-0.013	-0.003	0.014	0.178 <sup>b</sup>	0.139 <sup>c</sup>	0.034	0.087 <sup>c</sup>	0.023	0.030
	(0.086)	(0.039)	(0.045)	(0.038)	(0.090)	(0.053)	(0.032)	(0.026)	(0.082)	(0.098)
Grit	-0.026	0.125 <sup>b</sup>	0.076	0.151 <sup>c</sup>	0.243	0.127	0.115 <sup>b</sup>	0.129 <sup>c</sup>	0.173	0.266 <sup>b</sup>
	(0.118)	(0.057)	(0.058)	(0.042)	(0.153)	(0.086)	(0.047)	(0.038)	(0.116)	(0.120)

Variable	Austria		Czechia		Denmark		Germany		Greece	
	OLS	Selection	OLS	Selection	OLS	Selection	OLS	Selection	OLS	Selection
NUTS regions	Not	Not	Sig	Sig	Not	Not	Sig	Not	Not	Not
	Sig	Sig			Sig	Sig		Sig	Sig	Sig
Lambda ( $\lambda$ )		-0.011		-0.164		-0.269		-0.468 <sup>c</sup>		0.063
		(0.112)		(0.171)		(0.217)		(0.017)		(0.543)
Adjusted R <sup>2</sup>	0.42		0.43		0.46		0.19		0.18	

Standard errors in parenthesis. <sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

**Table A3.** Earnings Equations for Males – OLS (Left Columns) and Selection Corrected (Right Columns) for each of the Ten Countries

Variable	Hungary		Italy		Spain		Turkey		UK	
	OLS	Selection	OLS	Selection	OLS	Selection	OLS	Selection	OLS	Selection
Education	0.005	0.011 <sup>b</sup>	0.018	0.028 <sup>a</sup>	0.075 <sup>c</sup>	0.025	0.044 <sup>c</sup>	0.055 <sup>c</sup>	0.050 <sup>c</sup>	0.039 <sup>c</sup>
	(0.006)	(0.005)	(0.020)	(0.015)	(0.016)	(0.019)	(0.009)	(0.013)	(0.009)	(0.006)
Overeducation	-0.072 <sup>a</sup>	-0.055 <sup>a</sup>	-0.007	0.023	-0.564 <sup>c</sup>	-0.262 <sup>c</sup>	-0.255 <sup>c</sup>	-0.304 <sup>c</sup>	-0.311 <sup>c</sup>	-0.236 <sup>c</sup>
	(0.039)	(0.032)	(0.103)	(0.069)	(0.090)	(0.072)	(0.065)	(0.094)	(0.048)	(0.032)
Experience	0.028 <sup>c</sup>	0.006	0.036	-0.002	0.092 <sup>c</sup>	-0.001	0.014	0.015	0.073 <sup>c</sup>	0.012
	(0.009)	(0.008)	(0.036)	(0.025)	(0.023)	(0.021)	(0.013)	(0.022)	(0.011)	(0.008)
Experience	-0.001 <sup>b</sup>	0.000	-0.001	0.001	-0.002	0.000	0.000	0.000	-0.003 <sup>c</sup>	0.000
	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Perm. Contract	0.029	0.037	0.092	-0.027	0.276 <sup>c</sup>	0.212 <sup>c</sup>	0.141 <sup>c</sup>	0.117 <sup>a</sup>	0.215 <sup>c</sup>	0.050
	(0.032)	(0.026)	(0.080)	(0.052)	(0.089)	(0.066)	(0.050)	(0.069)	(0.051)	(0.035)
Full-time Job	0.306 <sup>c</sup>	0.031	-0.006	-0.138 <sup>b</sup>	0.244 <sup>c</sup>	0.179 <sup>b</sup>	-0.004	-0.214	0.304 <sup>c</sup>	0.136 <sup>c</sup>
	(0.073)	(0.068)	(0.086)	(0.058)	(0.091)	(0.070)	(0.099)	(0.183)	(0.045)	(0.030)
Married	-0.014	-0.006	0.077	0.126 <sup>a</sup>	0.096	0.055	-0.136 <sup>c</sup>	-0.104	0.186 <sup>c</sup>	0.163 <sup>c</sup>
	(0.033)	(0.028)	(0.088)	(0.072)	(0.095)	(0.104)	(0.051)	(0.089)	(0.044)	(0.030)
Immigrant	0.127	0.155 <sup>b</sup>	0.295	0.218	-0.124	0.086	0.378	0.093	-0.047	-0.086 <sup>a</sup>
	(0.090)	(0.079)	(0.204)	(0.149)	(0.206)	(0.210)	(0.416)	(0.593)	(0.069)	(0.046)
Work centrality	0.012	0.009	0.047	0.071	0.069	0.034	0.114 <sup>b</sup>	-0.028	0.118 <sup>c</sup>	0.053 <sup>b</sup>
	(0.031)	(0.026)	(0.076)	(0.053)	(0.074)	(0.068)	(0.053)	(0.087)	(0.036)	(0.026)
Grit	0.023	0.013	0.186 <sup>a</sup>	0.154 <sup>b</sup>	0.190 <sup>b</sup>	0.134 <sup>a</sup>	0.126 <sup>c</sup>	0.098	-0.010	0.052
	(0.035)	(0.031)	(0.097)	(0.069)	(0.092)	(0.080)	(0.047)	(0.065)	(0.054)	(0.036)
NUTS regions	Sig	Sig	Not	Not	Not	Not	Sig	Sig	Sig	Sig
			Sig	Sig	Sig	Sig				
Lambda ( $\lambda$ )		-0.13 <sup>c</sup>		-0.226		-0.442 <sup>b</sup>		-0.223		-0.073 <sup>a</sup>
		(0.028)		(0.213)		(0.194)		(0.337)		(0.039)
Adjusted R <sup>2</sup>	0.16		0.04		0.43		0.24		0.31	

Standard errors in parenthesis. <sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

**Table A4.** Earnings Equations for Females – OLS (Left Columns) and Selection Corrected (Right Columns) for each of the Ten Countries

Variable	Austria		Czechia		Denmark		Germany		Greece	
	OLS	Selection	OLS	Selection	OLS	Selection	OLS	Selection	OLS	Selection
Education	0.098 <sup>c</sup> (0.023)	0.055 <sup>c</sup> (0.012)	0.053 <sup>c</sup> (0.012)	0.022 <sup>c</sup> (0.006)	0.105 <sup>c</sup> (0.034)	0.088 <sup>c</sup> (0.031)	0.063 <sup>c</sup> (0.012)	0.058 <sup>c</sup> (0.008)	0.050 (0.035)	0.059 (0.040)
Overeducation	-0.148 (0.113)	-0.12 <sup>c</sup> (0.038)	-0.313 <sup>c</sup> (0.065)	-0.112 <sup>c</sup> (0.032)	-0.540 <sup>c</sup> (0.194)	-0.435 <sup>c</sup> (0.082)	-0.26 <sup>c</sup> (0.065)	-0.097 <sup>c</sup> (0.032)	-0.165 (0.111)	-0.150 (0.106)
Experience	0.085 <sup>c</sup> (0.025)	0.021 <sup>b</sup> (0.010)	0.062 <sup>b</sup> (0.028)	0.015 (0.013)	0.102 (0.074)	0.031 (0.030)	0.003 (0.016)	0.021 <sup>b</sup> (0.008)	0.103 <sup>b</sup> (0.041)	0.048 (0.044)
Experience <sup>2</sup>	-0.001 (0.002)	0.000 (0.001)	-0.002 (0.001)	0.000 (0.001)	-0.002 (0.004)	0.000 (0.002)	0.001 (0.001)	0.000 (0.000)	-0.006 <sup>b</sup> (0.003)	-0.002 (0.003)
Perm. Contract	0.446 <sup>c</sup> (0.108)	0.014 (0.039)	0.123 <sup>b</sup> (0.060)	-0.021 (0.027)	0.155 (0.172)	0.144 <sup>b</sup> (0.069)	0.264 <sup>c</sup> (0.060)	0.110 <sup>c</sup> (0.029)	0.097 (0.095)	0.034 (0.091)
Full-time Job	0.869 <sup>c</sup> (0.104)	0.159 <sup>c</sup> (0.036)	0.425 <sup>c</sup> (0.063)	0.030 (0.031)	0.882 <sup>c</sup> (0.166)	0.113 <sup>a</sup> (0.069)	0.348 <sup>c</sup> (0.054)	0.122 <sup>c</sup> (0.027)	0.198 <sup>a</sup> (0.103)	0.118 (0.098)
Married	0.309 <sup>b</sup> (0.122)	0.202 <sup>c</sup> (0.062)	-0.132 <sup>b</sup> (0.066)	0.056 <sup>a</sup> (0.034)	0.065 (0.160)	0.031 (0.076)	0.266 <sup>c</sup> (0.057)	0.206 <sup>c</sup> (0.042)	0.190 <sup>a</sup> (0.110)	0.123 (0.162)
Immigrant	-0.210 (0.150)	-0.170 <sup>b</sup> (0.085)	-0.028 (0.174)	0.104 (0.086)	1.453 <sup>b</sup> (0.723)	0.449 (0.493)	0.119 (0.086)	0.047 (0.065)	-0.165 (0.195)	-0.189 (0.196)
Work centrality	0.229 <sup>c</sup> (0.081)	0.141 <sup>c</sup> (0.044)	0.058 (0.054)	-0.001 (0.026)	-0.035 (0.141)	0.087 (0.074)	0.113 <sup>b</sup> (0.047)	0.194 <sup>c</sup> (0.035)	0.279 <sup>c</sup> (0.090)	0.236 <sup>c</sup> (0.089)
Grit	0.076 (0.125)	0.168 <sup>b</sup> (0.067)	-0.195 <sup>b</sup> (0.080)	-0.009 (0.038)	-0.061 (0.237)	0.126 (0.163)	0.010 (0.065)	0.093 <sup>a</sup> (0.049)	-0.027 (0.123)	0.016 (0.120)
NUTS regions	Not	Not	Sig	Sig	Not	Not	Not	Sig	Not	Not
	Sig	Sig			Sig	Sig	Sig		Sig	Sig
Lambda ( $\lambda$ )		0.543 <sup>c</sup> (0.037)		-0.032 (0.039)		0.333 (0.427)		0.578 <sup>c</sup> (0.021)		0.256 <sup>b</sup> (0.120)
Adjusted R <sup>2</sup>	0.34		0.29		0.34		0.17		0.09	

Standard errors in parenthesis. <sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

**Table A5.** Earnings Equations for Females – OLS (Left Columns) and Selection Corrected (Right Columns) for each of the Ten Countries

Variable	Hungary		Italy		Spain		Turkey		UK	
	OLS	Selection	OLS	Selection	OLS	Selection	OLS	Selection	OLS	Selection
Education	0.012 <sup>c</sup>	0.011 <sup>c</sup>	0.002	0.022	0.060 <sup>c</sup>	0.054 <sup>c</sup>	0.041 <sup>c</sup>	0.069 <sup>b</sup>	0.037 <sup>c</sup>	0.043 <sup>c</sup>
	(0.004)	(0.003)	(0.033)	(0.020)	(0.019)	(0.018)	(0.015)	(0.027)	(0.011)	(0.005)
Overeducation	-0.068 <sup>b</sup>	-0.07 <sup>c</sup>	0.028	-0.127 <sup>a</sup>	-0.427 <sup>c</sup>	-0.33 <sup>c</sup>	-0.135	-0.119	-0.187 <sup>c</sup>	-0.146 <sup>c</sup>
	(0.027)	(0.020)	(0.142)	(0.074)	(0.095)	(0.063)	(0.091)	(0.184)	(0.053)	(0.024)
Experience	0.024 <sup>c</sup>	0.013 <sup>c</sup>	0.092 <sup>a</sup>	0.038	0.066 <sup>c</sup>	0.037 <sup>b</sup>	0.050 <sup>c</sup>	0.029	0.103 <sup>c</sup>	0.030 <sup>c</sup>
	(0.005)	(0.004)	(0.051)	(0.027)	(0.025)	(0.017)	(0.017)	(0.046)	(0.011)	(0.005)
Experience <sup>2</sup>	-0.001 <sup>c</sup>	0.000 <sup>b</sup>	-0.005	0.002	-0.002	-0.001	-0.002 <sup>c</sup>	-0.002	-0.004 <sup>c</sup>	-0.001 <sup>b</sup>
	(0.000)	(0.000)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Perm. Contract	0.079 <sup>c</sup>	0.042 <sup>c</sup>	0.103	0.054	0.302 <sup>c</sup>	0.177 <sup>c</sup>	0.179 <sup>b</sup>	0.436 <sup>c</sup>	0.337 <sup>c</sup>	0.054 <sup>b</sup>
	(0.021)	(0.015)	(0.112)	(0.058)	(0.082)	(0.055)	(0.079)	(0.142)	(0.051)	(0.023)
Full-time Job	0.096 <sup>b</sup>	0.062 <sup>b</sup>	-0.025	-0.126 <sup>b</sup>	0.309 <sup>c</sup>	0.185 <sup>c</sup>	-0.345 <sup>c</sup>	-0.435 <sup>a</sup>	0.308 <sup>c</sup>	0.129 <sup>c</sup>
	(0.038)	(0.028)	(0.106)	(0.056)	(0.084)	(0.056)	(0.128)	(0.233)	(0.045)	(0.020)
Married	-0.028	-0.013	0.213	0.026	0.125	0.120	0.114	0.156	0.133 <sup>c</sup>	0.102 <sup>c</sup>
	(0.020)	(0.016)	(0.141)	(0.085)	(0.096)	(0.074)	(0.077)	(0.182)	(0.050)	(0.026)
Immigrant	0.056	0.051	1.054 <sup>b</sup>	0.496 <sup>a</sup>	-0.182	-0.139	0.064	-0.490	0.037	0.021
	(0.061)	(0.044)	(0.472)	(0.259)	(0.152)	(0.114)	(0.342)	(0.488)	(0.066)	(0.035)
Work centrality	0.017	0.035 <sup>b</sup>	0.180 <sup>a</sup>	0.130 <sup>a</sup>	0.076	0.040	0.093	0.242	0.041	0.064 <sup>c</sup>
	(0.020)	(0.015)	(0.097)	(0.067)	(0.071)	(0.057)	(0.074)	(0.155)	(0.042)	(0.022)
Grit	0.044 <sup>a</sup>	0.036 <sup>b</sup>	-0.154	-0.022	-0.031	0.046	0.189 <sup>b</sup>	0.229	0.021	0.009
	(0.024)	(0.018)	(0.069)	(0.087)	(0.095)	(0.068)	(0.081)	(0.184)	(0.058)	(0.031)
NUTS regions	Sig	Sig	Not Sig	Not Sig	Not	Not	Sig	Sig	Not	Sig
					Sig	Sig			Sig	
Lambda ( $\lambda$ )		0.018		0.354		0.326 <sup>a</sup>		0.494		0.294 <sup>c</sup>
		(0.019)		(0.202)		(0.181)		(0.356)		(0.014)
Adjusted R <sup>2</sup>	0.29		0.065		0.27		0.20		0.32	

Standard errors in parenthesis. <sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

**Table A6.** Comparison of Wage Penalty from OLS, Quantile and Selection-Corrected Regressions – Males Coefficients and (Std. Errors)

Country	Overeducation Penalty					
	Quartile 1	Quartile 2	Quartile 3	Wald Test Sig?#	OLS	Selection-Corrected
Austria	-0.087 (0.054)	-0.138 <sup>b</sup> (0.065)	-0.103 (0.082)	No	-0.293 <sup>b</sup> (0.019)	-0.040 (0.060)
Czechia	-0.031 (0.034)	-0.098 <sup>b</sup> (0.043)	-0.138 <sup>c</sup> (0.038)	Yes <sup>c</sup>	-0.154 <sup>c</sup> (0.055)	-0.136 <sup>c</sup> (0.039)
Denmark	-0.150 (0.104)	-0.334 <sup>c</sup> (0.115)	-0.432 <sup>c</sup> (0.091)	Yes <sup>a</sup>	-0.507 <sup>b</sup> (0.133)	-0.269 <sup>c</sup> (0.066)
Germany	0.175 <sup>c</sup> (0.056)	-0.111 <sup>c</sup> (0.034)	-0.049 <sup>c</sup> (0.054)	No	-0.159 <sup>c</sup> (0.048)	-0.102 <sup>c</sup> (0.031)
Greece	-0.273 <sup>c</sup> (0.063)	-0.272 <sup>c</sup> (0.077)	-0.287 (0.269)	No	-0.267 <sup>b</sup> (0.117)	-0.267 <sup>b</sup> (0.110)
Hungary	-0.127 <sup>c</sup> (0.045)	-0.143 <sup>c</sup> (0.031)	-0.073 <sup>b</sup> (0.034)	No	-0.072 <sup>a</sup> (0.039)	-0.055 <sup>b</sup> (0.032)
Italy	0.000 (0.000)	0.000 (0.000)	-0.127 (0.115)	No	-0.007 (0.103)	-0.023 (0.069)
Spain	-0.616 <sup>c</sup> (0.184)	-0.499 <sup>c</sup> (0.122)	-0.356 <sup>c</sup> (0.117)	No	-0.564 <sup>c</sup> (0.090)	-0.262 <sup>c</sup> (0.072)
Turkey	-0.074 <sup>c</sup> (0.026)	-0.156 <sup>c</sup> (0.052)	-0.262 <sup>c</sup> (0.091)	No	-0.255 <sup>c</sup> (0.065)	-0.304 <sup>c</sup> (0.094)
UK	-0.200 <sup>c</sup> (0.026)	-0.168 <sup>c</sup> (0.023)	-0.249 <sup>c</sup> (0.033)	No	-0.311 <sup>c</sup> (0.048)	-0.236 <sup>c</sup> (0.032)

Standard errors in parenthesis. <sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

# Wald test for equivalence of coefficients across quartiles.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

**Table A7.** Comparison of Wage Penalty from OLS, Quantile and Selection-Corrected Regressions – Females Coefficients and (Std. Errors)

Country	Overeducation Penalty					
	Quartile 1	Quartile 2	Quartile 3	Wald Test Sig?#	OLS	Selection-Corrected
Austria	-0.077 (0.134)	-0.250 <sup>a</sup> (0.130)	-0.157 <sup>b</sup> (0.072)	No	-0.0148 (0.113)	-0.120 <sup>c</sup> (0.038)
Czechia	-0.070 (0.050)	-0.154 <sup>c</sup> (0.044)	-0.119 <sup>c</sup> (0.044)	No	-0.313 <sup>c</sup> (0.065)	-0.112 <sup>c</sup> (0.032)
Denmark	-0.127 (0.266)	-0.314 <sup>a</sup> (0.177)	-0.528 <sup>c</sup> (0.101)	No	-0.540 <sup>c</sup> (0.194)	-0.435 <sup>c</sup> (0.082)
Germany	0.194 <sup>c</sup> (0.062)	-0.148 <sup>c</sup> (0.050)	-0.161 <sup>c</sup> (0.054)	No	-0.264 <sup>c</sup> (0.065)	-0.097 <sup>c</sup> (0.032)
Greece	-0.147 <sup>b</sup> (0.059)	-0.020 <sup>c</sup> (0.057)	-0.380 (0.319)	No	-0.165 (0.111)	-0.150 (0.106)
Hungary	-0.073 <sup>b</sup> (0.029)	-0.062 (0.038)	-0.044 (0.030)	No	-0.068 <sup>c</sup> (0.027)	-0.072 <sup>b</sup> (0.020)
Italy	0.000 (0.000)	0.000 (0.000)	-0.150 (0.121)	No	-0.028 (0.142)	-0.127 <sup>a</sup> (0.074)



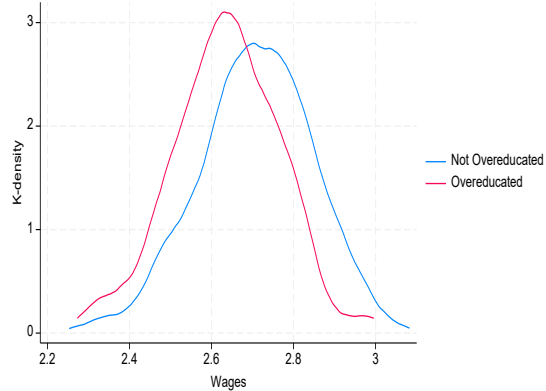
Country	Overeducation Penalty					
	Quartile 1	Quartile 2	Quartile 3	Wald Test Sig?#	OLS	Selection-Corrected
Spain	-0.540 <sup>c</sup> (0.113)	-0.417 <sup>c</sup> (0.077)	-0.406 <sup>c</sup> (0.084)	No	-0.427 <sup>c</sup> (0.095)	-0.331 <sup>c</sup> (0.063)
Turkey	-0.008 <sup>c</sup> (0.059)	-0.007 <sup>c</sup> (0.076)	-0.219 <sup>c</sup> (0.087)	Yes <sup>b</sup>	-0.135 (0.091)	-0.119 (0.184)
UK	-0.149 <sup>b</sup> (0.042)	-0.155 <sup>c</sup> (0.022)	-0.176 <sup>c</sup> (0.023)	No	-0.187 <sup>c</sup> (0.053)	-0.146 <sup>c</sup> (0.024)

Standard errors in parenthesis. <sup>a</sup> Significant at 10%, <sup>b</sup> significant at 5%, <sup>c</sup> significant at 1%.

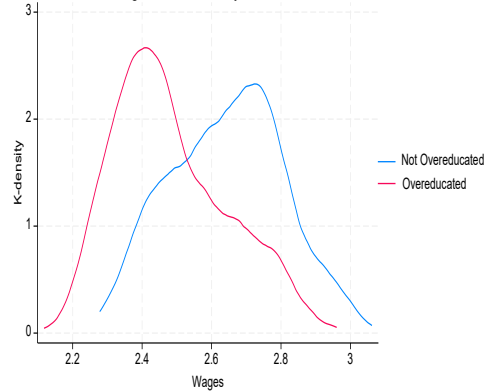
# Wald test for equivalence of coefficients across quartiles.

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

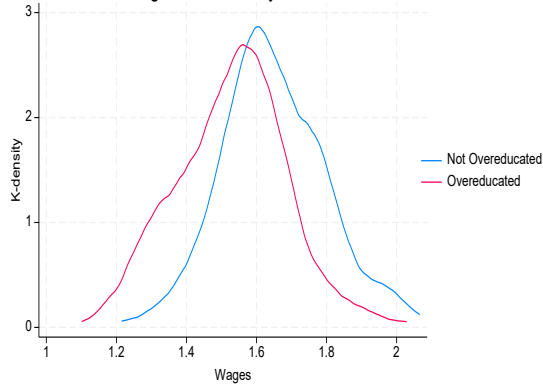
Predicted Wage Distribution by Overeducation - Austria - Males



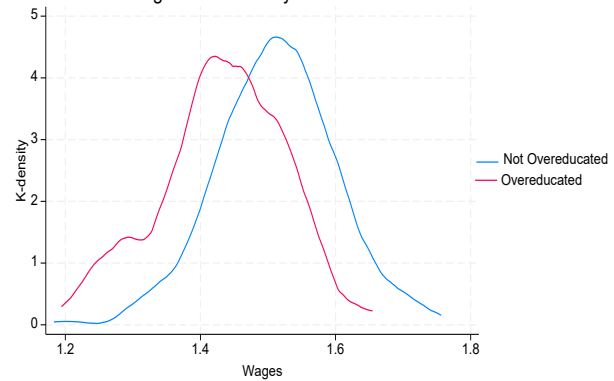
Predicted Wage Distribution by Overeducation - Austria - Females

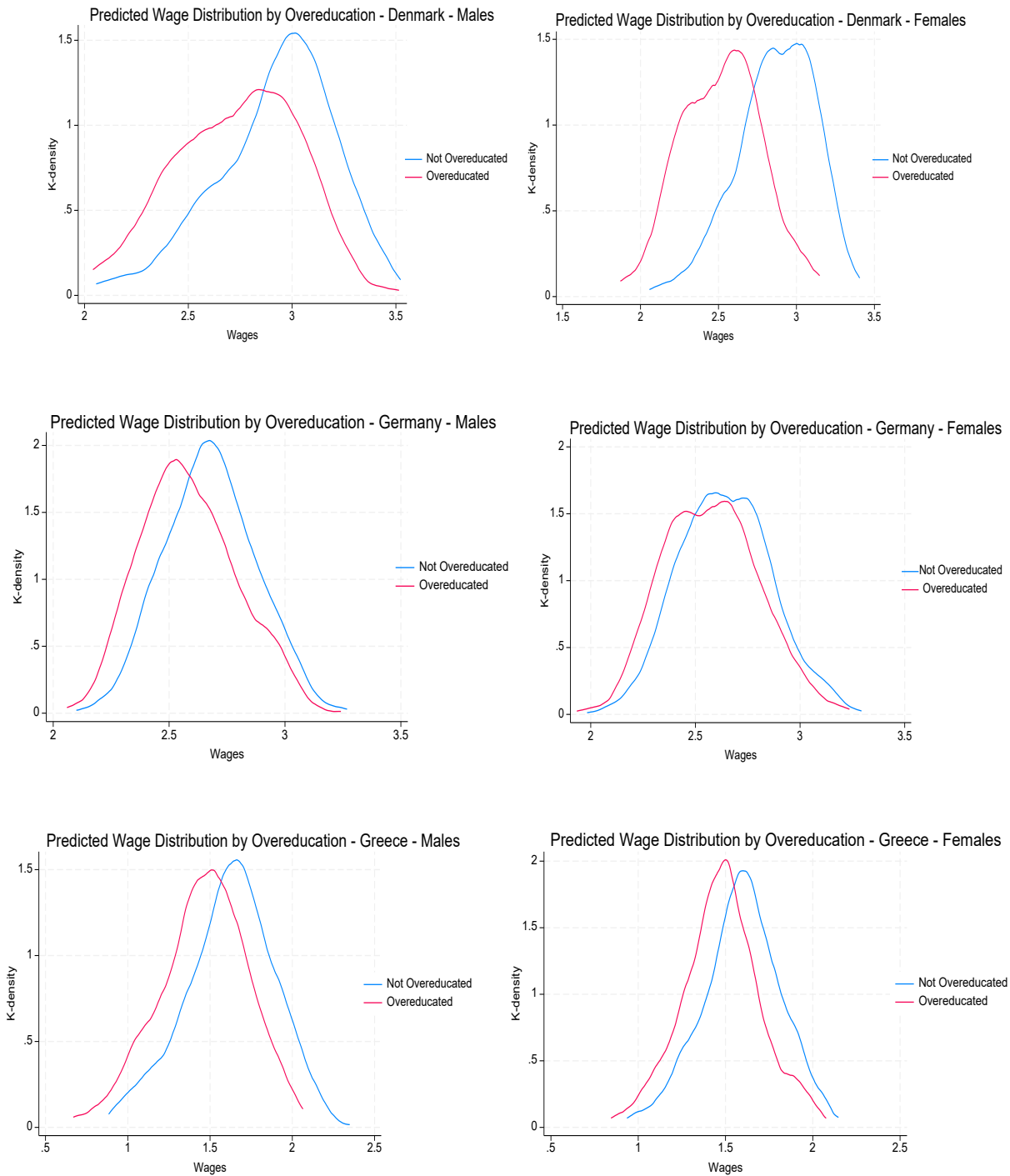


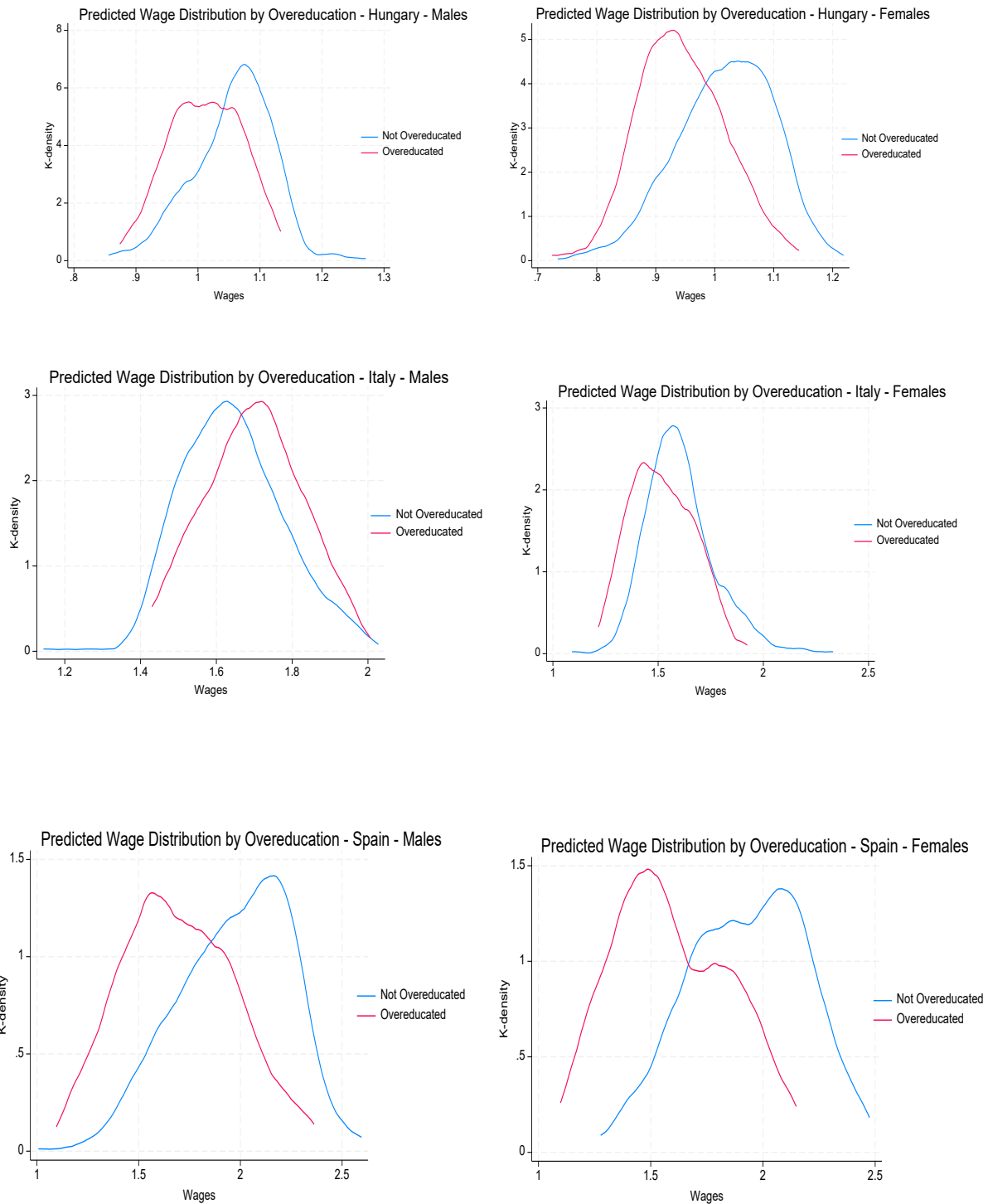
Predicted Wage Distribution by Overeducation - Czechia - Males



Predicted Wage Distribution by Overeducation - Czechia - Females







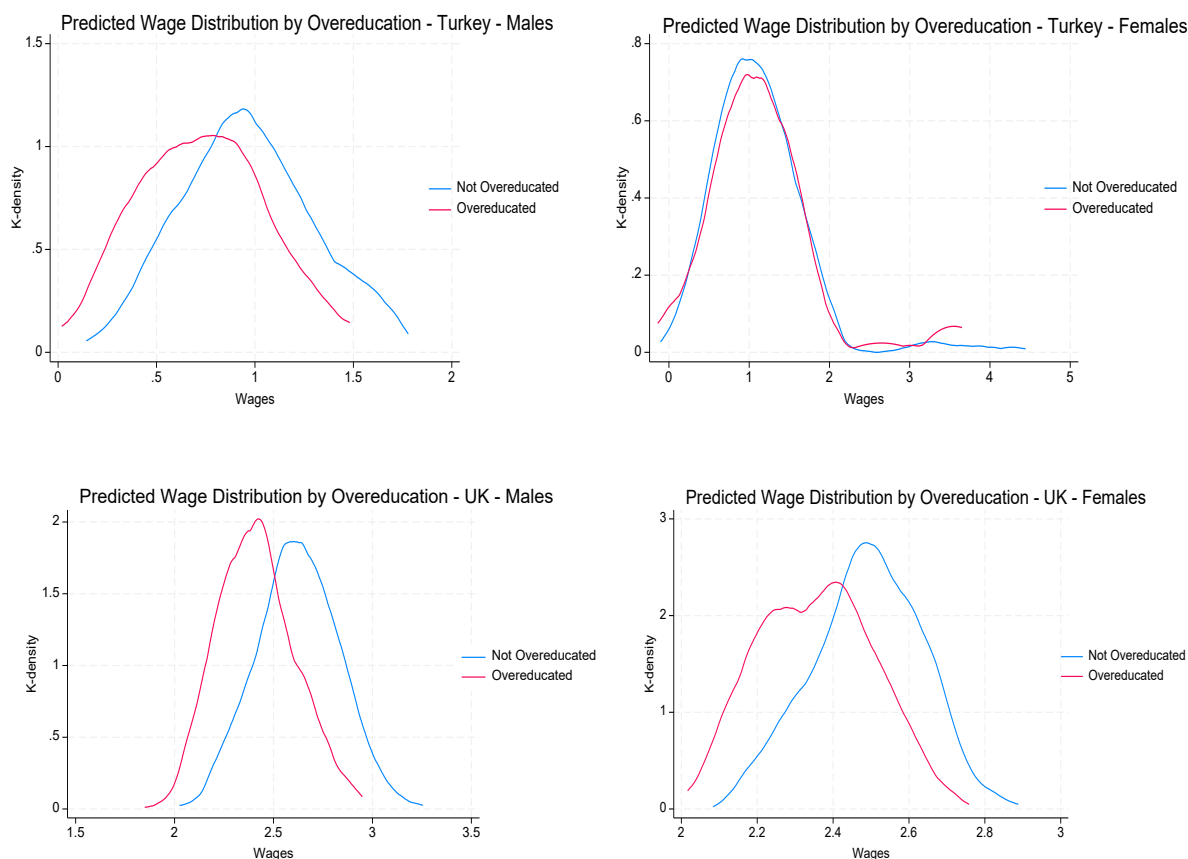


Figure A1. Predicted Wage Distribution by Overeducation for Males and Females

Source: current data analysis using data from Tosun, Hörisch, Schuck 2018.

## Różnice w wynagrodzeniach kobiet i mężczyzn z nadmiernym wykształceniem: doświadczenia młodych mężczyzn i kobiet w dziesięciu krajach europejskich

Artykuł przedstawia analizę wpływu nadmiernego wykształcenia na wynagrodzenia i różnice w wynagrodzeniach wśród 19 000 młodych mężczyzn i kobiet w wieku 18–35 lat w dziesięciu krajach europejskich. Na podstawie danych pochodzących z projektu „Cultural Pathways to Economic Self-sufficiency and Entrepreneurship (CUPESE)”, z uwzględnieniem pewnej endogeniczności wynikającej z pominięcia zmiennych dotyczących umiejętności i poszukiwania zatrudnienia, stwierdzono, że wynagrodzenia kobiet i dyskryminacja płacowa kobiet są zgodne z teorią poszukiwania pracy, podczas gdy wynagrodzenia oferowane mężczyznom są zgodne z teorią konkurencji na rynku pracy. Jednak po uwzględnieniu zmiennej poszukiwania zatrudnienia dyskryminacja płacowa młodych mężczyzn okazuje się niezgodna z przewidywaniami wynikającymi z tej teorii. Pomimo niższych wynagrodzeń bazowych kobiety w wielu krajach są bardziej dyskryminowane z tytułu nadmiernego wykształcenia niż mężczyźni, co wynika z rodzaju systemu instytucjonalnego i norm dotyczących płci. W artykule przedstawiono możliwe wyjaśnienia tych dysproporcji, a w podsumowaniu zaprezentowano zalecenia dotyczące polityki mającej na celu wyeliminowanie dyskryminacji wynikającej z nadmiernego wykształcenia.

**Słowa kluczowe:** nadmierne wykształcenie, dyskryminacja płacowa, model wyboru, teoria poszukiwania pracy, teoria konkurencji na rynku pracy