Gender gaps in skills, tasks, and employment outcomes

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Abstract

This report studies the gender differences in job tasks and their relationship with two important labour market outcomes: wages and skills mismatch. We disentangle gender gaps in occupational tasks and within-occupation, worker-level tasks, using worker-level PIAAC and EWCS data. We find that women perform more routine-intensive tasks than men, even more so in more developed countries. Moreover, women face larger pay penalties for working in more routine-intensive occupations. Within occupations, women perform more routine intensive tasks, but the associated pay penalties are, on average, similar to those experienced by men. We also show that in countries with more gender equal legislation and more egalitarian norms, the contribution of job tasks to the gender wage gap tends to be smaller. Analysing the incidence of skills mismatch, we show that the over-skilling decreased between 2005 and 2015, while under-skilling increased over this period, both for men and women. The expansion of non-routine cognitive occupations (analytical and interpersonal) induced by digitalisation can partially explain these changes in the incidence of skills mismatch. Women performing non-routine cognitive tasks (both analytical and interpersonal) are more likely to be under-skilled and less likely to be over-skilled. Among men, these links hold for non-routine analytical tasks only.

Keywords

Task content of jobs, skills, gender gaps, gender norms, skills mismatch, over-skilling, under-skilling

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1 Introduction

Information and Communication Technologies (ICT) and robots have been changing the world of work in the last few decades. Computers and other digital technologies have changed the structure of job tasks performed by humans. They have reduced the role of routine tasks - both manual and cognitive - and increased the role of non-routine cognitive tasks: analytical and interpersonal (Acemoglu & Autor, 2011). These task content changes occurred within and across occupations (Autor *et al.*, 2003; Spitz - Oener, 2006) and have led to job and wage polarisation in developed countries (Goos *et al.*, 2014). The hollowing out of middle-paid jobs has created winners and losers of technological progress and globalisation.

The gender dimension of these changes has been important but relatively understudied. On the one hand, routine-replacing technologies increase returns to social skills, which women tend to have a comparative advantage in (Deming, 2017), so they benefit more from ICT adoption than men (Jerbashian, 2019). On the other hand, women lag behind men in skills complementary to new technologies: women are less likely than men to study in Science, Technology, Engineering, and Mathematics (STEM) college programmes (Delaney & Devereux, 2019) and exhibit lower numeracy skills (Rebollo-Sanz & De la Rica, 2020). Nevertheless, adopting robots in European countries has narrowed the within-occupation and within-sector gender pay gap (Aksoy *et al.*, 2021). The results on the relationship between digitalisation and the incidence of skills mismatch are mixed (Lucifora & Origo, 2002; McGuinness *et al.*, 2021), and only few studies focus on gender differences.

Occupational segregation by gender and gender-based sorting to tasks within occupations are persistent phenomena. They both are essential sources of the gender wage gap (Bizopoulou, 2019; Blau & Kahn, 2017; Stinebrickner *et al.*, 2018) and, potentially, the gender gap in skills mismatch.

This paper concentrates on the gender differences in job tasks and their relationship with two important labour market outcomes: wages and skills mismatch. First, we explore the relationship between job tasks and wages, focusing on the role of gender norms (Section 2). We found that, on average, women perform more routine-intensive tasks than men because: (i) women work in more routine-intensity occupations; (ii) women do more routine tasks within occupations. Women face larger pay penalties for working in routine occupations. Within occupations, women perform more routine intensive tasks, but the associated pay penalties are, on average, similar to those experienced by men. We also show that in countries with more equal legislation and more egalitarian norms, the contribution of job tasks to the gender wage gap tends to be smaller.

Next, we describe the changes in the incidence of mismatch in recent years and assess the link between job tasks and skills mismatch (Section 3). The over-skilling decreased between 2005 and 2015, while under-skilling increased over this period, both for men and women. The expansion of non-routine cognitive tasks (analytical and interpersonal) induced by digitalisation can partially explain these changes in the incidence of skills mismatch. Our results show that under(over)-skilling is positively (negatively) linked to performing non-routine cognitive analytical tasks among women and men, while under(over)-skilling is positively (negatively) linked to performing non-routine interpersonal tasks among women only.

2 Gender, norms, and job tasks [1]

Gender-based sorting across occupations and tasks within occupations are common features of labour markets, and they are important sources of the gender wage gap (Bizopoulou, 2019; Blau & Kahn, 2017; Stinebrickner *et al.*, 2018). One of the potential explanations for the persistence of occupational segregation is the presence of gender norms regarding the role of men and women in society (Cortes & Pan, 2018). Building on the theoretical foundations set by Akerlof and Kranton (2000), economists started to study the relationship between gender norms and labour market outcomes. Gender norms are shown to be related to female employment (Fernández & Fogli, 2009; Fortin, 2005), differences in competitiveness (Gneezy *et al.*, 2009), and performance in math tests (Nollenberger *et al.*, 2016). In the context of task allocations, women more often than men volunteer, receive and accept requests for tasks with low promotability. The driver of these gender differences is the belief that women are more likely than men to volunteer (Babcock *et al.*, 2017).

Gender norms - different social expectations for men and women - may influence the sorting across job tasks and the prices of tasks. Counter-stereotypic behaviour is often subject to social and economic sanctions, such as limited opportunities for promotion and worse interpersonal relations (Parks-Stamm *et al.*, 2008; Rudman & Phelan, 2008). If society expects men to do less routine-intensive tasks than women, they may be penalised more than women for performing routine tasks. The emergence of comparable, cross-country data that allows measuring worker-level skills and job tasks has provided new opportunities to study the gender gap in job tasks, their contribution to the gender wage gap and the relationship with gender norms. Lewandowski *et al.* (2022) constructed worker-level measures of skills and job tasks for a broad set of high-, middle-, and low-income countries. They found that women perform more routine-intensive tasks than men with comparable jobs and skill levels.

In this section, we study the gender gap in job tasks, their contribution to the gender wage gap, and the relationship with gender norms and laws in a sample of high-, middle-, and low-income countries. We use PIAAC and STEP survey data. We disentangle gender gaps in occupational tasks and within-occupation, worker-level tasks. We find that women perform more routine-intensive tasks than men, even more so in developed countries. Moreover, women face larger pay penalties for working in more routine-intensive occupations. Within occupations, women perform more routine-intensive tasks, but the associated pay penalties are, on average, similar

[1] This section was written by Piotr Lewandowski and Marta Palczyńska.

to those experienced by men. We also show that in countries with more equal legislation and more egalitarian norms, the contribution of job tasks to the gender wage gap tends to be smaller, mainly because of less pronounced segmentation of men and women into more/less routine-intensive jobs.

Previous studies focused on the association between gender differences in skills and labour market outcomes. The contribution of numeracy skills in explaining the gender gaps in labour market participation and hourly wages is limited (De la Rica *et al.*, 2020; Rebollo-Sanz & De la Rica, 2020). Also, after accounting for worker-level job tasks, a gender gap in hourly wages remains significant (De la Rica *et al.*, 2020), which suggests that women are paid less than men for performing similar tasks. Tverdostup and Paas (2022) showed that the contributions of different components of human capital to explaining the gender wage gap vary significantly between countries. The work experience related to a current position is the only component of human capital consistently decreasing gender wage disparities. Gender differences in the allocation of workers with similar skill levels to more and less routine job tasks may help to understand why lower skill levels among women account for only a small share of existing gender gaps in labour market outcomes.

2.1 Data and descriptive statistics

2.1.1 Data

2.1.1.1 Measurement of worker tasks

Our worker-level data come from two comparable surveys: OECD's Programme for the International Assessment of Adult Competencies (Survey of Adult Skills (PIAAC) 2019) and the World Bank's Skills Measurement Program (The STEP Skills Measurement Program 2017). Our sample includes 37 countries in total.

PIAAC survey collected data in three rounds (in 2011-2012, 2014-2015, and 2017) in 39 high- or middle-income countries. We use data from 30 countries[2] for which data on wages and occupations at a 2-digit level are available. The survey respondents were 16–65. Sample sizes ranged from about 3,900 in Russia to about 9,400 in Poland (among the countries in our sample). STEP data are available for 14 low- or middle-income countries, out of which we use

[2] Austria, Belgium, Chile, Cyprus, Czechia, Denmark, Ecuador, Finland, France, Germany, Greece, Indonesia, Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Lithuania, Mexico, Netherlands, New Zealand, Norway, Poland, Russia, Slovakia, Slovenia, Spain, United Kingdom, United States. Scientific use files are used for Austria (Statistics Austria, 2014) and Germany (Rammstedt et al., 2016).

seven[3] because of data quality or variable availability.[4] The STEP surveys were conducted between 2012 and 2015 among urban residents aged 15–64, with sample sizes ranging from about 2,600 in Colombia to about 4,000 in Kenya. As the STEP surveys are urban surveys,[5] skilled agricultural workers (ISCO-6) are omitted in all countries to improve comparability.

To measure the task content of jobs, we use survey-based measures of task content of jobs at the worker level, constructed by Lewandowski *et al.* (2022). Respondents in PIAAC and STEP surveys answered a large number of questions about tasks done in their jobs. Using the US PIAAC sample, the authors selected job tasks questions that maximise consistency with the widely used measures of job tasks proposed by Acemoglu and Autor (2011) and based on the US Occupational Information Network (O*NET) database. Table 1 shows the questions used to construct task content measures.

Applying the same definitions to workers in all countries covered by the PIAAC and STEP surveys allows worker-specific measurements that can be aggregated to describe country-level differences in job tasks.

Table 1. Survey task items from US PIAAC selected to calculate task content measures consistent with O*NET occupation task measures

Task content	Non-routine cognitive analytical	Non-routine cognitive interpersonal	Routine cognitive	Manual
Task items	Solving problems Reading news (at least once a month) Reading professional journals (at least once a month) Programming (any frequency)	Supervising others Making speeches or giving presentations (any frequency)	Changing order of tasks – reversed (not able) Filling out forms (at least once a month) Making speeches or giving presentations – reversed (never)	Physical tasks

[3] Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Laos.
[4] The study do not use seven available STEP datasets: China (Yunnan), Macedonia, Philippines, Serbia, Sri Lanka, Ukraine, and Vietnam. For China, Yunnan is one of the poorer and more rural provinces in China so it might not reflect the dominant patterns of work in Chinese urban areas. The survey of Philippines does not include information on occupation on a 2-digit level. The survey of Sri Lanka includes too few observations in urban areas (about 650 workers), the Ukraine survey lacks one of the questions required for this study's task measures, and the Vietnam survey has low quality of data on skill use at work. For Macedonia and Serbia the foreign value added share in the production of final goods and services (FVA share) is not available.
[5] Laos is the only STEP country in which both urban and rural residents were surveyed. We dropped the rural part of the sample in order to ensure consistency.

Next, we define a measure of relative routine task intensity (RTI) using the following formula (Lewandowski *et al.*, 2022):

$$RTI = \ln(r_{cog}) - \ln\left(\frac{nr_{analytical} + nr_{personal}}{2}\right),$$

where r_{cog}, $nr_{analytical}$, and $nr_{personal}$ are routine cognitive, non-routine cognitive analytical, and non-routine cognitive personal task levels, respectively. The RTI increases with the relative importance of routine tasks and decreases with the relative importance of non-routine tasks. The manual tasks are omitted from the formula because the survey data do not allow distinguishing between routine and nonroutine manual tasks and the manual measure is less comparable across countries than the other task content measures (Lewandowski *et al.*, 2022). The RTI is standardised using its mean and standard deviation in the United States.

2.1.1.2 Measurement of gender norms and gender equality laws

To analyse the relationship between country-level gender norms and gender differences in task allocation and task prices (wage premia or penalties), we use indicators on legal gender inequalities and indicators on attitudes towards gender roles. The indicators on legal gender inequalities come from World Bank's Women, Business and the Law (WBL) database. The WBL database includes eight indicators covering mobility, workplace, pay, marriage, parenthood, entrepreneurship, assets, and pension. In addition, it includes a combined index, an average of the eight indicators. The information on laws in each country is collected through the collaboration of legal experts based in the World Bank with local experts and updated yearly (Hyland *et al.*, 2020). The paper uses four indicators directly related to labour market decisions: workplace, pay, parenthood, entrepreneurship, and the aggregated WBL index.[6] We take the average indicator from 5 years before each country's PIAAC/STEP survey. All the indicators are standardised in the sample of 37 countries.

The indicators on attitudes towards gender roles come from World Value Survey (WVS) and European Value Survey (EVS). Traditional views towards gender roles are measured by agreement/disagreement with the statements:

1. when jobs are scarce, men should have more right to a job than women (% agree);
2. being a housewife is just as fulfilling as working for pay (% agree);

[6] The questions used to construct the indicators are listed in the Table A1 in the Appendix.

3. a working mother can establish just as warm and secure a relationship with her children as a mother who does not work (% disagree);
4. both the husband and wife should contribute to household income (% disagree).

The first two questions are available in WVS/EVS for 34 countries, while the last two are for 30 countries. For each country, we take the average score from all WVS/EVS waves within ten years before PIAAC/STEP survey. If there is no data available within ten years before PIAAC/STEP survey, we take any available year. The indicators are standardised in the sample of 34/30 countries. Some indicators are reversed to make interpretation easier: the higher the indicators' values, the more equal the laws/norms are.

2.1.1.3 Occupational task groups

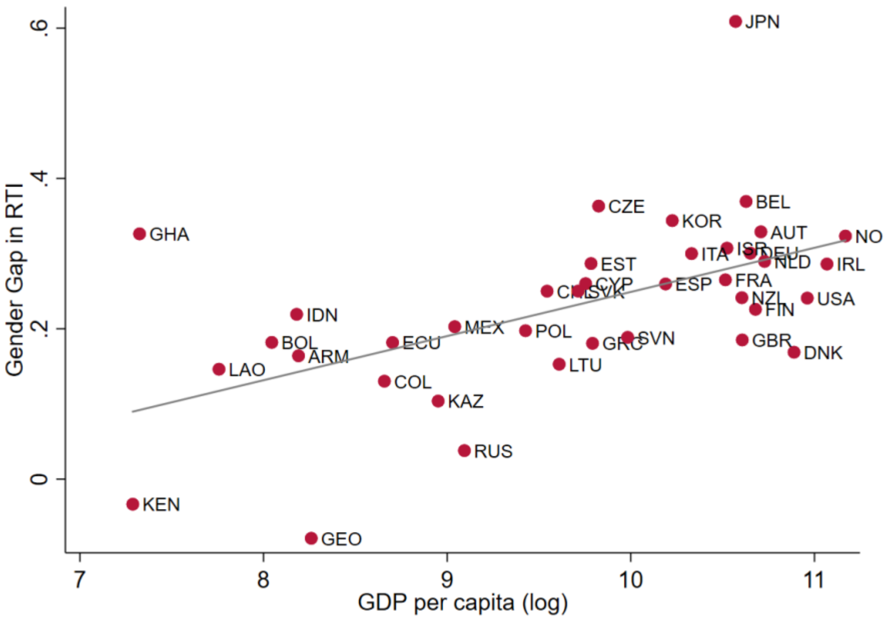
We classify occupations into the task groups according to the predominant task of their occupation: non-routine cognitive analytical (NRCA), non-routine cognitive personal (NRCP), routine cognitive (RC), and manual (M). Following Fonseca *et al.* (2018) and Lewandowski *et al.* (2020), we calculate the task content of occupations using the methodology of Acemoglu and Autor (2011) based on the O*NET data. Then, we assign each occupation to a task group based on the task with the highest intensity.[7] Occupations belong to the same task group independent of the country. Using occupational task groups allows us to assess whether gender gaps in tasks and task prices differ between various groups of occupations.

2.1.2 Cross-country differences in the gender gap in the task content of jobs and wages

We find that, on average, women perform more routine-intensive tasks than men (Figure 1). The gender gaps in tasks are present in all countries in our sample, except for Georgia and Kenya. Highly developed East Asian countries (Japan, Rep. of Korea) and Central Eastern European countries (Austria, Czech Republic) have the most significant gender gaps in average RTI. There is also a moderate, positive correlation between a country's development level and the size of gender gaps in the routine work intensity. In all analysed countries, women earn less on average, but the size of the gender wage gap is not related to the country's development level (Figure 2). However, at the country level, there is no relationship between the average gender gap in tasks and the gender gap in wages (Figure 3). Next, we will explore the relationship between tasks and wages at the occupation and worker levels.

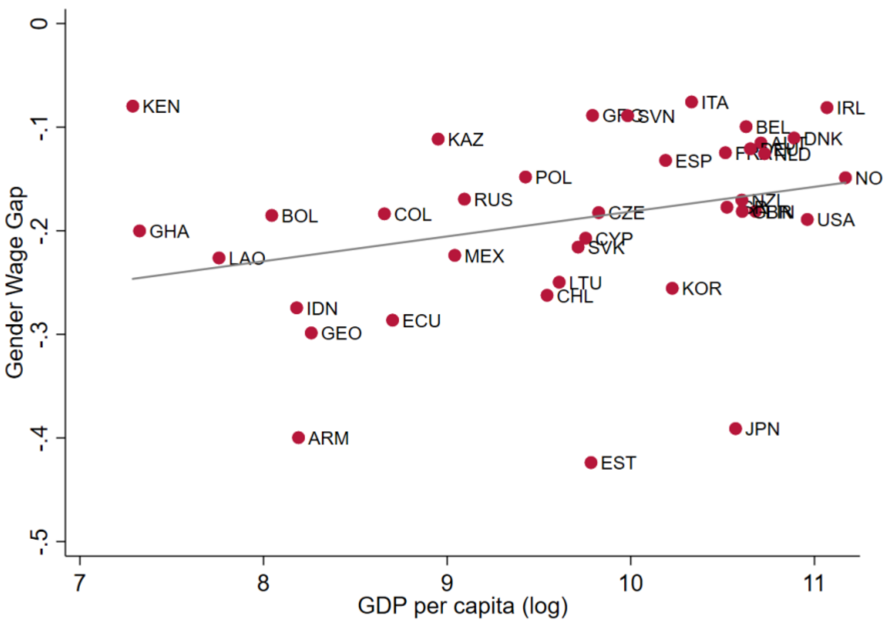
[7] The allocation of occupations to task groups is presented in the Table A2 in the Appendix.

Figure 1. The gender gap in the routine intensity of tasks (RTI) by countries' development level



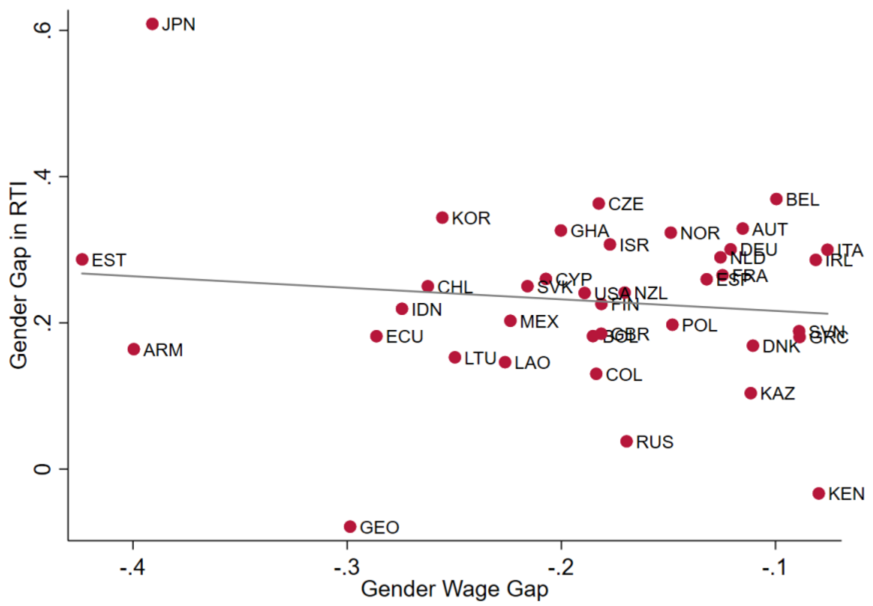
Note: R2=0.28. Adjusted gap: five age groups, three levels of education, four literacy levels, computer use, computer use^2, sectors, interactions between sector fixed effects and Ln(GDP per capita), country fixed effects, Foreign Value Added (FVA) share.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

Figure 2. Gender wage gap (GWG) by countries' development level



Note: R2=0.06. Adjusted gap: five age groups, three levels of education, four literacy levels, computer use, computer use^2, sectors, interactions between sector fixed effects and Ln(GDP per capita), country fixed effects, Foreign Value Added (FVA) share.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

Figure 3. Gender gap in the routine intensity of tasks (RTI) by gender wage gap (GWG)



Note: Adjusted gap: five age groups, three levels of education, four literacy levels, computer use, computer use^2, sectors, interactions between sector fixed effects and Ln(GDP per capita), country fixed effects, Foreign Value Added (FVA) share.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

2.2 Methodology

To study the gender differences in job tasks, first, we analyse the selection into more routine occupations. We estimate pooled OLS regression of the form:

$$\boldsymbol{RTI_{jc} = \beta_0 + \beta_1 F_i + \beta_2 Z_{sc} + \beta_3 G_{sc} + \beta_4 E_i + \gamma_s + \alpha_c + \varepsilon_{ijsc}} \qquad (1)$$

where, RTI_{jc} is the average RTI in occupation j in country c (excluding individual i); F_i is the gender of worker i; Z_{sc} is the technology used in sector s in country c; G_{sc} measures globalisation in sector s in country c; E_i are individual skills of worker i; γ_s are sectoral fixed effects; and α_c are country fixed effects. The standard errors are clustered at an occupation * country level. Next, we estimate the gender differences in the worker-level routine task intensity within four occupational task groups.

$$\boldsymbol{RTI_{ijsc} = \beta_0 + \beta_1 F_i + \beta_2 Z_{sc} + \beta_3 G_{sc} + \beta_4 E_i + \gamma_s + \alpha_c + \varepsilon_{ijsc}} \qquad (2)$$

where, RTI_{ijsc} is the routine task intensity of individual i in occupation j in sector s in country c. We estimate this model without and with occupational fixed effects.

Finally, to study the gender differences in the prices paid for performing routine jobs and tasks, we estimate pooled OLS regressions of the form:

$$\boldsymbol{lnw_{ijsc} = \beta_0 + \beta_1 F_i + \beta_2 RTI_{ijsc} + \beta_3 RTI_{ijsc} * F_i + \beta_4 RTI_{jc} + \beta_5 RTI_{jc} * F_i + \beta_6 Z_{sc} + \beta_7 G_{sc} + \beta_8 E_i + \gamma_s + \alpha_c + \varepsilon_{ijsc}} \quad (3)$$

where, w_{ijsc} is the hourly wage of individual i in occupation j in sector s in country c.

We control for both worker-level routine task intensity and average occupational RTI. This specification, which follows Autor and Handel (2013), allows accounting for the self-selection of workers into more and less routine-intensive occupations based on comparative advantages (Roy, 1951). It also allows us to quantify the role of gender differences in selection into more routine-intensive occupations and gender gaps in the allocation of tasks within occupations.

We measure technology by the share of workers in sector s in country c who use computers at work. PIAAC and STEP surveys include a measure of individual computer use. We aggregate this variable to the sector level as decisions about individual computer use and tasks are potentially made simultaneously. We use a quadratic specification to allow for a potential nonlinear relationship between computer use and wages. We measure globalisation by the foreign value-added share in the production of final goods and services (FVA share).

We measure workers' skills by education level (primary, secondary, tertiary) and their interaction with gender, age (measured by 10-year age groups), and literacy (four proficiency levels). Literacy is defined as *'The ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential.'* (OECD, 2013: p. 59).

To capture the role of economic structures, we use fixed effects for 18 sectors based on the 1-digit codes of the International Standard Industrial Classification (ISIC Rev.4), and their interactions with GDP per capita (log, demeaned). In all worker-level regressions, standard errors are clustered at the country-sector level. We estimate wage models for all workers and separately for workers in four occupational task groups described in Section 2.1.

To assess if the gender differences in the allocation of tasks and their prices vary with the gender norms and legal gender inequalities in a country, first, we use the Blinder-Oaxaca decomposition to estimate the parameters for endowment and coefficient effects of RTI_{ijsc} and RTI_{jc} for each country separately. Second, we regress the estimated parameters on gender norms and legal inequalities indicators.

2.3 Gender differences in tasks and task prices at the occupational and individual level

2.3.1 Gender Gap in tasks

2.3.1.1 Selection into routine occupations

Women work in more routine-intensive occupations than men (Table 2). When looking at the worker level (equation 1), on average, women's occupations are 0.07 SD[8] more routine (Table 2, column 1). We also analyse the relationship between female share and the occupational RTI at the occupation/country level, which confirms this result. The occupations with a higher female share have a higher mean RTI: 10 p.p. increase in the share of women in an occupation is related to 0.04 SD higher mean RTI of this occupation (Table 2, column 2).

Table 2. Gender differences in the selection to routine occupations

	Individual workers (1)		Occupation # country (2)
Female	0.069*** (0.010)	Female share	0.408*** (0.049)
N	117,361		1,350

Note: *p<0.05, **p<0.01, ***p<0.001. SE in parentheses. Model 1: We use standardised weights that give each country equal weight. Additional controls: three education levels, four literacy levels, five age groups, Women*education level interactions, sectors, interactions between sector fixed effects and Ln(GDP per capita), country fixed effects, Foreign Value Added (FVA) share, computer use, computer use^2. The standard errors are clustered at an occupation * country level. Model 2: estimation on variables' means in occupation (ISCO-2d)#country cells.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

2.3.1.2 Selection to routine tasks within occupations

While women work in more routine occupations than men, they also do more routine-intensive tasks within occupations. On average, the difference between women and men in RTI at the worker level is 0.23 SD (Table 3). Accounting for the occupational structure reduces the gender gap in RTI by 6%. The most considerable reduction in the RTI gender gap is among workers in non-routine cognitive personal occupations suggesting that there are the most significant gender differences in the selection to routine occupations within this group of occupations. When controlling for the occupation, we observe the smallest gender gap in RTI among workers in non-routine cognitive personal occupations (0.13 SD) and the biggest in routine cognitive and manual occupations (0.24-0.25 SD).

[8] The RTI is standardised using its mean and standard deviation in the United States.

Table 3. The gender gap in RTI within occupations

	All workers	Occupational groups			
		Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Manual
Average RTI at the worker level	0.243 (0.004)	-0.407 (0.009)	-0.465 (0.009)	0.282 (0.007)	0.720 (0.006)
Gender Gap in RTI at the worker level	0.229*** (0.012)	0.162*** (0.019)	0.159*** (0.019)	0.294*** (0.020)	0.270*** (0.021)
Gender Gap in RTI at the worker level (controlling for ISCO-2d)	0.215*** (0.012)	0.167*** (0.019)	0.125*** (0.018)	0.248*** (0.019)	0.243*** (0.022)
N	117,361	19,141	18,880	33,169	46,171

Note: *p<0.05, **p<0.01, ***p<0.001. SE in parentheses. We use standardised weights that give each country equal weight. Additional controls: three education levels, four literacy levels, five age groups, Women*education level interactions, sectors, interactions between sector fixed effects and Ln(GDP per capita), country fixed effects, Foreign Value Added (FVA) share, computer use, computer use^2. The standard errors are clustered at a sector * country level.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

2.3.2 Gender gap in task prices

Now, we assess if there are gender differences in wage penalties associated with more routine work at the occupational and worker levels. First, we estimate the gender wage gap (GWG), controlling for socio-demographic characteristics (including worker-level literacy) and sectoral characteristics, but not for RTI. We find that, in our sample, women earn 18.2% less than men with similar observable characteristics (Table 4, column 1). Second, we show that workers who perform more routine intensive tasks have lower wages. Accounting for the intensity of routine tasks reduces the estimated GWG as women perform more routine-intensive jobs. The estimated GWG amounts to 15.7% when we control for workers' RTI (Table 4, column 2), and it is virtually the same when we additionally control for occupational RTI (Table 4, column 3). Third, RTI is an important dimension of gender occupational segregation: the estimates of pay penalties associated with worker-level RTI (within occupation) are identical in models with RTI at the occupation level (Table 4, column 3) and with occupational fixed effects (ISCO-2-digit) instead of RTI at the occupation level (Table 4, column 4). The estimates of the GWG are very close to each other.

Notably, women face a bigger pay penalty for working in more routine-intensive occupations than men. Working in an occupation with an RTI higher by one is associated with 22.2% lower wages among women and 17.8% lower wages among men (Table 4, column 5). For example, the RTI difference of about one between occupations corresponds to the average difference between vocational education teachers (ISCO-232) and child care workers and teachers' aides (ISCO-532). At the same time, the penalty for performing more routine tasks within an occupation does not differ by gender. Hence, our results suggest that while women tend to work in more routine-intensive occupations and perform more routine tasks within occupations, the gender pay penalties associated with more routine work are present at the occupational level rather than within occupations.

Table 4. The correlates of wages – occupational and worker-level tasks

	All workers				
	(1)	(2)	(3)	(4)	(5)
Women	-0.182***	-0.157***	-0.156***	-0.139***	-0.145***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
RTI at the worker level		-0.107***	-0.072***	-0.072***	-0.078***
		(0.004)	(0.004)	(0.004)	(0.005)
RTI at the occupation level			-0.197***		-0.178***
			(0.010)		(0.012)
Women * RTI_occupation					-0.044**
					(0.015)
Women * RTI_worker					0.012
					(0.007)
Occupation 2-digit	No	No	No	Yes	No
N	102,916	102,916	102,916	102,916	102916
R^2	0.930	0.932	0.933	0,934	0.933

Note: *p<0.05, **p<0.01, ***p<0.001. SE in parentheses. We use standardised weights that give each country equal weight. Additional controls: three education levels, four literacy levels, five age groups, Women*education level interactions, sectors, interactions between sector fixed effects and Ln(GDP per capita), country fixed effects, Foreign Value Added (FVA) share, computer use, computer use^2. The standard errors are clustered at a sector * country level. The top and bottom 1% of the wage distribution in each country are excluded.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

Next, we explore the heterogeneity between workers in various occupational groups that typically differ in their task composition and skill demand. The GWG differs substantially between the occupational task groups (Table 5). It is the largest among workers in manual occupations (24.2%) and the smallest and insignificant among workers in non-routine cognitive personal (6.8%). Higher RTI, both at a worker and occupation level, is associated with lower wages.

Interestingly, we find no significant gender gap in the wage penalty for performing routine tasks within particular occupational groups (Table 5, columns 2-5). This result contrasts with a significantly higher wage penalty for women working in more routine occupations in the pooled sample (Table 4 and Table 5, column 1). This finding suggests that the segmentation of men and women largely drives the gender pay gap associated with routine work estimated across all workers into broad groups of occupations that differ in typical task demand (four occupational task groups) rather than by differences associated with performing more or less routine work within particular groups, for instance, various types of managerial or analytical occupations.

Moreover, in occupations that stand out with the higher routine task demand, namely routine cognitive, women have smaller penalties than men for performing more routine tasks within particular occupations, while women constitute the majority of workers in these jobs. This result may suggest that performing the most routine-intensive tasks in typical routine occupations is a strong negative signal about men's abilities, as men rarely perform such jobs. Also, it can indicate a sanction for counter-stereotypic behaviour.

Table 5. The correlates of wages by occupational groups

		Occupational groups			
	All workers	Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Manual
	(1)	(2)	(3)	(4)	(5)
Women	-0.145***	-0.140***	-0.068	-0.132***	-0.242***
	(0.013)	(0.038)	(0.046)	(0.018)	(0.033)
RTI at the occupation level	-0.178***	-0.025	-0.160***	-0.165***	-0.097***
	(0.012)	(0.046)	(0.036)	(0.033)	(0.025)
Women * RTI_occupation	-0.044**	-0.063	-0.024	-0.071	0.055
	(0.015)	(0.055)	(0.044)	(0.044)	(0.034)
RTI at the worker level	-0.078***	-0.079***	-0.111***	-0.092***	-0.064***
	(0.005)	(0.011)	(0.014)	(0.011)	(0.007)
Women * RTI_worker	0.012	-0.010	0.017	0.035*	0.015
	(0.007)	(0.015)	(0.021)	(0.014)	(0.010)
N	102,916	16,685	16,384	28,941	40,906
R^2	0.933	0.927	0.932	0.936	0.937

Note: *p<0.05, **p<0.01, ***p<0.001. SE in parentheses. We use standardised weights that give each country equal weight. Additional controls: three education levels, four literacy levels, five age groups, Women*education level interactions, sectors, interactions between sector fixed effects and Ln(GDP per capita), country fixed effects, Foreign Value Added (FVA) share, computer use, computer use^2. The standard errors are clustered at a sector * country level. Top and bottom 1% of the wage distribution in each country are excluded
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

2.4 Gender norms and the task content of jobs

In this section, we examine if the cross-country differences in the task allocations' and task prices' contributions to the GWG vary with the gender norms and legal equality. First, we present the results of Blinder-Oaxaca decomposition for the pooled sample as a benchmark. Then, we re-estimate our baseline models for particular countries and calculate the Blinder-Oaxaca decomposition for each country. Finally, we regress the overall GWG and the components associated with occupational and worker's tasks - endowments and prices/returns - against the country-level gender norms and legal inequalities indicators.

In the pooled sample, only the worker-level RTI (both endowments and prices) contributes to the GWG (Table 6). Women would earn more if they did the same amount of routine tasks as men, but they would earn less if they experienced the same prices for routine tasks as men.

Generally, countries with more gender-equal legislation tend to have a smaller GWG. This relationship holds for workplace equality, parent equality, entrepreneurship equality, and the synthetic indicator of legal equality (WBL index) (Table 7A). However, the associations with task-related components of the GWG are less pronounced. We find that in countries with stronger equality in parenting-related legislation, the contribution of endowments in occupational RTI tends to be smaller (Figure 4A). This result means that the segmentation of men and women into more and less routine-intensive occupations is less pronounced. Also, in these countries, the contribution of prices of worker-level tasks tends to be smaller, which suggests that there is more gender equality in paying for similar tasks within occupations (Figure 4B). Interestingly, it is men who experience lower pay for routine tasks within occupations in countries with less equal parenting legislation. Overall, the countries with more equal parenting legislation have lower GWG and smaller total contributions of all task-related factors.

Regarding gender norms, countries with more egalitarian norms towards the labour market tend to have a lower GWG (Table 7B). In countries with more egalitarian norms towards earning income,[9] the contribution of endowments in RTI tends to be smaller, especially at a worker level (Figures 4C-4D). In countries with more egalitarian attitudes, the differences in job tasks performed by men and women are smaller, especially in the allocation of more and less routine tasks within particular occupations. The results are qualitatively the same if we measure the gender norms by men's or women's answers (Appendix, Table A6).

[9] With lower shares of people who disagree that "both the husband and wife should contribute to household income."

Table 6. Contributions to GWG of the allocation and prices of tasks

Endowments		Coefficients	
Occupational RTI	Worker-level RTI	Occupational RTI	Worker-level RTI
(1)	(2)	(3)	(4)
-0.002	0.008***	0.004	-0.004*
(0.004)	(0.002)	(0.004)	(0.002)

Note: The Blinder-Oaxaca decomposition with control variables: three education levels, four literacy levels (1 PV used), five age groups, sectors, Foreign Value Added (FVA) share, computer use, computer use^2, country fixed effects. Standard errors in parentheses. *p<0.05, **p<0.01, ***p<0.001.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

Table 7. Gender norms and laws and the differences in the allocation and prices of tasks on the country level

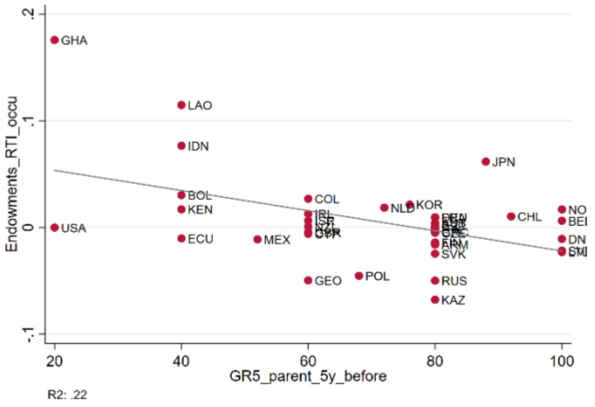
	Endowments		Coefficient		Total contribution of RTI	GWG
	Occupational RTI	Worker-level RTI	Occupational RTI	Worker-level RTI		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Gendered laws						
Workplace	-0.003 (0.007)	-0.002 (0.003)	-0.022 (0.012)	-0.001 (0.003)	-0.028 (0.018)	-0.044* (0.017)
R^2	0.004	0.015	0.087	0.008	0.068	0.151
N	37	37	37	37	37	37
Pay	0.000 (0.007)	-0.002 (0.003)	0.002 (0.013)	0.003 (0.003)	0.003 (0.018)	-0.034 (0.018)
R^2	0.000	0.011	0.001	0.034	0.001	0.091
N	37	37	37	37	37	37
Parent	-0.021** (0.007)	-0.001 (0.003)	-0.021 (0.012)	0.007** (0.003)	-0.036* (0.017)	-0.047** (0.017)
R^2	0.218	0.005	0.081	0.189	0.108	0.177
N	37	37	37	37	37	37
Entrepreneurs hip	-0.005 (0.007)	-0.000 (0.003)	0.009 (0.013)	0.004 (0.003)	0.009 (0.018)	-0.047** (0.017)
R^2	0.011	0.000	0.016	0.065	0.007	0.176
N	37	37	37	37	37	37
WBL index	-0.007 (0.007)	-0.001 (0.003)	-0.012 (0.012)	0.004 (0.003)	-0.015 (0.018)	-0.054** (0.017)
R^2	0.025	0.005	0.025	0.063	0.020	0.234
N	37	37	37	37	37	37

B. Attitudes towards gender roles						
Scarce jobs to man	-0.009 (0.007)	-0.000 (0.003)	-0.011 (0.008)	0.003 (0.003)	-0.018 (0.014)	Scarce jobs to man
R2	0.050	0.000	0.058	0.034	0.050	R2
N	34	34	34	34	34	N
Being a housewife fulfilling	0.009 (0.007)	-0.004 (0.003)	-0.012 (0.008)	-0.005 (0.003)	-0.011 (0.014)	Being a housewife fulfilling
R^2	0.047	0.052	0.064	0.077	0.020	R2
N	34	34	34	34	34	N
Working mother	-0.004 (0.005)	-0.001 (0.003)	-0.020* (0.009)	0.000 (0.003)	-0.025 (0.015)	Working mother
R^2	0.022	0.004	0.157	0.001	0.091	R2
N	30	30	30	30	30	N
HH income contributions	-0.010* (0.005)	-0.008** (0.003)	0.001 (0.009)	0.000 (0.003)	-0.017 (0.015)	HH income contribution s
R^2	0.134	0.219	0.000	0.000	0.041	R2
N	30	30	30	30	30	N

Note: Model with an intercept. WBL & WVS indices are standardised. The higher the indicators' values, the more equal the laws/norms are. Control variables in the Blinder-Oaxaca decomposition: three education levels, four literacy levels (1 PV used), five age groups, sectors, Foreign Value Added (FVA) share, computer use, computer use^2. Standard errors in parentheses. *p<0.05, **p<0.01, ***p<0.001.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

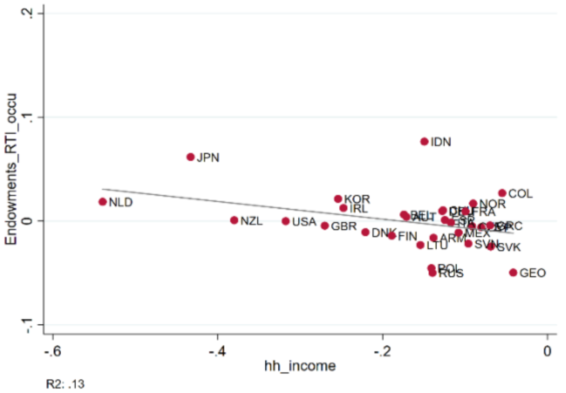
Figure 4. Gender norms and the differences in the allocation and prices of tasks

A. Laws: Parent (Endowments RTI occupation)

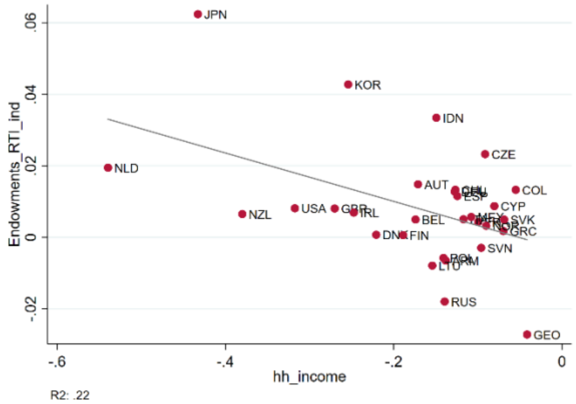


B. Laws: Parent (Coefficient RTI worker)

C. Attitudes: HH income contributions (Endowments RTI occupation)



D. Attitudes: HH income contributions (Endowments RTI worker)



Note: Regression with an intercept. WBL & WVS indices are standardised. The higher the indicators' values, the more equal the laws/norms are. Standard errors in parentheses *p<0.05, **p<0.01, ***p<0.001. Control variables in the Blinder-Oaxaca decomposition: three education levels, four literacy levels (1 PV used), five age groups, sectors, Foreign Value Added (FVA) share, computer use, computer use^2.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

3 Gender and skills mismatch[10]

Having skills that match the needs of employers is important in ensuring the sustainable integration of workers into the labour market. However, many workers are in jobs where their skills do not match the needs of the job. Across the European Union, 45% of workers feel they are in this mismatch situation (CEDEFOP, 2015). Skill mismatch can have negative effects on workers and society. For example, workers with skill mismatch are less engaged in their work (Badillo Amador *et al.*, 2012; Mcguinness & Wooden, 2009) and are less satisfied (Badillo Amador *et al.*, 2012). At a macroeconomic level, skill mismatch reduces the productivity of an economy (Adalet McGowan *et al.*, 2017). The skill mismatch concept hides two distinct situations. On the one hand, over-skilling occurs when an employee possesses more skills or knowledge than are required for their current job. This can lead to feelings of frustration and boredom that can affect their job satisfaction. On the other hand, under-skilling occurs when an employee lacks the necessary skills or knowledge to effectively perform their job duties. It can lead to feelings of inadequacy and a lack of confidence in their ability to perform their job than can potentially result in decreased productivity and job performance.

In 2020, the European Commission has addressed the issues of skill mismatch by putting in place a new skills strategy aimed at improving existing skills and training people in new skills (European Commission, 2020). This strategy is all the more important as European labour markets are massively impacted by, on the one hand, digitalisation that influences the task content of occupations (Autor, 2019; Lewandowski *et al.*, 2022). As underlined by Deming (2017) automation advancements lead workers to reduce the time they dedicate to routine tasks leaving space to develop their social skills, particularly useful to perform non-routine cognitive tasks. Ernst *et al.* (2018) underline, that Artificial Intelligence advancements are associated with an increase in the use of digital skills, social, emotional skills, and cognitive skills, and with a decrease in physical and manual skills, and basic cognitive skills. On the other hand, European labour markets are also affected by globalisation which reallocates jobs across business sectors (Autor *et al.*, 2013; Guren *et al.*, 2015).

The existing literature reveals mixed links between digitalisation and the potential skill mismatch felt by employees (Lucifora & Origo, 2002; McGuinness *et al.*, 2021). Few studies give attention to the difference that can appear between men and women. In many studies on skill

[10] This section was written by Laetitia Hauret, Ludivine Martin, and Nela Šalamon.

mismatch, gender is only a control variable. In this context, the research questions examined in the study at hand are the following:

- How has skills mismatch (under- and over-skilling) of men and women changed over the period 2005-2015?
- Is there a link between the type of tasks performed and their skill mismatch?
- Does the type of tasks play a role in the difference in the skill mismatch feeling between men and women (i.e. in gender skill mismatch gap)?

To conduct our analysis, we use data from the European Working Conditions Survey from 2005 to 2015. Based on a European country sample, we highlight that the skill mismatch feeling decreases between 2005 and 2015 for both sexes. However, this decrease is only due to a decrease in over-skilling, while under-skilling during the same period grew. We find that the type of tasks is linked to the report of being under (over)-skilled by men and women. Finally, in some sub-groups of countries, the type of tasks plays a role in explaining the gender skill mismatch gap.

3.1 Related literature

3.1.1 Skill mismatch, digitalisation, task evolution

In the existing literature, results are mixed regarding the link between technological changes and skill mismatch. On the one hand, Lucifora and Origo (2002), using data about unemployment and vacancies collected in EU countries in 1990, 1995, and 1999, find that technological development is not related to skill mismatch. On the other hand, McGuinness *et al.* (2021), on data from 28 European countries collected in 2014, show that the use of new technologies (e.g. machinery, ICT systems) is positively related to employees' sense of skill mismatch. Haskel and Martin (2001), on UK data collected in the 1990s, find that skills shortages are higher in firms that use new technologies (e.g. computer-aided design, word processing, computer control of production). Mendes De Oliveira *et al.* (2000), on Portuguese data collected in 1991, highlight technology-induced pockets of over-education and under-education.

Job polarisation induced by technological change leads also to skill mismatch. Sparreboom and Tarvid (2016), using data from 26 European countries collected in the 2000s', show that due to job polarisation, medium-skilled workers are more prone to suffer from skill mismatch than other workers. Zago (2020), using US data from 2005 to 2015, finds that job polarisation negatively influences skill-to-job match quality, especially for low-skilled workers.

To the best of our knowledge, few studies already investigated whether technological change and job polarisation affect women's and men's skills matching differently. Nevertheless, we can quote Moro-Egido (2020) who finds that women who perform non-routine tasks are more likely to be over-skilled while this relationship is not found for men.

3.1.2 Skill mismatch and gender

Literature on educational mismatch or skill mismatch has paid little attention to the issue of gender (Moro-Egido, 2020). Some arguments support the hypothesis that women are more prone to be over-qualified than men. For instance, according to Frank's (1978) theory of differential overqualification, married women may be more subject to mismatch because as second earners in the household, the location of their job depends on the location of their partner's job. Therefore, women face lower job search mobility and may accept a job that does not suit their qualifications. Empirical evidence testing the hypotheses of Frank's theory remains scarce. Nevertheless, Büchel and Battu (2003) highlight that in West Germany, married women suffer from a higher risk of being in a job which does not fully utilise their educational attainment compared to unmarried women and men (whatever their marital situation). Moreover, as women are more often in charge of family life, they need more flexibility in their job which can lead them to a worse match (Addison *et al.*, 2020). Some authors also point out that differences in the criteria used by firms to select male and female applicants or discrimination may lead to a different matching quality (Bills, 1988).

Regarding the link between gender and educational mismatch, the results of empirical studies are mixed (Quintini, 2011). On the one hand, based on Italian data, Cutillo and Di Pietro (2006) find that women graduates are less prone to be overeducated than their men counterparts. Li and Miller (2012) get the same result for Australian graduates. On the other hand, McGuinness and Bennett (2007) find that women who graduated in Northern Ireland are more likely to be overeducated compared to men. A first factor that may contribute to greater over-education among women is job sorting, which refers to the process by which individuals are placed into different jobs or occupations based on their characteristics, such as their education, skills, and experience. A second factor that may contribute to greater over-education among women is the promotion constraints. Battu *et al.* (2000) point out the sensitivity of the results to the way over-education is measured (objectively or subjectively)[11] and the specificities of the country.

[11] The objective measurement is based on the assessment by professional job analysts who attempt to determine the level and type of education required for each occupation. The subjective measurement is based on workers

Regarding the evolution of the over-education in the European Union in the 2000s, McGuinness *et al.* (2018) highlight that the phenomenon has only increased in some countries and that the trend has been very gradual. Over-education is increasing and higher for women compared to men in most of countries except in Italy and Slovakia.

Studies that examine skill mismatch by gender remain scarce. Falter (2009) based on Swiss data finds that women are more likely to be over-skilled and are less likely to be under-skilled than men. Caroleo and Pastore (2018), based on 2005 data on the professional trajectories of young Italian graduates, find that five years after their graduation, women are, everything else equal, more likely to feel over-skilled than men. Addison *et al.* (2020), using the US National Longitudinal Survey of Youth from 1979 and 1997 (NLSY79 and NLSY97), show that women are more prone to be mismatched than their men counterparts. However, they show, by comparing different cohorts, that the situation of women about skill mismatch is improving, contrary to that of men.

The individual consequences of over-skilling, contrary to the consequences of under-skilling, have been widely highlighted in the literature (e.g. Sánchez-Sánchez & McGuinness, 2015). For instance, being over-skilled results in a wage penalty (e.g. Mavromaras *et al.*, 2009 on Australian data from 2001 to 2006; McGuinness & Sloane, 2011 on UK graduates in 1999/2000 interviewed 5 years later; Salahodjaev, 2015 on Czech graduates in 1999/2000 interviewed 5 years later) and in lower job satisfaction (e.g. Congregado *et al.*, 2016 on EU-15 data for the period 1994-2001; Salahodjaev, 2015). Most studies find that over-skilling is more harmful to women than men (Addison *et al.*, 2020 on US data collected in 1979 and 1997; Moro-Egido, 2020 on data from 28 European countries collected in 2014; Salahodjaev, 2015). However, McGuinness and Sloane (2011) conclude to a wage penalty for being over-skilled only for men.

3.2 Data and method

3.2.1 Data

To conduct our analysis, we use data from the European Working Conditions Survey from 2005 to 2015. We conduct our analysis on 23 European countries,[12] all of them ranked as high-income countries by the OECD. These countries allow for a broad representation of countries

assessment of their own job. Women are more likely to be overeducated in studies, which use a subjective measurement.

[12] Due to data constraints, the EU-28 countries that are not included are Bulgaria, Croatia, Luxembourg, Malta, Republic of Cyprus and Romania.

both geographically and across welfare regime types according to the typology of Esping-Andersen (1990). The countries studied are divided into four groups as the following: Nordic countries (Denmark, Finland, Norway, Sweden), Western countries (Austria, Belgium, France, Germany, Ireland, The Netherlands, United Kingdom), Southern countries (Greece, Italy, Portugal, Spain), and Eastern countries (Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia). All countries examined are quite homogeneous in their legal equality and thus mostly no discrimination according to gender. Nordic countries generally rank higher in the Gender Gap Index,[13] followed by Western countries; even if there is some distinction between countries.[14] Eastern countries or those with a strong catholic tradition have a higher number of maternity leave days. Nordic and Western countries are characterised by high support for working-life balance policies, while Eastern countries have lower levels of support. There are also cultural differences and some differences in the labour market, especially gender differences in the use of part-time work. Finally, Southern countries are characterised by the largest gender difference in activity rates of men and women (except Portugal where the low level of wages pushes women to participate in the labour market as underlined by Kaiser, 2007).

3.2.2 Outcome variables

The EWCS data allow us to measure skill mismatch at the level of an individual worker. We use a subjective measure of skill mismatch as in Green and McIntosh (2007); McGuinness *et al.* (2021); Moro-Egido (2020). The subjective approach is not free from measurement error. Hartog (2000) highlights, in the context of education that employees tend to overestimate their job demands. This overestimation of job demands can lead to an overestimation of under-education. However, the subjective measure of educational mismatch was also found to lead to an overestimation of over-education (European Commission, 2015). Nevertheless, the subjective measure has several advantages compared to other measures. For instance, the subjective measure focuses on a specific job and not on an aggregation of jobs. Moreover, this measure has the advantage to be up-to-date (Hartog, 2000).

The worker self-assessment used in this paper relies on the following question: 'Which of the following statements would best describe your skills in your own work? (1) I need further

[13] WEF Global Gender Gap Index rankings 2006-2015.

[14] We can notice some differences between countries like: Hungary and Slovakia do not explicitly by law mandate equal remuneration; in Slovenia a woman cannot carry out work in an industrial job in the same way as a man; in Germany, Finland and the United Kingdom the government does not administer 100% of maternity leave benefits, and in Slovakia paid leave is not available to fathers; in Austria, Poland, Slovakia, the Czech Republic and Lithuania the age at which men and women can retire with full pension benefits are not the same.

training to cope well with my duties, (2) My present skills correspond well with my duties, (3) I have the skills to cope with more demanding duties.' We consider that an employee is under-skilled when he/she selects the first item, is well-matched when he/she selects the second item and he/she is over-skilled when he/she selects the third item.

3.2.3 Variable of interest

To quantify the exposure to de-routinisation, we use occupational measures (ISCO-08 3 digit) based on the O*NET database provided by Lewandowski *et al.* (2021) and elaborated on the task content measures of Acemoglu and Autor (2011). Each occupation recorded in the EWCS database is assigned the measures of de-routinisation.

Table 8. O*NET task items used for the construction of aggregate task content measures

Task content	Chosen task items
NRCA – Non-routine cognitive analytical	Analysing data/information; thinking creatively; interpreting information for others
NRCP – Non-routine interpersonal tasks	Establishing and maintaining personal relationships; guiding, directing and motivating subordinates; coaching/developing others
NRM – Non-routine manual	Operating vehicles, mechanised devices or equipment; spending time using hands to handle, control or feel objects, tools or controls; manual dexterity; spatial orientation
RC – Routine cognitive	The importance of repeating the same tasks; the importance of being exact or accurate; structured vs. unstructured work
RM – Routine manual	The pace is determined by the speed of equipment; controlling machines and processes; spending time making repetitive motions

3.2.4 Control variables

To establish the effects of de-routinisation and automation more precisely, we control for a number of confounding factors, in particular, macroeconomic conditions regarding exposure to globalisation using the Wang, Wei, Yu and Zhu (2017) indicators from the RIGVC UIBE (2016) database and exposure to offshorability measured for each occupation from Blinder and Krueger (2013).

We also control for a large scale of individual characteristics (e.g. age, having child(ren), educational level), and working conditions (open-ended contract, full-time, tenure, tenure squared, computer use). We also take into account other trends in working conditions that mays affect jobs in the same period, i.e. the job discretion, and the intensification of work as underlined by Green and Mostafa (2012). We also control for firm characteristics (size, business sectors).

Due to missing observations, the initial sample of 68,223 observations is restricted to 67,971 observations, with 31,250 men and 36,721 women. The descriptive statistics of all variables are presented in Appendix Table A7.

3.2.5 Method

Probit

To evaluate the evolution of under-skilling and of over-skilling over the period 2005 to 2015, we run probit models by gender by pooling the three waves of the survey.

The estimated model is the following:

$$Y=\alpha+\beta\text{'wave}++\pi\text{'TASK}+\theta\text{'MACRO}+\delta\text{'SOCIO\_DEMO}+\gamma\text{'WORK}+\Omega\text{'FIRM}+\vartheta\text{'COUNTRY\_GP}+\varepsilon \quad (1)$$

where Y is the outcome variable (under-skilling in one model and over-skilling in a second model), ‘wave’ dummy variables for the survey waves, ‘TASK’ for the task content measures, ‘MACRO’ for the macroeconomic globalisation conditions, ‘SOCIO_DEMO’ for the individual characteristics, ‘WORK’ for the working conditions, ‘FIRM’ for the employers characteristics, ‘COUNTRY_GP’ for the country groups dummies, , α is the constant and ε is the error term.

Decomposition

In an additional analysis, we use the results of the probit analyses conducted by gender to decompose the gender difference in, on the one hand, under-skilling and, on the other hand, over-skilling. We use a variant of the Blinder (1973) and Oaxaca (1973) decomposition done by Daymont and Andrisani (1984) model applied to the nonlinear model. This model estimates the share of the gender difference that is attributable to a difference in characteristics between men and women and the share of the gender difference that is attributable to gender differences in the coefficients on those characteristics. This model allows us to construct the counterfactual by asking the following question: what would be the probability of women being under-skilled if they had the same characteristics as men, and what would be the probability of women of being under-skilled if they valued the same characteristics as men?

The estimated model is the following:

$$\Delta_M^F = \{E_{\beta_M}(Y_{iM}|X_{iM}) - E_{\beta M}(Y_{iF}|X_{iF})\} + \{E_{\beta_M}(Y_{iF}|X_{iF}) - E_{\beta_F}\langle Y_{iF}|X_{iF}\rangle\} \quad (2)$$

where Yij is the outcome variable indicating the fact that a person i of group j (j=M, F) feels under-skilled (under-skilling in one model and over-skilling in a second model), Xij is a vector of the values of tasks characteristics, sociodemographic characteristics, working conditions, firm's characteristics, macro characteristics for person i of group j, and Bj the vector of coefficients for group j.

The first term of the equation represents the share attributable to differences in being under- (respectively over-) skilled that is due to differences in the covariates. The second term represents the share attributable to differences in the evaluation of these covariates.

We run this model, for the most recent year available in our data, i.e. 2015, on all countries studied and by country group.

3.3 Results

3.3.1 Evolution of skill mismatch and gender differences

As shown in Table 9, between 2005 and 2015, the prevalence of the skill mismatch feeling decreased both for men and women. While in 2005, 46% of women (48% of men) felt they had skills that were mismatched with their job, 41% of women (43% of men) felt that way in 2015. However, this observed decrease hides differences in the evolution of the under- and over-skilling. Similar trends are observed for men and women. Indeed, while over the period, the under-skilling affects a larger proportion of employees in 2015 than in 2005, less employees feel being over-skilled.

Table 9. Evolution of skill mismatch over time

	Men			Women			Men			Women		
	2005	2010	2015	2005	2010	2015	t-test 2005-10	t-test 2005-15	t-test 2010-15	t-test 2005-10	t-test 2005-15	t-test 2010-15
Skill mismatch	0.4755	0.4375	0.4304	0.4661	0.4418	0.4167	***	***	ns	**	***	***
Under-skilled	0.1263	0.1383	0.1467	0.1369	0.1471	0.1567	**	***	**	**	***	**
Over-skilled	0.3492	0.2992	0.2837	0.3292	0.2947	0.26	***	***	**	***	***	***

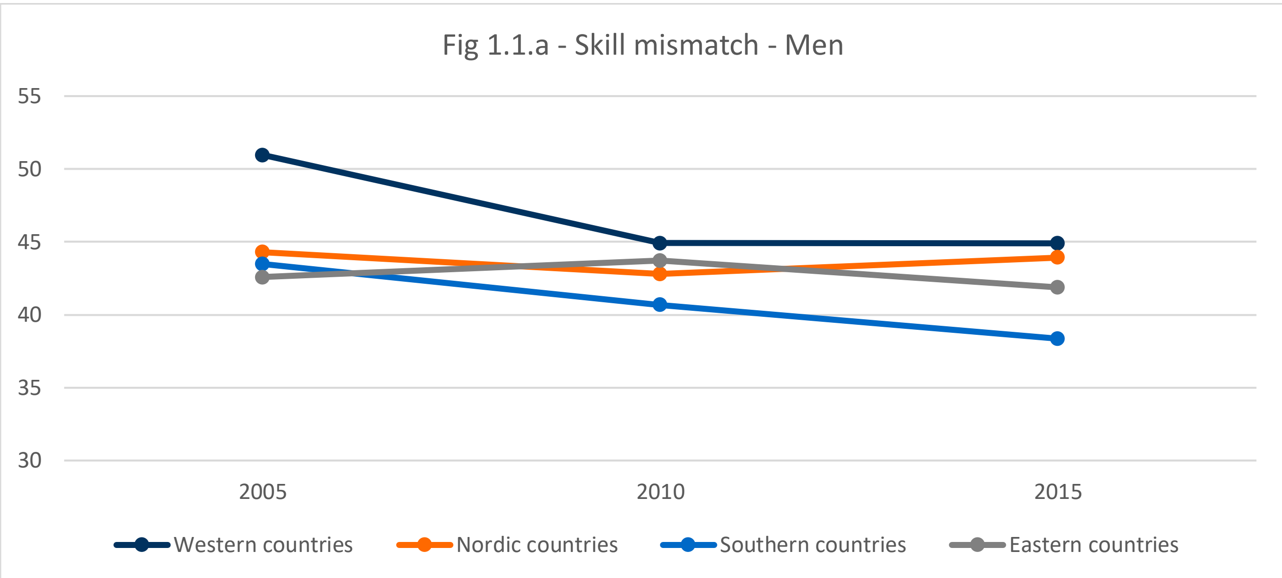
Note: t-test comparing the year 2010 or 2015 with 2005 significant at 1% when ***, 5% when **, not significant when ns.
Source: EWCS data

Moving on to skill mismatch by country groups (Figure 5),[15] we observe that workers in western countries are the ones that declared the highest levels of skill mismatch whatever their gender. While men and women in southern countries declared a level of skill mismatch closed to those working in Nordic and Eastern countries in 2005 (and 2010 for women), workers in southern countries declared the lowest level in 2015. The trend is downward except for men in Nordic countries and for women in Eastern countries.

Regarding under-skilling, in 2015, workers of Western countries are above the others whatever the gender. Men working in Southern and Eastern countries declared similar lowest levels while women working in Southern countries declared the lowest level. The trend is upward except in Eastern countries and in Southern countries for women.

Regarding over-skilling, the trend, whatever the gender, is downward, except for men working in Eastern countries. In 2015, for men, the levels of over-skilling are similar in the different countries, around 30%, except in Southern countries where it is lower. In 2015, for women it is in the Eastern group of countries where it is highest (around 28%).

Figure 5. Evolution of skill mismatch over time by country groups



[15] The detailed descriptive statistics by country are provided in Appendix Table A8.

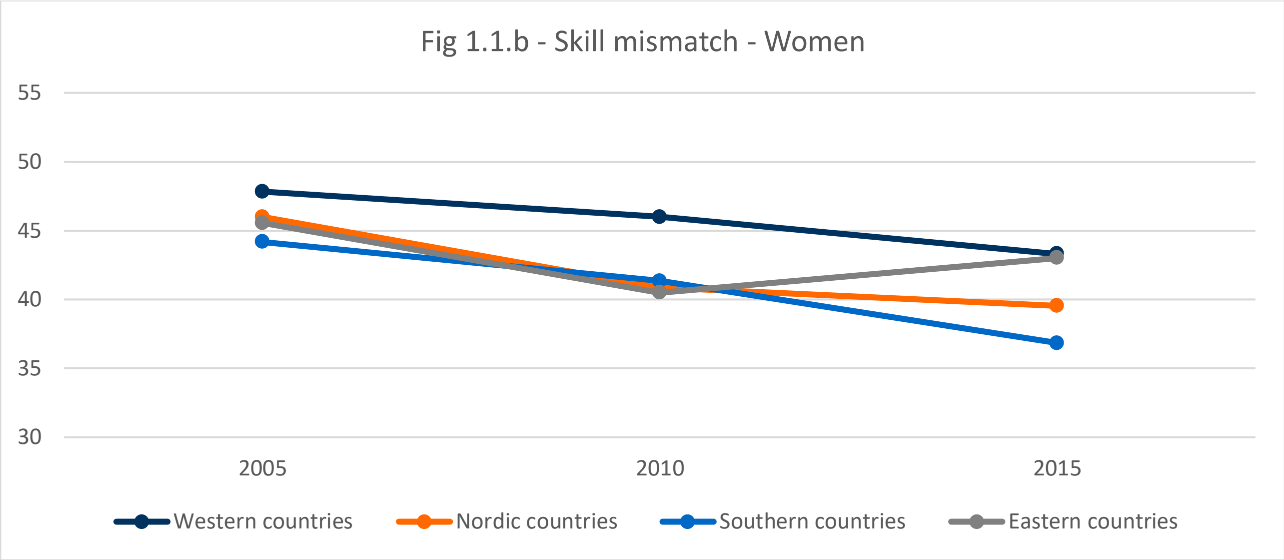


Fig 1.1.b - Skill mismatch - Women
55
50
45
40
35
30
2005
2010
2015
Western countries
Nordic countries
Southern countries
Eastern countries

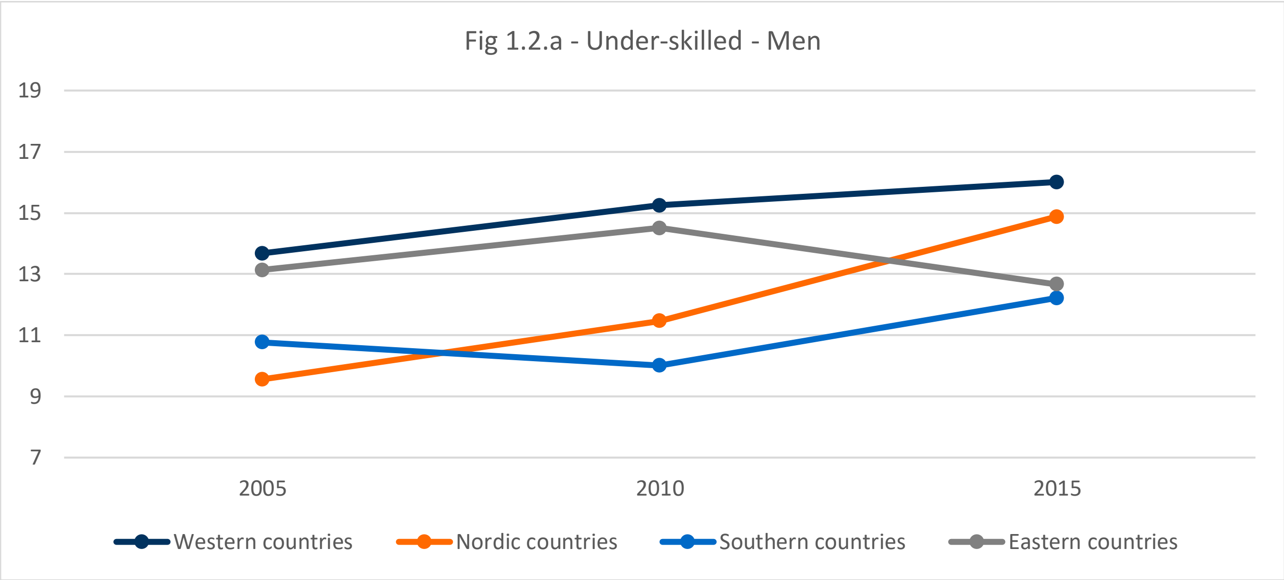


Fig 1.2.a - Under-skilled - Men
19
17
15
13
11
9
7
2005
2010
2015
Western countries
Nordic countries
Southern countries
Eastern countries

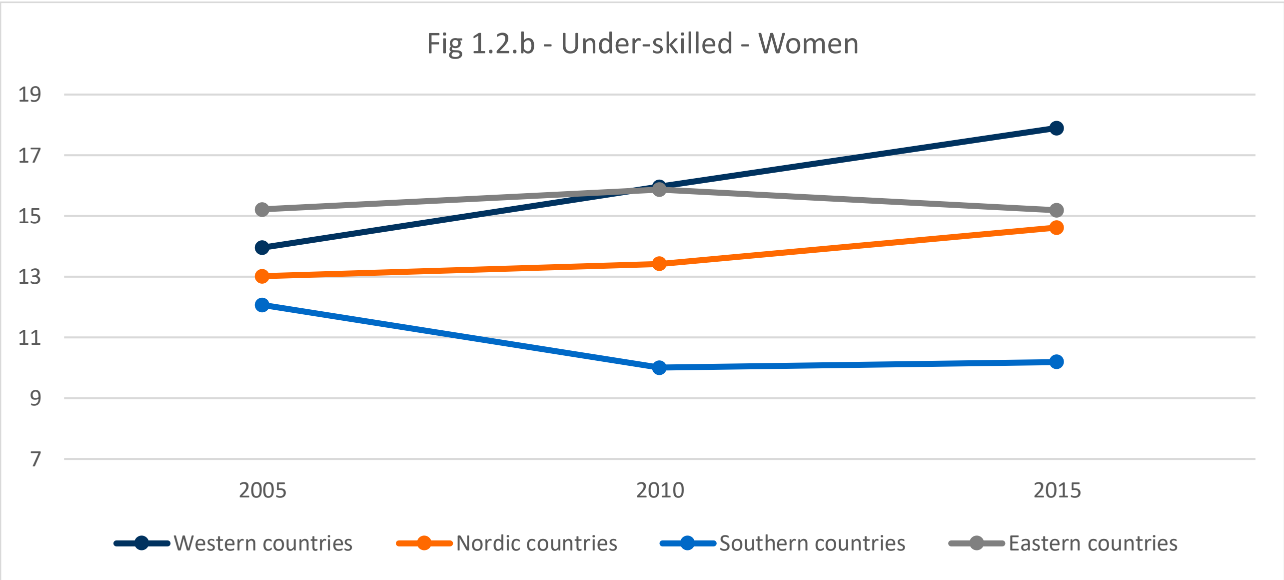


Fig 1.2.b - Under-skilled - Women
19
17
15
13
11
9
7
2005
2010
2015
Western countries
Nordic countries
Southern countries
Eastern countries

Fig 1.3.a - Over-skilled - Men

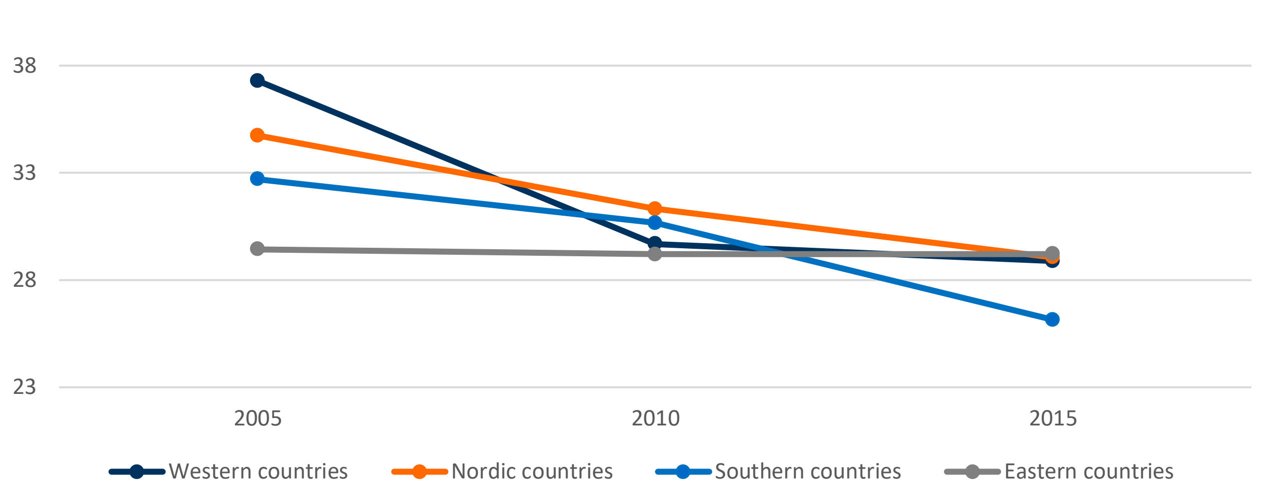
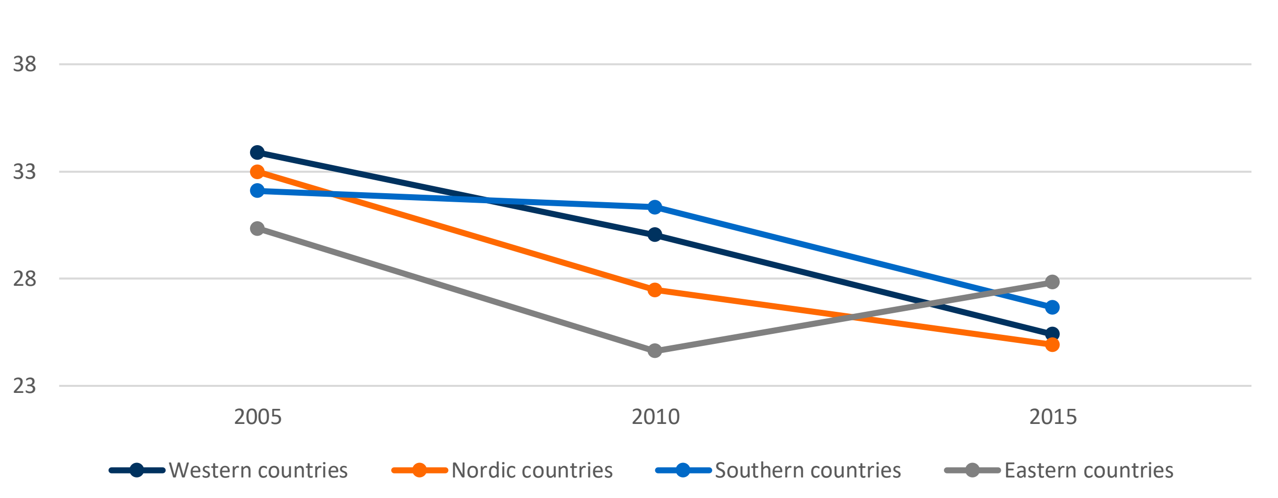


Fig 1.3.b - Over-skilled - Women

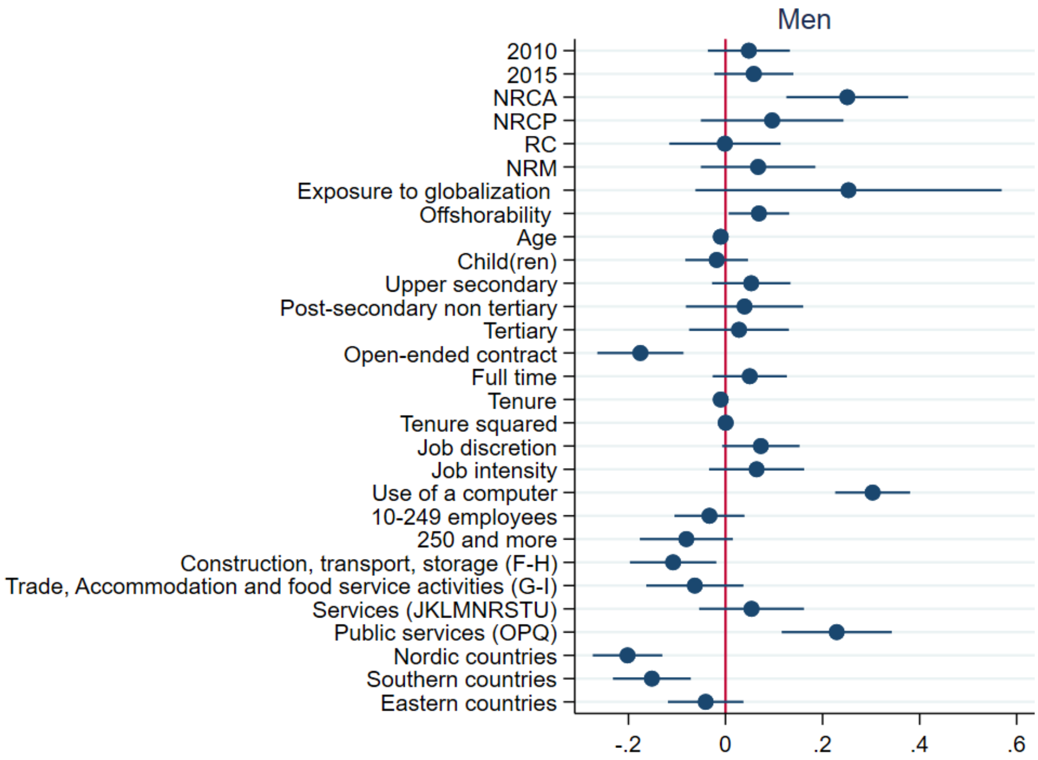


Sources: EWCS data, 2005, 2010, 2015. Weighted figures.

In order to assess whether the drivers of over- and under-skilling differ in the case of women and of men, we run probit models on the two sub-populations separated.

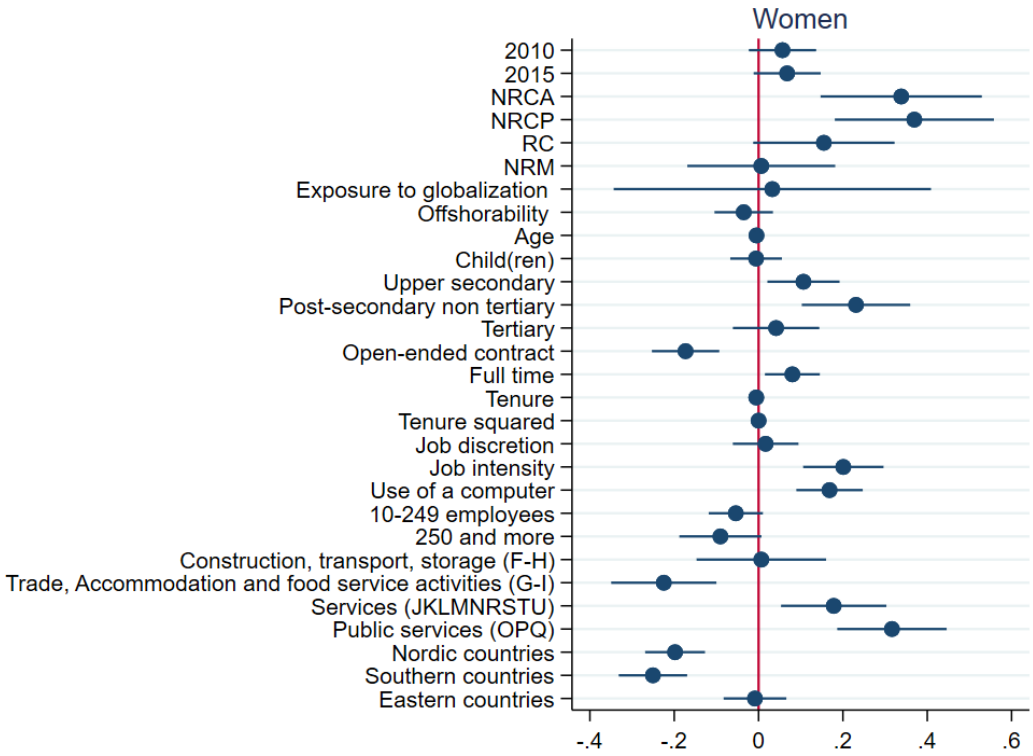
Figures 6 and 7 present the results for the drivers of the under-skilling feeling for men and women.

Figure 6. Under-skilling of men



Source: EWCS data, 2005, 2010, 2015. Weighted estimations

Figure 7. Under-skilling of women



Source: EWCS data, 2005, 2010, 2015. Weighted estimations

Others things equal, we observe, using the results of the probit models conducted separately on men and women, that the evolution of the under-skilling feeling is only significant for women in 2015.

As underlined by Deming (2017); Ernst *et al.* (2018), while manual and routine tasks decrease due to automation advancements, workers have more time to devote to tasks requiring cognitive skills. Nevertheless, in our study we observe that in comparison to routine manual (RM) tasks, performing non-routine cognitive analytical (NRCA) is positively linked with the under-skilling feeling of both men and women.

For women, the situation is worse, as all type of tasks except non-routine manual (NRM) are positively associated with this feeling.

Regarding macro variables, only the measure of offshorability of each occupation is positively linked to the under-skilling feeling of men.

Regarding the individual characteristics, the age is negatively related to this feeling for both men and women. Education (upper secondary and post-secondary non tertiary) is positively linked to the under-skilling of women.

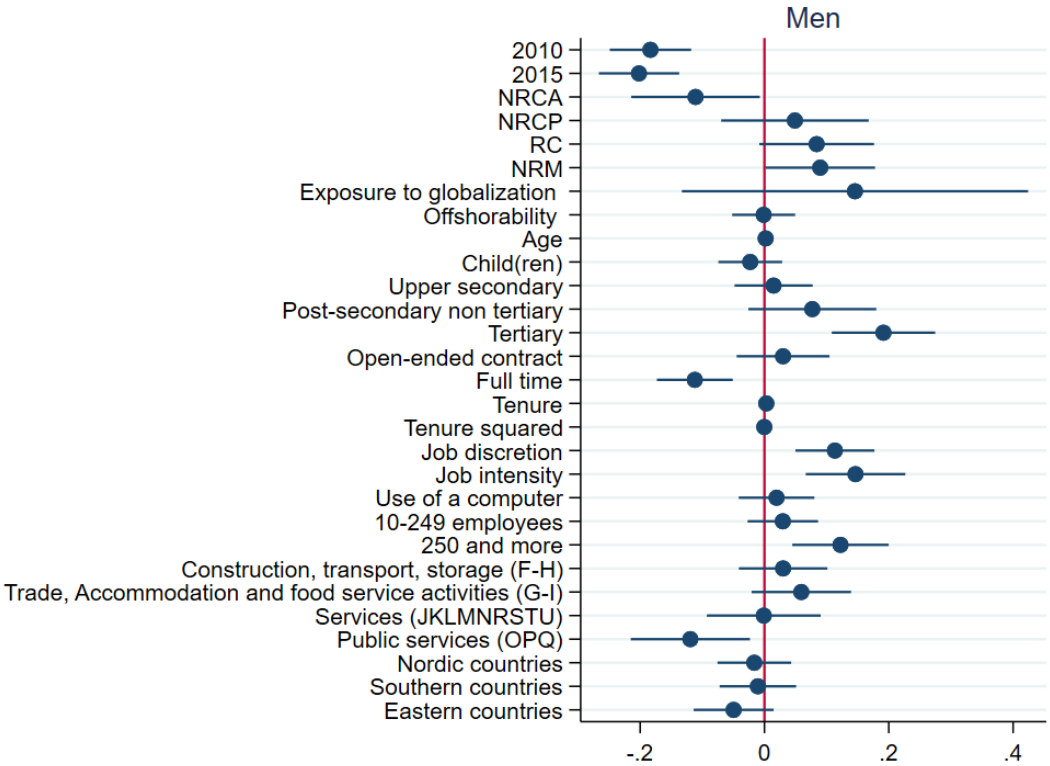
Regarding the contract characteristics, having an open-ended contract is negatively related to this feeling for both men and women. Working full-time is positively linked to the under-skilling feeling of women. Tenure is only significant for men with a U-shape. While job discretion is positively related to this feeling for men, it is the job intensity that is positively related to this feeling for women. The use of a computer is positively related to this feeling both for men and women.

Moving on to firms' characteristics, the under-skilling feeling appears above 10 employees for women and only above 249 for men. Compared to the industry, men and women working in the public services is negatively linked to the under-skilling feeling. For man working in construction, transport, storage (F-H) is negatively linked to this feeling. For women, working in trade, accommodation and food service activities (G-I) is negatively linked to this feeling and working in services (JKLMNRSTU) is positively linked to this feeling.

Finally, the country groups reveal differences across European regions shared by men and women. Working in a Nordic or a Southern country is negatively linked to the under-skilling feeling in comparison with Western countries (in reference) and Eastern countries (non-significant).

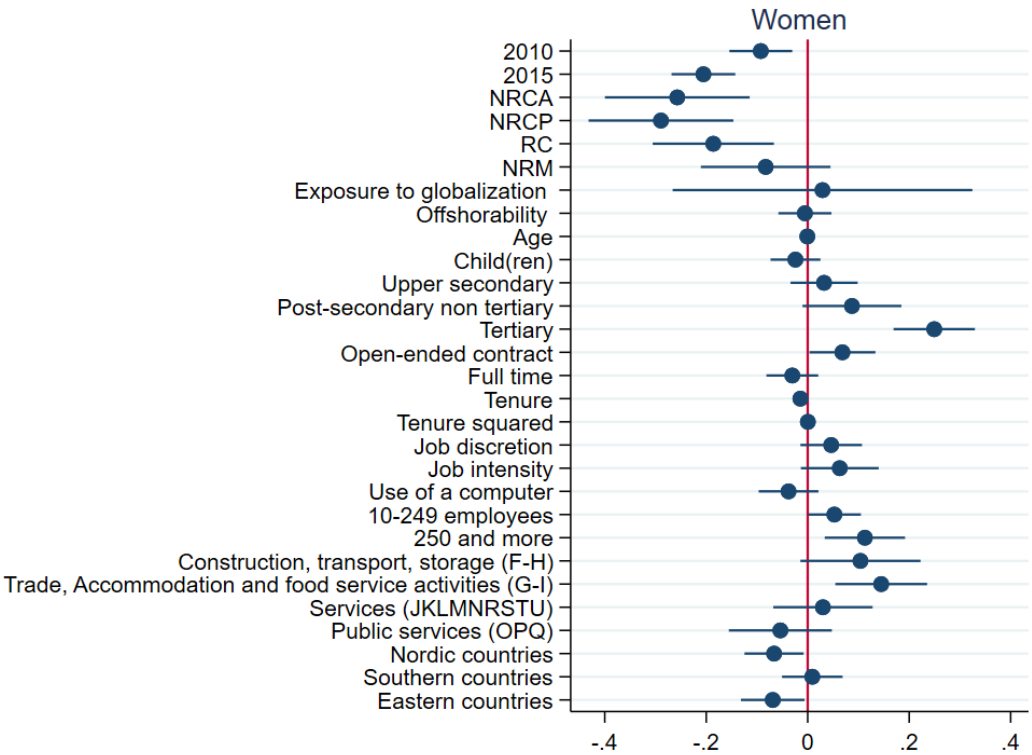
Figures 8 and 9 present the results for the drivers of the over-skilling feeling for men and women.

Figure 8. Over-skilling of men



Source: EWCS data, 2005, 2010, 2015. Weighted estimations

Figure 9. Over-skilling of women



Source: EWCS data, 2005, 2010, 2015. Weighted estimations

Using the results of the probit models conducted separately on men and women, we observe that the evolution of the over-skilling is negatively related to the 2010 and 2015 dummies confirming the reduction of this feeling across the studied period for both men and women shown in the descriptive statistics presented in Table 9.

In terms of tasks, in comparison to routine manual (RM) tasks, performing non-routine cognitive analytical (NRCA) is negatively linked with the over-skilling of both men and women. Routine cognitive (RC) and non-routine manual (NRM) are positively associated with this feeling among men. All types of tasks except non-routine manual (NRM) are negatively associated with this feeling among women.

Regarding the individual characteristics, only the post-secondary non-tertiary and tertiary education levels are positively linked to the over-skilling of women and only tertiary for men.

Regarding the contract characteristics, having an open-ended contract is positively related to this feeling for women. Working full-time is negatively linked to the over-skilling of men. Tenure is significant for women with a U-shape and only the tenure squared for men. Job discretion and job intensity are positively related to this feeling for men only.

Moving on to firms' characteristics, the over-skilling appears above 10 employees for women and only above 249 for men. Compared to the industry, men working in public services are negatively linked to over-skilling. For women working in construction, transport, storage (F-H) or in trade, accommodation and food service activities (G-I) are positively linked to this feeling.

Finally, the country groups reveal differences across European regions only for women. Working in a Nordic or an Eastern country is negatively linked to the over-skilling feeling in comparison with Western countries (in reference) and Southern countries (non-significant).

3.3.2 Decomposition of skill mismatch gender gap in 2015

The results of the decomposition for the under-skilling are presented in Table 10. For 2015, this table shows the mean differential in the under-skilling between women and men and the percentages associated with differences in mean values of characteristics and in the coefficients.

Table 10. Under-skilling: Blinder-Oaxaca decomposition results, by country group, 2015, probit model

	All countries		Nordic countries		Western countries		Eastern countries		Southern countries	
	Contribution	%	Contribution	%	Contribution	%	Contribution	%	Contribution	%
Total	-0.010	100	0.0025	100	-0.019*	100	-0.03*	100	0.020	100
Part diff. means	-0.017***	177	-0.012*	-518.13	-0.02***	108.27	-0.033***	130.30	-0.010**	-53.81
Part diff. coef.	0.007	-77	0.015	618.13	0.001	-8.27	0.007	-30.30	0.031***	153.81

Source: EWCS data, 2015. *Notes*: * significant at 10%; ** significant at 5%; *** significant at 1%. Weighted estimations

When we pool all the countries studied, the women and men are, on average, equally likely to express under-skilling. For the Nordic and Southern countries, the results do not show, also a significant gender difference in under-skilling.

However, we observe a significant gender difference in Western and Eastern countries. In these groups of countries, on average, more women than men feel under-skilled. For these groups of countries, most of the gender difference is attributable to a difference in characteristics between men and women. Differences in characteristics explain 108% and 130%, respectively, of the overall gender difference in under-skilling. Therefore, if women and men will have similar characteristics, the gap in the under-skilling between men and women would decrease.

Although in the Southern countries, the difference in the under-skilling of men and women is not significant (p=0.11), it is interesting to note that the main part of the difference is attributable to a difference in coefficients (153.8%); men and women value differently their characteristics. Moreover, in Southern countries, if women and men had the same characteristics, the gender gap in under-skilling would increase.

To go deeper in the analysis, we study the role of the type of tasks in being under-skilled between men and women (Table 11). We find that for Eastern countries, the largest part (53%) of the contribution of differences in means comes from differences in task characteristics. For Western countries, differences in tasks do not contribute to explaining significantly the gender difference. In Western countries, the largest part (181.9%) of the contribution of differences in means comes from differences in firm characteristics (sector, size). For Nordic countries, it is interesting to note that if women and men would perform the same type of tasks in their work, the gender difference in the under-skilling would be even less.

Table 11. Under-skilling: decomposition results by variable type, probit model

	All countries				Nordic countries			
	Diff. means		Diff. coefficients		Diff. means		Diff. coefficients	
Variable type	Contribution	%	Contribution	%	Contribution	%	Contribution	%
Total	-0.017	100	0.007		100	-0.012	100	0.015
Sociodemographic	0.000	-0.474	-0.036	-472.146	0.002	-21.587	-0.124	-818.117
Working conditions	0.005*	-29.311	0.023	300.855	-0.011***	92.847	-0.036	-241.014
Firm	-0.022***	123.85	-0.002	-31.287	-0.020***	157.624	-0.118	-777.069
Macro	0.000	-2.237	0.009	121.354	0.009	-73.521	-0.039	-262.723
Tasks	-0.001	10.392	-0.014	-187.665	0.007**	-55.3631	0.054	356.571
Country	0.000	-2.2148	0.008**	104.969				
Constant			0.020398	263.916			0.279	1,842.35
	Western countries				Eastern countries			
	Diff. means		Diff. coefficients		Diff. means		Diff. coefficients	
Variable type	Contribution	%	Contribution	%	Contribution	%	Contribution	%
Total	-0.020	100	0.001	100	-0.03284	100	0.007637	100
Sociodemographic	-0.000	2.052	-0.026	-1679.43	-0.00751*	22.88	-0.11205	-1467.22
Working conditions	0.013**	-65.507	0.020	1294.13	-0.008**	24.724	0.074	971.211
Firm	-0.037***	181.934	0.001	112.033	-0.007	22.12792	0.011	153.6625
Macro	0.002	-11.992	0.005	365.230	0.007*	-22.774	0.043	571.048
Tasks	0.001	-6.4876	-0.009	-597.118	-0.017**	53.042	-0.031	-407.195
Constant			0.009	605.158			0.021268	278.5
	Southern countries							
	Diff. means		Diff. coefficients					
Variable type	Contribution	%	Contribution	%				
Total	-0.010	100	0.031	100				
Sociodemographic	-0.000	3.639	-0.003	-10.443				
Working conditions	0.001	-10.952	0.015	50.360				
Firm	-0.002	26.752	-0.057	-185.419				
Macro	-0.003	33.629	-0.002	-7.978				
Tasks	-0.005	46.930	0.017	56.821				
Constant			0.061	196.660				

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Weighted estimations.
Sociodemographic: age, level of education, having at least one child; Working conditions: open-ended contract, full time, tenure, tenure squared, job discretion, job intensity, use of a computer; Firm: size, sector; Macro: exposure to globalisation, offshorability; Tasks: type of tasks; Country: country group.
Source: EWCS data, 2015

Regarding over-skilling, we observe that, for all countries pooled, on average less women than men feel over-skilled (Table 12). This result is also found for the Nordic and Western country groups. However, for Eastern and Southern countries the difference between women and men is not statistically significant at the threshold of 10%.

For the pooled countries as a whole, the Nordic countries and the Western countries, the main part of the gender difference is attributable to a difference in coefficients (60.8%, 77.9% and 60% respectively). For these countries, if women valued the same characteristics as men, the gender difference in under-skilling would decrease.

Except in the Southern countries, the largest part of the contribution of differences in means comes from differences in firm characteristics (Table 13). In Southern countries, differences in task characteristics between men and women explain the largest part of the differences in means (200%). Regarding differences in coefficients, the largest contributor is either the socio-demographic variables (age, level of education, having child(ren)) either working conditions (Open-ended contract, Full time, Tenure, Tenure squared, Job discretion, Job intensity, Use of a computer).

Table 12. Over-skilling: Blinder-Oaxaca decomposition results, by country group, 2015, probit model

	All countries		Nordic countries		Western countries		Eastern countries		Southern countries	
	Contribution	%	Contribution	%	Contribution	%	Contribution	%	Contribution	%
Total	0.023***	100	0.041***	100	0.034**	100	0.014	100	-0.004	100
Part diff. means	0.009**	39.189	0.009	22.047	0.013**	39.958	0.007	56.673	0.005	-104.4
Part diff. coef.	0.014*	60.811	0.032**	77.952	0.020*	60.041	0.006	43.326	-0.010	204.4

Source: EWCS data, 2015. Estimations

Table 13. Over-skilling: decomposition results by variable type, probit model

	All countries				Nordic countries			
	Diff. means		Diff. coefficients		Diff. means		Diff. coefficients	
Variable type	Contribution	%	Contribution	%	Contribution	%	Contribution	%
Total	0.009	100	0.014	100	0.009	100	0.032	100
Sociodemographic	-0.003***	-40.400	0.109**	759.179	-0.014***	-159.915	-0.105	-327.627
Working conditions	-0.000	-7.596	0.015	110.699	0.000	6.472	0.142	441.645
Firm	0.008*	89.324	-0.064**	-446.786	0.018*	198.901	-0.033	-102.211
Macro	0.002	23.152	-0.019	-138.7	0.000	10.287	0.017	54.997
Tasks	0.003	37.225	0.034	240.657	0.004	44.251	0.097	303.212
Country	-0.00016	-1.70586	-0.008	-60.189			-0.087	
Constant			-0.05251	-364.862				-270.018
	Western countries				**Eastern countries**			
	Diff. means		Diff. coefficients		Diff. means		Diff. coefficients	
Variable type	Contribution	%	Contribution	%	Contribution	%	Contribution	%
Total	0.013	100	0.020	100	0.007	100	0.006	100
Sociodemographic	-0.000	-2.667	0.143**	686.100	-0.003	-44.835	1.030	16,910.58
Working conditions	0.001	12.894	0.009	46.117	-0.002	-32.023	0.917	15,056.98
Firm	0.012*	89.483	-0.086*	-416.812	-0.011	-144.101	-0.157	-2584.56
Macro	0.002	17.648	-0.011	-54.837	0.003	39.537	-0.553	-9081.86
Tasks	-0.002	-17.358	0.010	50.917	0.022**	281.422	0.382	6,280.733
Constant			-0.044	-211.486			-1.613	-26481.9
	Southern countries							
	Diff. means		Diff. coefficients					
Variable type	Contribution	%	Contribution	%				
Total	0.005	100	-0.010	100				
Sociodemographic	-0.008***	-160.088	-0.043	428.836				
Working conditions	2.25E-05	0.437	-0.095	945.773				
Firm	0.009	188.8103	-0.013	137.469				
Macro	-0.006	-129.167	-0.031	314.310				
Tasks	0.010*	200.007	0.111	-1,102.61				
Constant			0.06	-623.783				

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Weighted estimations.
Sociodemographic: age, level of education, having at least one child; Working conditions: open-ended contract, full time, tenure, tenure squared, job discretion, job intensity, use of a computer; Firm: size, sector; Macro: exposure to globalisation, offshorability; Tasks: type of tasks; Country: country group.
Source: EWCS data, 2015

4 Conclusions

In this report, we have studied the relationship between job tasks and gender differences in two important labour market outcomes: wages and skills mismatch.

First, we explored the gender gap in job tasks in 37 high-, middle-, and low-income countries. We used PIAAC and STEP data which measure job tasks on a worker level, allowing the task content of occupations to differ between countries and workers. We found that, on average, women perform more routine-intensive tasks than men. This effect results from two phenomena. First, women work in more routine-intensity occupations. Second, women do more routine tasks within occupations.

Women face larger pay penalties for working in routine occupations. Within occupations, women perform more routine intensive tasks, but the associated pay penalties are, on average, similar to those experienced by men. Women only have a smaller penalty for performing routine tasks in the routine cognitive group of occupations. This result may suggest that doing routine-intensive tasks in typical routine occupations is a strong negative signal about men's abilities, as men rarely perform such jobs. It can also indicate a sanction for counter-stereotypic behaviour if society expects men to do less routine intensive tasks than women.

We also investigated if the contributions of the gender gaps in tasks to the gender wage gap are related to the gender equality of countries' legislation and gender norms. We showed that in countries with more equal parenting legislation, the contribution of job tasks to the gender wage gap tends to be smaller. Moreover, egalitarian norms towards earning income are related to the smaller role of RTI endowments in GWG.

Second, we studied the changes in the incidence of mismatch in recent years, and assessed the link between job tasks and skills mismatch in 23 European countries. We used data from the EWCS from 2005 to 2015. The incidence of skill mismatch decreased between 2005 and 2015, because of a decrease in over-skilling. At the same time, under-skilling increased for men and women. These evolutions in skill mismatch can partially be explained by the expansion of non-routine cognitive analytical tasks and non-routine cognitive interpersonal tasks induced by digitalisation. Our results show that under(over)-skilling of women and men are positively (negatively) linked to non-routine cognitive analytical tasks and that under(over)-skilling of women are positively (negatively) linked to non-routine interpersonal tasks.

In 2015, in Western countries and in Eastern countries, a gender gap exists in under-skilling and a gender gap exists in over-skilling in Western countries. For Western countries, differences in firms' characteristics mainly drive the gender gap in under-skilling. The over-skilling gap is mainly driven by the fact that socio-demographic variables are differently related to the over-skilling of men and women. The type of tasks does not play a significant role in the skill mismatch gender gap in this country group. Conversely, in Eastern countries, differences in the type of tasks performed by women and men explained a substantial part of the gender gap in under-skilling.

We add to the existing literature in three ways. First, we show an important dimension of gender occupational segregation and task allocation: routine intensity. Second, our study is the first to show the relationship between countries' gender legislation and norms and the role of task-related factors in shaping the gender wage gap. Third, our study improves the understanding of the gender gap in skills mismatch and highlights the role that job tasks can play in shaping this gap.

Our study remains subject to certain limitations. In the skill mismatch analysis, the task information is related to occupations and can be an imperfect measure of concrete individual tasks. Moreover, personality traits, not available in the EWCS may play a role in the self-assessment of skill mismatch and should be the subject of future research.

Appendix

Table A1. Questions used to measure legal differences between men and women in the Women, Business and the Law data set in four domains used in this study

Workplace
1. Can a woman get a job in the same way as a man?
2. Does the law prohibit discrimination in employment based on gender?
3. Is there legislation on sexual harassment in employment?
4. Are there criminal penalties or civil remedies for sexual harassment in employment?
Pay
1. Does the law mandate equal remuneration for work of equal value?
2. Can women work the same night hours as men?
3. Can women work in jobs deemed dangerous in the same way as men?
4. Are women able to work in the same industries as men?
Parenthood
1. Is paid leave of at least 14 weeks available to mothers?
2. Does the government administer 100% of maternity leave benefits?
3. Is paid leave available to fathers?
4. Is there paid parental leave?
5. Is dismissal of pregnant workers prohibited?
Entrepreneurship
1. Does the law prohibit discrimination in access to credit based on gender?
2. Can a woman sign a contract in the same way as a man?
3. Can a woman register a business in the same way as a man?
4. Can a woman open a bank account in the same way as a man?

Source: World Bank (2020)

Table A2. The allocation of occupations to occupational task groups (ISCO-08)

Task group	ISCO-08 code	Occupation
NRCA	21	Science and Engineering Professionals
	22	Health Professionals
	24	Business and Administration Professionals
	25	Information and Communications Technology Professionals
	26	Legal, Social, and Cultural Professionals
	31	Science and Engineering Associate Professionals
	35	Information and Communications Technicians
NRCP	11	Chief Executives, Senior Officials, and Legislators
	12	Administrative and Commercial Managers
	13	Production and Specialised Services Managers
	14	Hospitality, Retail and Other Service Managers
	23	Teaching Professionals
	32	Health Associate Professionals
RC	33	Business and Administration Associate Professionals
	34	Legal, Social, Cultural, and Related Associate Professionals
	41	General and Keyboard Clerks
	42	Customer Services Clerks
	43	Numerical and Material Recording Clerks
	44	Other Clerical Support Workers
	52	Sales Workers
RM	72	Metal, Machinery, and Related Trades Workers
	73	Handicraft and Printing Workers
	75	Food Processing, Woodworking, Garment, and Other Craft and Related Trades Workers
	81	Stationary Plant and Machine Operators
	82	Assemblers
	94	Food Preparation Assistants
NRM	51	Personal Services Workers
	53	Personal Care Workers
	54	Protective Services Workers
	61	Market-oriented Skilled Agricultural Workers
	62	Market-oriented Skilled Forestry, Fishery, and Hunting Workers
	63	Subsistence Farmers, Fishers, Hunters, and Gatherers
	71	Building and Related Trades Workers (excluding Electricians)
	74	Electrical and Electronic Trades Workers
	83	Drivers and Mobile Plant Operators
	91	Cleaners and Helpers
	92	Agricultural, Forestry, and Fishery Labourers
	93	Labourers in Mining, Construction, Manufacturing, and Transport
	95	Street and Related Sales and Services Workers
	96	Refuse Workers and Other Elementary Workers

Note: The allocation is based on Hardy et al. (2018), see data section for details.

Table A3. Predicted incidence of men and women in occupational groups

	Occupational groups			
	Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Manual
Men	0.174	0.164	0.199	0.463
	(0.003)	(0.003)	(0.004)	(0.004)
Women	0.130	0.143	0.373	0.354
	(0.003)	(0.003)	(0.005)	(0.005)

Note: Predicted probabilities from a multinomial logit. SE in parentheses. We use standardised weights that give each country equal weight. Additional controls: three education levels, four literacy levels, five age groups, Women*education level interactions, sectors, interactions between sector fixed effects and Ln(GDP per capita), country fixed effects, Foreign Value Added (FVA) share, computer use, computer use^2. The standard errors are clustered at a sector * country level.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

Table A4. Gender differences in the selection to routine occupations (the sample used in wage regressions)

	Individual workers (1)		Occupation # country (2)
Female	0.067***	Female share	0.415***
	(0.011)		(0.050)
N	102,916		1,349

Note: *p<0.05, **p<0.01, ***p<0.001. SE in parentheses. Model 1: We use standardised weights that give each country equal weight. Additional controls: three education levels, four literacy levels, five age groups, Women*education level interactions, sectors, interactions between sector fixed effects and Ln(GDP per capita), country fixed effects, Foreign Value Added (FVA) share, computer use, computer use^2. The standard errors are clustered at an occupation * country level. Model 2: estimation on variables' means in occupation (ISCO-2d)#country cells.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

Table A5. The gender gap in RTI within occupations (the sample used in wage regressions)

	All workers	Occupational groups			
		Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Manual
Average RTI at the worker level	0.249	-0.404	-0.462	0.273	0.730
	(0.004)	(0.009)	(0.010)	(0.008)	(0.006)
Gender Gap in RTI at the worker level	0.226***	0.162***	0.145***	0.296***	0.274***
	(0.013)	(0.020)	(0.020)	(0.022)	(0.022)
Gender Gap in RTI at the worker level (controlling for ISCO2d)	0.214***	0.164***	0.108***	0.248***	0.249***
	(0.013)	(0.020)	(0.019)	(0.021)	(0.022)
N	102,916	16,685	16,384	28,941	40,906

Note: *p<0.05, **p<0.01, ***p<0.001. SE in parentheses. We use standardised weights that give each country equal weight. Additional controls: 3 education levels, four literacy levels, five age groups, Women*education level interactions, sectors, interactions between sector fixed effects and Ln(GDP per capita), country fixed effects, Foreign Value Added (FVA) share, computer use, computer use^2. The standard errors are clustered at a sector * country level.
Source: Own estimations based on PIAAC, STEP, O*NET, World Bank, and RIGVC UIBE (2016) data

Table A6. Gender norms and the differences in the allocation and prices of tasks: norms measured by men's and women's answers separately

	Endowments		Coefficients		Total contribution of RTI	GWG
	Occupational RTI	Worker-level RTI	Occupational RTI	Worker-level RTI		
	(1)	(2)	(3)	(4)	(5)	(6)
Attitudes towards gender roles						
Men's answers						
Scarce jobs	-0.009	0.000	-0.012	0.003	-0.018	-0.057**
	(0.007)	(0.003)	(0.008)	(0.003)	(0.014)	(0.016)
R^2	0.049	0.000	0.064	0.030	0.051	0.273
N	34	34	34	34	34	34
Being a housewife fulfilling	0.010	-0.003	-0.010	-0.005	-0.008	-0.011
	(0.007)	(0.003)	(0.008)	(0.003)	(0.014)	(0.019)
R2	0.061	0.041	0.041	0.093	0.009	0.010
N	34	34	34	34	34	34
Working mother	-0.004	-0.001	-0.017	0.001	-0.021	0.003
	(0.005)	(0.003)	(0.009)	(0.003)	(0.015)	(0.019)
R^2	0.020	0.003	0.118	0.003	0.066	0.001
N	30	30	30	30	30	30
HH income contributions	-0.011*	-0.008**	0.002	0.001	-0.016	-0.020
	(0.005)	(0.003)	(0.009)	(0.003)	(0.015)	(0.019)
R^2	0.151	0.235	0.002	0.002	0.038	0.036
N	30	30	30	30	30	30
Women's answers						
Scarce jobs	-0.007	-0.000	-0.008	0.003	-0.013	-0.053**
	(0.007)	(0.003)	(0.008)	(0.003)	(0.014)	(0.017)
R^2	0.028	0.001	0.031	0.029	0.025	0.234
N	34	34	34	34	34	34
Being a housewife fulfilling	0.008	-0.004	-0.013	-0.004	-0.013	-0.016
	(0.007)	(0.003)	(0.008)	(0.003)	(0.014)	(0.019)
R2	0.040	0.057	0.079	0.065	0.027	0.020
N	34	34	34	34	34	34
Working mother	-0.004	-0.001	-0.021*	-0.000	-0.026	-0.005
	(0.005)	(0.003)	(0.009)	(0.003)	(0.015)	(0.019)
R^2	0.019	0.003	0.182	0.000	0.101	0.002
N	30	30	30	30	30	30
HH income contributions	-0.009	-0.007*	0.000	-0.000	-0.016	-0.017
	(0.005)	(0.003)	(0.009)	(0.003)	(0.015)	(0.019)
R^2	0.109	0.192	0.000	0.000	0.040	0.029
N	30	30	30	30	30	30

Note: Model with an intercept. WBL & WVS indices are standardised. Standard errors in parentheses *p<0.05, **p<0.01, ***p<0.001. Control variables in the Blinder-Oaxaca decomposition: three education levels, four literacy levels (1 PV used), five age groups, sectors, Foreign Value Added (FVA) share, computer use, computer use^2.

Table A7. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Skill mismatch	0.4414	-	-	-
Under-skilled	0.1430	-	-	-
Over-skilled	0.2984	-	-	-
Man	0.5190	-	-	-
Age	40.8960	11.14	20	64
Child(ren)	0.3180	-	-	-
Lower secondary (Ref.)	0.2085	-	-	-
Upper secondary	0.4218	-	-	-
Post-secondary non tertiary	0.0650	-	-	-
Tertiary	0.3013	-	-	-
Open-ended contract	0.8626	-	-	-
Full time	0.6574	-	-	-
Tenure	9.6467	9.11	1	60
Tenure squared	176.0658	296.17	1	3,600
Job discretion	0.6538	-	-	-
Job intensity	0.4457	-	-	-
Use of a computer	0.5564	-	-	-
Nb of employees <10 (Ref.)	0.2779	-	-	-
10-249	0.5571	-	-	-
250 and more	0.1613	-	-	-
Industry (ABCDE) (Ref.)	0.2162	-	-	-
Construction, transport, storage (F-H)	0.1512	-	-	-
Trade, Accommodation and food service activities (G-I)	0.1801	-	-	-
Services (JKLMNRSTU)	0.1746	-	-	-
Public services (OPQ)	0.2779	-	-	-
Exposure to globalisation	0.1539	0.0970	0.0436	0.8746
Offshorability	-0.0324	0.6359	-0.8282	1.5
NRCA	0.1432	-	-	-
NRCP	0.1585	-	-	-
RC	0.2861	-	-	-
NRM	0.3145	-	-	-
RM	0.0977	-	-	-
Western countries	0.5969	-	-	-
Nordic countries	0.0591	-	-	-
Southern countries	0.2108	-	-	-
Eastern countries	0.1333	-	-	-
Nb. Observations	67,971			

Note: Weighted figures. Standard deviations are only reported for non-binary variables.
Sources: EWCS 2005, 2010, 2015

Table A8. Evolution of skill mismatch feelings over time

Skill mismatch		Men			Women	
	2005	2010	2015	2005	2010	2015
Nordic countries						
Denmark	45.58	43.01	48.13	49.51	39.47	45.66
Finland	36.19	32.52	35.21	39.66	39.4	28.45
Norway	43.99	39.8	41.01	43.22	36.63	37.17
Sweden	47.66	50.26	46.71	48.7	45.04	42.95
Western countries						
Austria	54.28	44.89	54.27	51.76	32.92	53.1
Belgium	40.1	40.25	45.3	34.01	35.29	36.31
France	57.35	41.67	46.33	54.13	38.03	42.69
Germany	46.46	45.14	44.41	47.44	49.85	45.44
Ireland	56.27	49.13	48.39	48.47	42.96	47.17
Netherlands	47.14	43.48	43.51	39.99	44.75	36.79
United Kingdom	54.22	48.19	43.12	46.56	47.01	42.06
Southern countries						
Greece	59.52	53.13	40.48	49.28	53.92	43.69
Italy	42.9	36.72	35.09	42.43	33.6	33.01
Portugal	36.91	26.87	28.35	35.33	36.93	21.86
Spain	42.55	46.12	43.4	47.97	48	43.93
Eastern countries						
Czechia	34.5	41.43	41.51	34.38	36.74	40.64
Estonia	51.69	44.25	49.22	54.22	48.1	51.94
Hungary	53.28	54.14	44.61	50.14	50.46	46.98
Slovakia	46.88	47.43	39.83	43.82	46.97	37.38
Slovenia	46.44	54.39	51.16	45.41	48.09	46.6
Latvia	44.1	55.77	40.31	46.96	49.72	36.11
Lithuania	40.02	36.65	36.25	49.17	42.33	40.2
Poland	40.67	39.89	41.22	47.23	35.93	43.73
Total	47.55	43.75	43.04	46.61	44.18	41.67

Under-skilled						
		Men			Women	
	2005	2010	2015	2005	2010	2015
Nordic countries						
Denmark	11.37	15.09	17.32	14.86	15.11	20.82
Finland	11.5	9.07	10	17.61	15.05	8.41
Norway	14.32	10.88	13.4	16.46	11.1	13.34
Sweden	5.08	10.92	16.29	7.54	12.72	15
Western countries						
Austria	28.67	26.83	33.48	27.75	16.62	24.86
Belgium	10.82	11.01	16.17	11.25	8.98	13.96
France	7.75	8.13	17.47	11.92	9	20.22
Germany	20.53	20.11	17.84	21.68	22.8	23.66
Ireland	10.71	7.93	14.12	9.54	6.99	11.34
Netherlands	13.69	13.07	14.4	6.5	10.05	12.2
United Kingdom	7.24	7.3	10.34	6.54	7.2	9.18
Southern countries						
Greece	15.29	10.12	6.03	12.38	10.71	3.88
Italy	13.05	10.19	13.21	15.74	9.75	11.59
Portugal	11.11	5.2	9.78	9.95	8.79	5.72
Spain	7.4	10.93	12.67	8.52	10.47	10.78
Eastern countries						
Czechia	12.03	17.45	17.52	12.59	17.97	20.15
Estonia	18.43	20.03	23.47	21.53	23.46	34.28
Hungary	10.98	12.49	9.98	14.78	18.85	13.53
Slovakia	10.26	15.45	19.15	9.29	20.11	12.48
Slovenia	10.71	12.91	13.69	12.83	10.28	14.35
Latvia	13.34	14.75	8.75	14.42	12.31	9.59
Lithuania	16.54	17.17	17.96	26.29	22.33	26.13
Poland	14.4	13.45	9.6	15.97	13.26	13.03
Total	12.63	13.83	14.67	13.69	14.71	15.67

Over-skilled						
		Men			Women	
	2005	2010	2015	2005	2010	2015
Nordic countries						
Denmark	34.21	27.92	30.81	34.65	24.35	24.84
Finland	24.68	23.45	25.21	22.05	24.36	20.04
Norway	29.67	28.93	27.61	26.76	25.53	23.83
Sweden	42.58	39.34	30.42	41.16	32.33	27.96
Western countries						
Austria	25.61	18.06	20.8	24.01	16.3	28.23
Belgium	29.28	29.25	29.13	22.76	26.31	22.35
France	49.6	33.54	28.86	42.21	29.03	22.47
Germany	25.94	25.03	26.57	25.76	27.04	21.78
Ireland	45.56	41.2	34.27	38.93	35.98	35.83
Netherlands	33.45	30.4	29.11	33.49	34.7	24.59
United Kingdom	46.98	40.89	32.78	40.02	39.81	32.88
Southern countries						
Greece	44.23	43.01	34.45	36.9	43.21	39.81
Italy	29.85	26.53	21.89	26.69	23.85	21.42
Portugal	25.8	21.67	18.57	25.37	28.14	16.14
Spain	35.14	35.19	30.73	39.45	37.52	33.14
Eastern countries						
Czechia	22.47	23.99	24	21.8	18.77	20.48
Estonia	33.26	24.21	25.75	32.69	24.64	17.65
Hungary	42.3	41.64	34.63	35.36	31.61	33.45
Slovakia	36.62	31.98	20.68	34.53	26.86	24.9
Slovenia	35.73	41.49	37.48	32.58	37.81	32.26
Latvia	30.77	41.03	31.56	32.54	37.41	26.52
Lithuania	23.49	19.48	18.29	22.88	20	14.06
Poland	26.27	26.44	31.62	31.27	22.67	30.7
Total	34.92	29.92	28.37	32.92	29.47	26

Notes: Weighted figures.
Source: EWCS 2005, 2010, 2015

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