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Structural Labour Market Change and Gender Inequality in Earnings

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Abstract: Research from the US argues that women will benefit from a structural labour market change as the importance of social tasks increases and that of manual tasks declines. This article contributes to this discussion in three ways: (a) by extending the standard framework of task content of occupations in order to account for diversity of social tasks; (b) by developing measures of occupational task content tailored to the European context; and (c) by testing this argument in 13 European countries. Data are analysed from the European Skills, Competences, Qualifications and Occupations Database and the European Structure of Earnings Survey. The analysis demonstrates that relative to men the structural labour market change improves earnings potential of women working in low- and middle-skilled occupations but not those in high-skilled occupations. Women are overrepresented in low paid social tasks (e.g. care) and are paid less for analytical tasks than men.

Keywords: task content of occupations, care work, wages, gender, Europe

JEL codes: J16, J21, J23, J24

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1 Introduction

Globalisation, digitalisation and population ageing have substantially changed the demand for different types of work, driving a structural change in the labour market (D. Autor et al., 2006; Goos et al., 2014; World Bank, 2018). The importance of non-routine cognitive work has increased, benefitting workers who are able to perform complex analytical tasks (e.g. data analysis or programming) as well as social tasks which require interactions with people (e.g. communication or recognition of emotions). At the same time, demand for workers who perform non-routine manual tasks (e.g. physical work) and routine (repetitive) work, which are most susceptible to automation or offshoring, has been in decline. These processes have led to substantial disparities in labour market opportunities for high-, low-and middle-skilled workers and a further widening of income inequalities (Acemoglu & Autor, 2011; Hardy et al., 2018; Oesch & Piccitto, 2019).

While there has been a marked increase in the amount of empirical research done on how these processes affect the labour market situation of highly educated versus less-educated workers, much less is known on how the changing task content of work affects women's position in the labour market relative to men's (Howcroft & Rubery, 2019). Despite the enormous progress women in developed countries have made in gaining and maintaining employment over the last several decades, they are still less likely to be in full-time employment and earn lower wages (Matysiak & Cukrowska-Torzewska, 2021). These differences have been so persistent that some scholars have even hypothesised that the progress toward gender equality in the labour market has stalled (England, 2010). Will the ongoing structural change in labour demand help women improve their relative position in the labour market? Or, conversely, will gender inequalities persist or even widen further?

There is no simple answer to these questions. On the one hand, women may benefit from these structural trends: First, they are increasingly better educated than men and thus may more easily take up jobs which require non-routine cognitive work. Research shows that women have been more successful than men in moving from jobs involving routine tasks into jobs intense in non-routine cognitive tasks (Black & Spitz-Oener, 2010; Brussevich et al., 2019). Second, women may benefit from the growing demand for social tasks brought about by the expansion of non-production business activities, such as management, marketing or customer service, as well as high-quality early school education, childcare, elderly care and healthcare (Bacolod & Blum, 2010; Cortes et al., 2018; Deming, 2017). Social tasks cannot be easily automated and women –

consistent with gender-essentialist beliefs – are considered to be better endowed with social and emotional skills (Charles & Bradley, 2009; Charles & Grusky, 2018).

On the other hand, however, jobs requiring social tasks range widely. Those that involve providing service to others (e.g. care), which are usually female-dominated, are often devalued and poorly paid (England, 2005; Levanon et al., 2009). This is in contrast to top-level managerial jobs, which are more often done by men. Women also remain less less likely to pursue STEM degrees (science, technology, engineering and mathematics) and are underrepresented in STEM jobs (Matysiak & Cukrowska-Torzewska, 2021). Finally, women, particularly older women, continue to do routine jobs more than men (Brussevich et al 2019). All these arguments put into question whether women will indeed benefit from the structural change in the labour market.

The aim of this article is to contribute to this debate. In terms of theory, two distinct strands of the literature are tied together: the economic literature on the task content of occupations and the sociological literature on the sources of occupational sex segregation. The former has been developed to describe changes in labour demand brought about by digitalisation and globalisation (D. Autor et al., 2006; Autor et al., 2003). It classifies occupational tasks into three major groups: abstract tasks (nonroutine cognitive, in other words), which are further divided into analytical and social tasks; routine tasks; and (non-routine) manual tasks. The latter strand concerns the literature on occupational sex segregation, particularly the devaluation of work done by females (England, 2005; Liu & Grusky, 2013). The article argues that there is a wide diversity of social tasks in the world of work and those which are usually done by women have traditionally paid less. This undermines women's opportunities to benefit from the structural change in the labour market.

In order to verify this claim this article extends the task content of occupations in a way that social tasks are divided into two subgroups: outward and inward ones. Outward social tasks involve interactive service work with the customers of one's organisation (e.g. providing care, education or other services), while inward tasks are done with individuals from the same organisation or peers (e.g. management, supervision, teamwork). The task structure of occupations is evaluated using data from the European Skills, Competences, Qualifications and Occupations Database (ESCO). Next, the microdata from the European Structure of Earnings Survey (2002 – 2018) is employed for assessing wage returns to and gender differences in occupational tasks. The analyses are based on 13 European countries—Bulgaria, Czechia, Denmark, Estonia, Greece, France, Italy, Lithuania, Latvia, Norway, Poland, Slovakia and the United Kingdom—around 2018. In addition, for a smaller number of countries (Bulgaria, Czechia, Estonia, Lithuania, Latvia, Poland and Slovakia) developments over a period of nearly two decades (2002-2018) are traced.

The study also contributes to the methods of measuring the task content of occupations. That content is assessed for countries in Europe, based on data available in ESCO on occupational skill requirements pertinent to European labour markets. Research in the field has so far usually relied on the O*NET database, which provides information on the task content of occupations in the US. Recently, Lewandowski et al. (2022) demonstrated that the content of occupations in Europe differs from the content of occupations in the US. As such, measures based on European data may be more appropriate. The task measure introduced in this article has the additional advantage of being based on a large number of task items, which provides additional flexibility. In this article, this flexibility is employed to study different types of social tasks. Building on our approach, one could also consider other departures from the canonical model, which would set the focus on other task subcategories as well (ICT-, finance- or law-related tasks, to name three) while retaining consistency with other research on the task content of jobs.

2 Changing demand for tasks

Structural change in the labour market is often described with a task-based approach which characterises jobs as collections of tasks of different types that are done with varying degrees of routineness (Acemoglu & Autor, 2011; Autor et al., 2003). By altering the structure of tasks required to perform a certain job, structural transformations such as technological change, globalisation or population ageing change the demand for labour (Autor & Handel, 2013).

Three broad categories of tasks are observed in the literature: abstract (non-routine cognitive), routine and non-routine manual tasks (Acemoglu & Autor, 2011; Autor et al., 2003). The first group encompasses tasks which require creative thinking, problem solving and complex organisation and communication. These may be analytical tasks, like data analysis, programming or planning, or social tasks, requiring interactions with people, including teamwork, negotiations and conflict solving. At the current technology level, abstract tasks are least exposed to automation or offshoring while routine tasks, by definition, are those that “can be accomplished by machines following explicit programmed rules” (Autor et al., 2003, p. 1283). Routine tasks are well structured and repetitive, do not involve complex communication, decision-making or adaptability to situations, but instead require following clearly defined procedures. Finally, non-routine manual tasks require physical adaptability and/or strength, body coordination, spatial orientation and/or finger dexterity (e.g. cleaning, repairing, renovating).

Over the last four decades the demand for abstract tasks, usually performed by high-skilled workers, has increased across developed countries (Autor et al., 2003; Hardy et al., 2018; World Bank, 2018). The rapid development of the high-tech sector and the explosion of digital data has generated enormous demand for analytical tasks. At the same time, the importance of social tasks has increased with the continuous expansion of the service sector as well as the growing demand for education, childcare and healthcare services. In parallel, the demand for routine tasks has been in decline (D. Autor et al., 2006; Goos et al., 2014; World Bank, 2018). Workers performing highly routine jobs have to adjust to the new situation by either upgrading their skills or competing for jobs involving non-routine manual tasks, putting downward pressure on the wages of manual workers. As a result of these changes, wage returns on abstract tasks are not only higher in comparison to routine and manual tasks (Autor & Handel, 2013; De La Rica et al., 2020), but have also grown, contributing to increasing inequalities between highly skilled and low- and mid-skilled workers (Bacolod & Blum, 2010; Cortes et al., 2018).

3 Gender and the structural change in the labour market

How structural changes affect labour market outcomes of workers across different social strata has been well documented, but the impact of these changes on women's versus men's outcomes is less clear (Howcroft & Rubery, 2019). On the one hand, women are more exposed to automation and offshoring since they do more routine tasks at work than men (Brussevich et al., 2019; Piasna & Drahokoupil, 2017). Women also pursue STEM (science, technology, engineering and math) degrees less often (OECD, 2015) and are more likely to leave STEM jobs to pursue careers in unrelated fields (Cech & Blair-Loy, 2019).

On the other hand, women may also benefit from the ongoing structural transformations. Even though they still perform more routine tasks at work than men, they also move more quickly out of routine and into abstract tasks as they attain higher education (Black & Spitz-Oener, 2010; Cortes et al., 2020). Brussevich et al. (2019) demonstrates that gender inequalities in the risk of job loss due to automation narrow down across generations across all OECD countries. Likewise, Bacolod and Blum (2010) find that women transition into jobs involving nonroutine cognitive tasks faster than men and that this process contributes roughly 20% to the narrowing of the gender wage gap observed in the US in the 1980s.

Women may also benefit from the increasing importance of social tasks (Bacolod & Blum, 2010; Cortes et al., 2018; Deming, 2017). According to the gender essentialist beliefs, women have better social skills than men (Charles & Bradley, 2009; Charles & Grusky, 2018). Women are also overrepresented in jobs that require social skills, i.e. in the service sector, education or healthcare (Matysiak & Cukrowska-Torzewska, 2021). At the same time, research from the US finds that the demand for social skills has been increasing even more quickly than for analytical skills. Using data spanning the years 1980 to 2012, Deming (2017) demonstrates that jobs requiring high levels of social interaction expanded by nearly 12 percentage points, while jobs requiring high math but fewer social skills declined by 3.3 percentage points. The same study reports an increase in the wage returns for social skills from 2% to 3.7% and a decline in returns for analytical skills by 25% (from 20% to 15%) over the years 1979-1997. Bacolod and Blum (2010)find an increase in wage premiums for analytical skills, though weaker than for social skills and for an earlier period. Both studies determine that the growing importance of social skills creates opportunities for women in the labour market. Cortes et al. (2018) even concluded that these changes will imply the "end of men and rise of women in the high-skilled labour market".

4 Occupational sex segregation and devaluation of female job tasks

Whether women will indeed benefit from the increasing demand for social tasks can be questioned, however, as social tasks range widely. Two groups of social tasks are commonly distinguished (Kilbourne et al., 1994; Levanon & Grusky, 2016; Liu & Grusky, 2013). The first group covers managerial tasks, such as supervision, coaching, motivating and coordinating workers, delegating work, building and leading teams. Managerial tasks entail expressing authority and are executed in order to achieve one's goals. The second group, dubbed interactive service work by England (2005), covers social tasks that are used to perform service work, often for clients and customers of one's employer. Interactive service work usually requires understanding the needs of others, recognising emotions, having empathy and the ability to listen. These tasks are commonly performed by social and healthcare workers, teachers or therapists, among others.

Men are more likely to hold managerial positions than women, while occupations that rely on interactive service work are female-dominated (Roos & Stevens, 2018; Schäfer et al., 2012). This is consistent with gender essentialist beliefs which associate masculinity with authority and leadership, and feminity with warmth and nurturance (Charles & Grusky, 2018). The latter jobs also pay substantially less (Kilbourne et al., 1994; Levanon & Grusky, 2016; Liu & Grusky, 2013). This is particularly true for care occupations (England et al., 2002) even as expectations of interactive service workers, including care workers, have increased over time. Childcare in the twenty-first century entails not only providing safety, nutrition and entertainment to children, but also stimulating children's cognitive abilities and developing their social skills (Duffy, 2011). Working as a nurse or a midwife requires a formal university degree in an increasing number of European countries (Lahtinen et al., 2014).

Numerous theories explain the persistence of low pay in interactive service occupations. Compensating differentials theory posits that these jobs are held mainly by women who trade attractive pay for work conditions compatible with parenting (Filer, 1985). The theory of gendered valuation, also referred to as devaluation perspective, presupposes that jobs which are done by women, like everything which is female, are undervalued (Kilbourne et al., 1994). In keeping with this perspective, care work is particularly undervalued due to its association with unpaid care work done at home (England, 2005; England et al., 2002). It is also argued that interactive service work is poorly paid because it is considered *a calling*. Workers performing interactive service work, and care work in particular, are not considered to be motivated by profit, but rather by altruism, love and concern (England, 2005; England et al., 2002). Finally, interactive service work is considered a public good, since it benefits not only its recipients but also broader society. The debate on which of these explanations is most accurate continues today (Hodges, 2020; Levanon et al., 2009; Magnusson, 2008; Perales, 2013). Irrespective of the reasons, the fact that interactive service work is persistently less paid than other social tasks throws into question the notion that increasing demand for social tasks will indeed benefit women. This study contributes to this debate.

5 Data and methods

For the present research, the framework of the task content of occupations was used, and further enriched thanks to a division of social tasks into two groups. The first group encompasses social tasks which involve interactive service work done for clients or customers of one's organisation, such as recognising emotions, showing empathy and being able to listen, understand and adjust to another's needs. The category thus encompasses teaching, caring, listening and talking to clients or making speeches to general audiences. For simplicity, these were referred to as outward social tasks. The second category covers tasks that involve interactions with individuals from the same organisation, such as managerial or supervisory tasks, coordinating the work of others, teamwork or dealing with hierarchies within the organisation. These are inward social tasks. In this framework, both types of social tasks fall into the category of abstract tasks, together with analytical tasks, and abstract tasks form a separate group from routine and nonroutine manual tasks.

On the basis of this framework, the task structure of occupations in Europe was evaluated, using the information stored in the European Skills / Competences Qualification and Occupations Database (ESCO). The task measures were then standardised using the information about occupational structure from the EU Labour Force Surveys (EU LFS) and linked by occupation (3rd digit in the ISCO-08 classification) to individual data on workers and companies from the European Structure of Earnings Survey (SES). The combined data is then used to examine wage returns to and gender differences in work tasks.

5.1 Data

The European Union Structure of Earnings Survey (SES) is an excellent source of data on earnings, hours worked and occupations as it is obtained directly from employers. It also contains information on worker characteristics (sex, age, education level, tenure, occupation, hours worked) and firm characteristics (size, economic sector, location). The data is reported to Eurostat every four years by EU Member States and countries belonging to the European Free Trade Association. The first available SES survey was done in 2002 and subsequent waves took place in 2006, 2010, 2014 and 2018. The database houses data on enterprises operating in the countries, exclusive of agriculture. The inclusion of public administration workers and workers in firms with fewer than ten employees varies by country and depends on the collection instrument the governments employ. In the main sample, most countries included those workers apart from Denmark, France, Greece and Italy which did not include companies employing fewer than 10 employees and Denmark and Greece which did not cover public administration.

While SES offers numerous advantages, it also has limitations. First, there is no information on workers' family characteristics, including partnership or parenthood status. Second, countries were allowed to report occupations using either two- or three-digit ISCO codes. Finally, SES has applied a new classification of occupations (ISCO-08) since the 2010 wave and a direct one-to-one match between occupations before and after that date is not always possible.

Overall, our main analyses on SES data concern 12 countries which provided occupational data at the 3-digit level (Bulgaria, Czechia, Denmark, Estonia, France, Greece, Italy, Lithuania, Latvia, Norway, Poland and Slovakia) observed in 2018. It also includes the United Kingdom, which at the time of this study provided data to Eurostat for 2014 but not for 2018. We excluded countries which used 2-digit ISCO codes as we believed that aggregating data at the higher level would result in a substantial loss of information. We also dropped three countries—Cyprus, Luxembourg and Malta— which differ considerably from the rest of the EU in terms of the size and the structure of their economic activity. Details on the country selection and sample size can be found in Table 1 in the Appendix.

The second data source used in this study is the European Skills/Competences Qualifications and Occupations (ESCO) database. ESCO was created as part of a European Commission initiative to harmonise the definition of occupations across the Member States. The database contains information on the skills / competences, qualifications and attitudes required to perform each occupation. The data stems from various sources, including national classifications, online job ads and curricula. The first complete version of ESCO was released in 2017 and it has been updated continuously since. In this study, we use the ESCO version 1.0.8.

ESCO builds on the 4-digit international classification of occupations 2008 (ISCO-08). At its most disaggregated level, ISCO-08 lists 436 occupations, which are further disaggregated into 2942 detailed occupations within ESCO. For example, the ISCO-08 code 2422 (Policy administration professionals) has 14 sublevels in ESCO and these are further divided (e.g. the code 2422.10– policy officer– has 15 sublevels ranging from agricultural to social services policy officer). Each ESCO occupation is described by a set of essential and optional skills, competences, attitudes and types of knowledge required. The adjective “essential” serves to identify the core components of occupations, while “optional” identifies context / industry-specific items. Notably, some items may be optional for some occupations but essential for others. In this analysis, the focus was on the essential tasks (similarly to e.g. Zilian et al. (2021)).

Measures of task content of occupations

The ESCO database was used in order to construct the measures of task content of the occupations. These measures are replicable and the respective codes will be shared through a data repository upon a publication of this manuscript. In order to construct them, we utilised the information on‘skills’and‘competences’ required to perform a certain occupation (“contact customers”, “forecast product demand”, “extinguish fires”) as well as the‘attitudes’ (“cope with pressure”, “willingness to learn”). The ‘required knowledge’ characteristics were not considered, as they are more concerned with the associated type of education. This approach is consistent with Acemoglu and Autor (2011), who interpret skills, competences and attitudes as an indication of tasks performed.

Overall, ESCO provides approximately 10,000 skills, competences and attitudes (hereafter called items). For the present research, 97% of them were grouped into four categories: (I) social (which we further split into inward and outward oriented), (II) analytical, (III) manual and (IV) routine (Acemoglu & Autor, 2011; D. H. Autor et al., 2006). The original definitions were followed as closely as possible: social tasks are those that are relevant for interpersonal interactions; analytical tasks are those connected to the mental process used to solve problems and digital skills; manual tasks refer to those that have a space-based component, such as driving, handling products or repairing; and routine tasks are those that are sufficiently well-understood so that a machine could be programmed to execute them. Consistent with the past literature, the routine content of an occupation identifies not only routine tasks, but also reflects how tasks are executed (Fernández-Macías & Bisello, 2022). Variables were identified within ESCO to show the non-routineness of occupations particularly when defining competences, e.g. whether jobs require one to show adaptability or cope with uncertainty.

Following the classification of the skills/competences and attitudes, the measures of the task content of occupations were constructed. This involved three steps. The first was to determine how many of the skills/competences and attitudes grouped into a given category were essential to perform a given occupation. On average, 20 items were assigned to each occupation, though there was large variation across occupations. Second, the measures were aggregated to the 3-digit ISCO-08 level so that they could be linked with the SES data. The aggregation was handled stepwise. The task content was computed first at the lowest ESCO level. The task content at the immediately higher level of the ESCO classification is an average from all occupations that appear below it. Once the task content for each occupation was obtained at the second lowest level, the procedure was repeated at the third level until the ISCO-08 three-digit level was reached (3 steps). Our approach is summarised by the below equation, where n_j is the number of categories at the four digit level for occupation o; $n_{k(j)}$ is the number of occupations below category j, and $n_{l(j,k)}$ is the number of occupations in the most disaggregated category (following j and k).

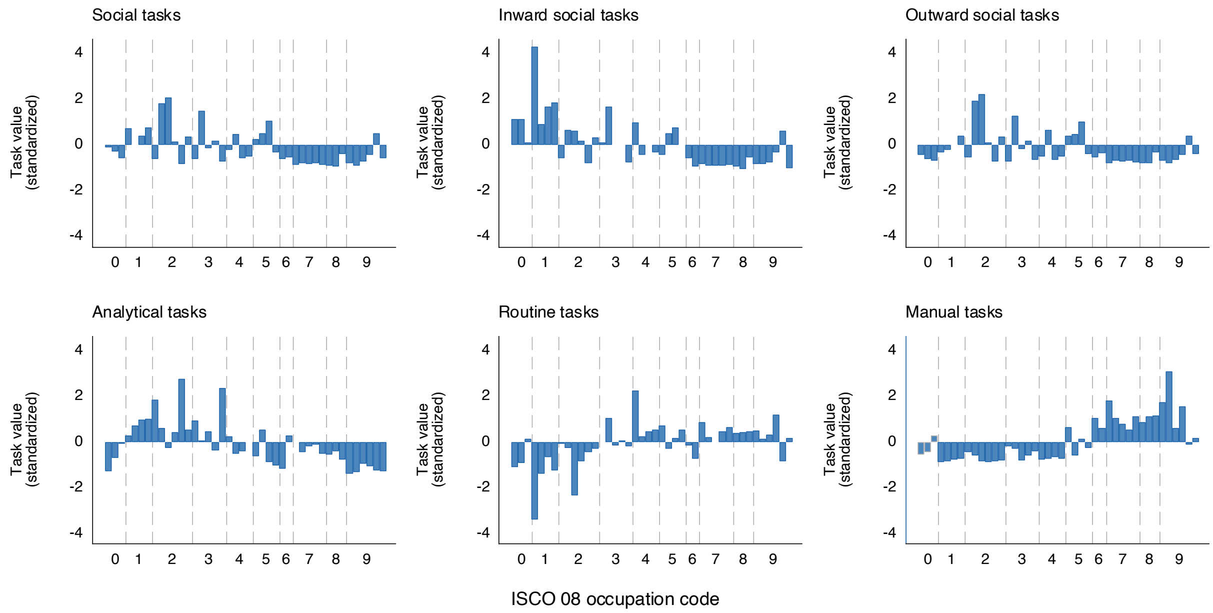
$$task\ content_o = \sum_{j,k,l} \frac{1}{n_j} \frac{1}{n_{k(j)}} \frac{1}{n_{l(k,j)}} tasks_{o,j,k,l} \qquad (1)$$

Hence, the task content in occupation o is a weighted sum of the task content in each occupation (j,k,l) listed at the lower level. Additionally, the non-routine task content was deducted from the routine task content to arrive at an aggregate routineness measure.

Finally, the measures were standardised in order to facilitate the interpretation of findings. The standardisation was done using data from all EU countries, not only those present in SES. This approach is consistent with how ESCO was conceived and allows a direct comparison of coefficients across tasks and samples. The standardisation was performed using weights computed from the 2018 EU Labour Force Survey (for Poland we used the national 2018 LFS as the EU LFS for this country contains less detailed occupational information). In all further discussions and analyses, a one-unit difference of a task measure should be interpreted as a difference in one standard deviation from the average of (most) EU workers in 2018.

Figure 1 presents the average task content for different occupations in the EU. Analytical and social tasks proved to be most commonly performed in occupations at the top of the occupational hierarchy (ISCO codes 1-3: managers, professionals and associated technicians). Routine task content is particularly high among clerical workers (ISCO code 4), but also in sales occupations (ISCO code 5) and for most plant and assembly line work (ISCO code 7), most craft and related trades work (ISCO code 8) and some elementary occupations (ISCO code 9). Finally, manual tasks are most common at the bottom of the occupational hierarchy (ISCO codes 6 and higher and in particular 9).

Figure 1: Task content of occupations by 2-digit ISCO 08 codes, European Union 2018



Note: Standardized task content of occupations aggregated to 2 digits ISCO-08 codes. The occupations listed in the horizontal axis are: 0 Armed forces occupations, 1 Managers, 2 Professional occupations, 3 Technicians and associated professionals, 4 Clerical support workers, 5 Service sales workers, 6 Skilled agricultural, forestry and fishery workers, 7 Craft related trades workers, 8 Plant and machine operators and assemblers, and 9 Elementary occupations.

After the measures were constructed, two validation tests were done to minimise the risk that some of the items were erroneously categorised. For the first test, experts in the field of task content of jobs were asked to classify thirty randomly selected ESCO items into one of the four categories: analytical, social, routine and manual. Five experts, who remain anonymous, responded. The percentage of agreement came in above 60%. This was twice of what would be expected by random chance alone, which is why the initial classification remained unchanged.

Second, the constructed measures were compared to those proposed by Acemoglu and Autor (2011), which were based on the O*NET occupational data. To this end, their classification was mapped to EU LFS (2018) data. The correlations between our measures and those based on O*NET range from 0.47 for routine tasks to 0.71 for manual tasks (see Table 3 in the Appendix). In general, these correlations are similar or higher than those obtained by Autor and Handel (2013), who compared O*NET-based measures with the measures based on US Princeton Data Improvement Initiative (PDII) data, as well as by those obtained de la Rica et al. (2020), who correlated the O*NET- based measures with measures constructed using the data from the Survey of Adult Skills (PIAAC). These relatively high correlations suggest the measures used for this article can be viewed with confidence.

5.2 Models

Once the task measures were constructed, they were linked with the microdata from the EU SES using data on occupations coded at the 3-digit ISCO-08 level. These data were used to first evaluate returns to tasks and second to assess gender differences in the task content of occupations.

To determine wage returns, the log hourly wage was regressed against the constructed task measures and a series of controls. Two models were estimated, depending on whether social tasks were considered jointly (model 1a) or whether a distinction was made between social inward and outward tasks (Model 1b). Gender differences in wage returns were also examined. To this end, the task content of occupations was interacted with worker's gender (Models 2a and 2b). Next, whether occupations performed by men and women differ in their task content was studied, with the occupational task measures regressed against gender. One regression was estimated for each task measure, yielding a total of six models (Models 3a-3f).

All these regressions include controls for worker-specific characteristics– gender, age, education level and tenure– and job-related characteristics– type of the contract (full-/part-time), sector, firm ownership (public/private) and firm size. All regressions include country fixed effects. In the case of wage regressions, the proportion of women in an occupation was also controlled (derived from the SES data) as past research demonstrated that female-dominated occupations tend to pay lower wages (Leuze & Strauß, 2016; Magnusson, 2008). Following Moulton (1990), the standard errors were clustered at the occupation level.

6 Results

6.1 Wage returns to occupational tasks

The findings, based on the pooled sample of 13 European countries (Models 1a-1b), suggest workers gain positive wage returns to analytical tasks but negative to routine and manual tasks (see Table 1 below and Table 3 in the Appendix for the full model estimates). An increase in the analytical task content of an occupation by one standard deviation (SD) leads to an increase in the wage premium by exp(0.045), i.e. by 4.6%. At the same time, a similar increase in the routine or manual content of an occupation reduces wages by around 6%. Only social tasks do not command a wage premium / penalty. This stands in contrast with what other researchers have found. Closer investigation reveals that aggregation of social tasks into a single category conceals important differences in wage returns to inward social tasks and outward social tasks. Inward social tasks generate wage premiums – at the level of 2.6% per one SD increase in the task content. Outward social tasks, meanwhile, accrue quantitatively similar wage penalties. Overall, only analytical and inward social tasks bring positive wage returns, with wage returns to analytical tasks commanding 46% more than those from inward social tasks.

Wage returns to occupational tasks depend on workers' gender (Models 2a-2b). Women do not receive any wage premium for working in occupations featuring analytical tasks. In this respect, the situation of women stands in clear contrast to that of men, for whom one SD increase in the analytical content results in a wage increase at 6.5%. At the same time, women are better rewarded for social tasks than men. While inward social tasks bring wage premiums for women at the level of 3.7%, they do not appear to be related to men's wages. The social outward task content drags down wages for men, whereas for women the relation is much weaker and not statistically significant. Men are also more penalised for working in more routine occupations than women. Women appear to have lower returns for manual tasks, but the difference is only significant at the .15 level.

Table 1. Wage returns to occupational tasks on the pooled sample (total and by gender), coefficients estimated using SES 2018

		Occupational skill requirements / tasks					
		Social	Social inward	Social outward	Analytical	Routine	Manual
total	(1)	-0.017	-	-	0.045**	-0.060***	-0.062***
		[0.01]			[0.02]	[0.02]	[0.02]
total	(2)	-	0.026*	-0.028**	0.038**	-0.060***	-0.055***
			[0.01]	[0.01]	[0.02]	[0.02]	[0.02]
men	(3)	-0.031*	-	-	0.066***	-0.078***	-0.054**
		[0.02]			[0.02]	[0.02]	[0.02]
women	(4)	-0.003	-	-	0.016	-0.044**	-0.072***
		[0.01]			[0.02]	[0.02]	[0.02]
difference							
(p-value)	(5)	0.035	-	-	0.001	0.003	0.240

men	(6)	-	0.023	-0.045***	0.063***	-0.071***	-0.046**
			[0.02]	[0.01]	[0.02]	[0.02]	[0.02]
women	(7)	-	0.036**	-0.018	0.004	-0.049***	-0.068***
			[0.02]	[0.01]	[0.02]	[0.02]	[0.01]
difference							
(p-value)	(8)	-	0.311	0.046	0.000	0.049	0.142

Note: Rows (1) and (2) display estimated wage returns to tasks from Models 1a and 1b respectively, rows (3) and (4) give wage returns for women and men separately extracted from Model 2a and rows (6) and (7) from Model 2b. Rows (5) and (8) display the significance test for the difference in wage returns for women and men. The models are estimated on a pooled sample of 13 European countries: Bulgaria, Czechia, Denmark, Estonia, France, Greece, Italy, Lithuania, Latvia, Norway, Poland, Slovakia and UK. The data from UK comes from 2014.
Significance levels: * 0.1, ** 0.05, *** 0.01

6.2 Gender differences in tasks

Whether the growing demand for social and analytical tasks and declining demand for routine and manual tasks will benefit women or not depends not only on wage returns to tasks but also on how frequently women perform certain tasks in comparison to men. The latter question is addressed here by referring to the estimates from Models 3a-f (see Table 2 for the main findings and Table 4 in the Appendix for the full model estimates).

In contrast to the past studies, this one did not find that women were more present in occupations with high routine content, i.e. occupations most exposed to automation and offshoring. In fact, the risks were the same for women and men. This finding puts men at a disadvantage relative to women given that men experience stronger wage penalties for working in routine occupations than women. Furthermore, women clearly benefit from being less likely than men to work in occupations with high manual content which is negatively related to earnings. However, women are overrepresented in occupations that prominently feature outward social tasks, which bring them no wage returns. No gender differences were observed in the frequency of working in occupations featuring analytical tasks and inward social tasks. The latter finding suggests that women do not reap the benefits they could potentially win from working in occupations featuring inward social tasks which offer them the highest wage returns.

Table 2: Gender differences in task content of occupations, coefficients estimated based on SES 2018

	Social	Social Inward	Social Outward	Analytical	Routine	Manual
Woman	0.350**	0.154	0.388**	-0.064	0.069	-0.231*
	[0.11]	[0.09]	[0.12]	[0.10]	[0.12]	[0.09]
R-squared	0.278	0.225	0.252	0.164	0.168	0.308

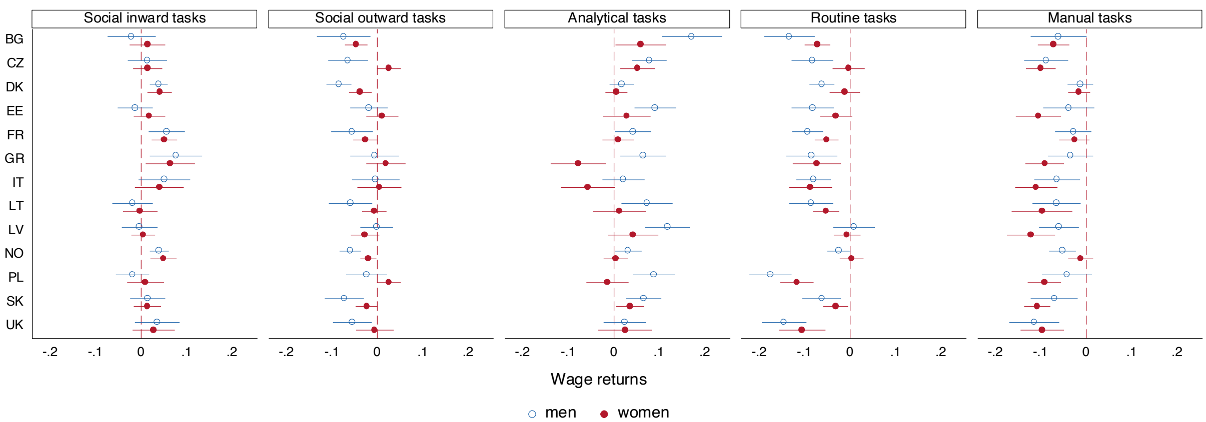
Notes: The findings come from Models 5a-5f, estimated on a pooled sample of 13 European countries: Bulgaria, Czechia, Denmark, Estonia, France, Greece, Italy, Lithuania, Latvia, Norway, Poland, Slovakia and UK. The data from UK comes from 2014. Significance levels: * 0.1, ** 0.05, *** 0.01

6.3 Heterogeneity analysis

In this section two potential sources of heterogeneity in our findings are explored: variation across countries and over time. Models 2a and 2b (wage regressions) are expanded to include interactions between the dimension of interest (country and year fixed effects). The resulting regressions then include a three-way interaction, task x gender x country / year. In the case of gender differences in tasks, models 3 a-f are expanded to include two-way interactions between gender and country / year.

The results for heterogeneity across countries are presented in Figure 2 (wage returns) and Figure 3 (gender differences in tasks). Figure 2 reveals that wage returns observed in the pooled sample were consistent within countries as well. Social inward tasks did not bring significant returns in most countries. Only in Denmark, France, Greece and Norway were the returns positive. Social outward tasks were associated with either no returns or slightly negative returns for men and women alike, except for in Czechia and Poland, where women received slightly positive returns. Finally, the point estimates of wage returns to analytical tasks were higher for men than for women in all countries but the Czechia, Denmark and the UK (outcomes of significance tests for gender differences in wage returns are available on request). Analytical tasks resulted in null wage returns for women in most countries except for the three CEE countries (Bulgaria, Czechia and Slovakia) where they yielded wage premium, and Greece and Italy, where, surprisingly, they resulted in wage penalties. Finally, routine and manual tasks largely yielded negative wage returns both for women and men in the vast majority of the countries. Men were slightly more penalised for routine work than women in Czechia, Denmark, France and Poland, and less penalised for manual tasks in Estonia, Greece, Italy and Latvia.

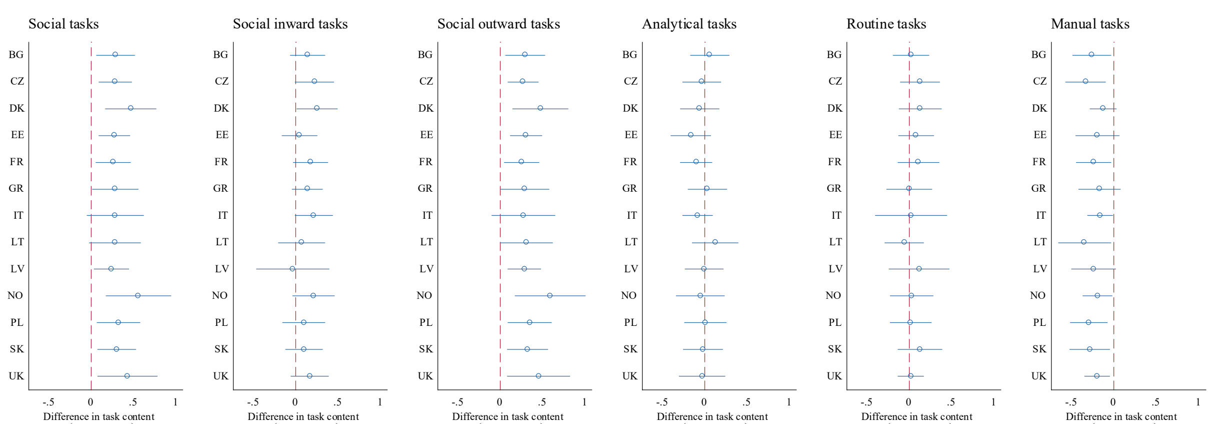
Figure 2. Wage returns to occupational tasks by gender and country in 2018, 90% CI



Note: The findings come from Models 3a and 3b estimated on a pooled sample of 13 European countries: Bulgaria, Czechia, Denmark, Estonia, France, Greece, Italy, Lithuania, Latvia, Norway, Poland, Slovakia and UK. The data from UK comes from 2014.

Figure 3 shows that gender differences in tasks were homogeneous across European countries. In all cases, women worked in occupations that had a higher social content, a difference driven by social outward tasks (except for Greece and Italy). We did not find gender differences in the analytical and routine content of occupations in any country. Women usually worked less often in highly manual occupations, apart from in Estonia and Greece, where no gender differences were observed.

Figure 3. Gender differences in occupational task content by country in 2018, 90% CI

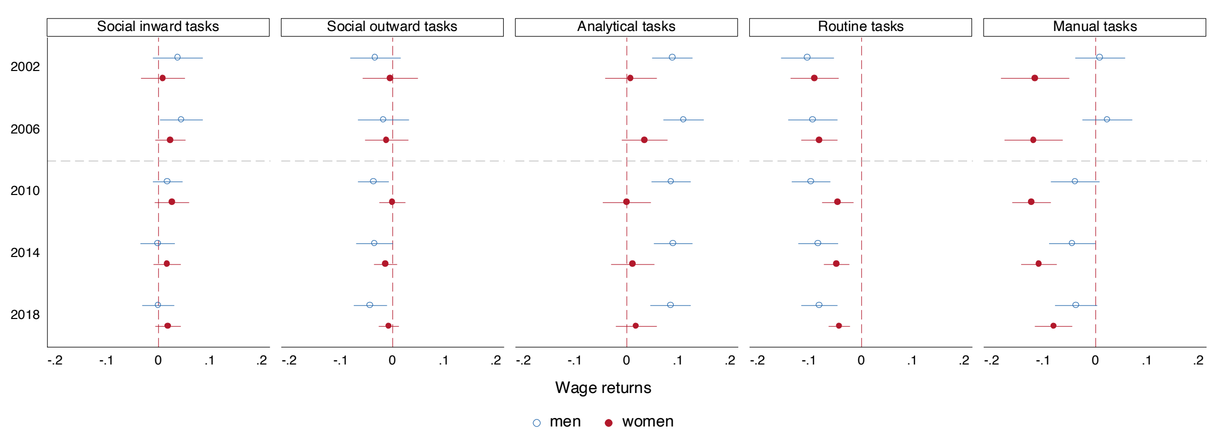


Note: Findings come from the Model 3a-f estimated on a pooled sample of 13 European countries: Bulgaria, Czechia, Denmark, Estonia, France, Greece, Italy, Lithuania, Latvia, Norway, Poland, Slovakia and UK. The data from UK comes from 2014.

Aside from differences across the countries, our research also examined evolution over time. Given that SES is collected every four years since 2002, the trajectories of wage returns and gender differences in tasks can be seen over the previous 16 years. Analysing changes over time added two layers of complexity, however. First, only a few of the countries – Bulgaria, Czechia, Estonia, Lithuania, Latvia, Poland and Slovakia, all located in Central and Eastern Europe – collected detailed data on occupations in every fourth year. While the results from the previous analysis suggest that cross-country heterogeneity was moderate, extrapolating the results to other countries should be done with care. Second, a new classification of occupations was introduced in 2008, creating two separate samples. One, covering the 2002-2006 period, employed the old ISCO-88 classification; while the most recent sample (2010-2018), employed the new ISCO-08 classification. Given the changes in the classification, coefficients from the two periods are not directly comparable.

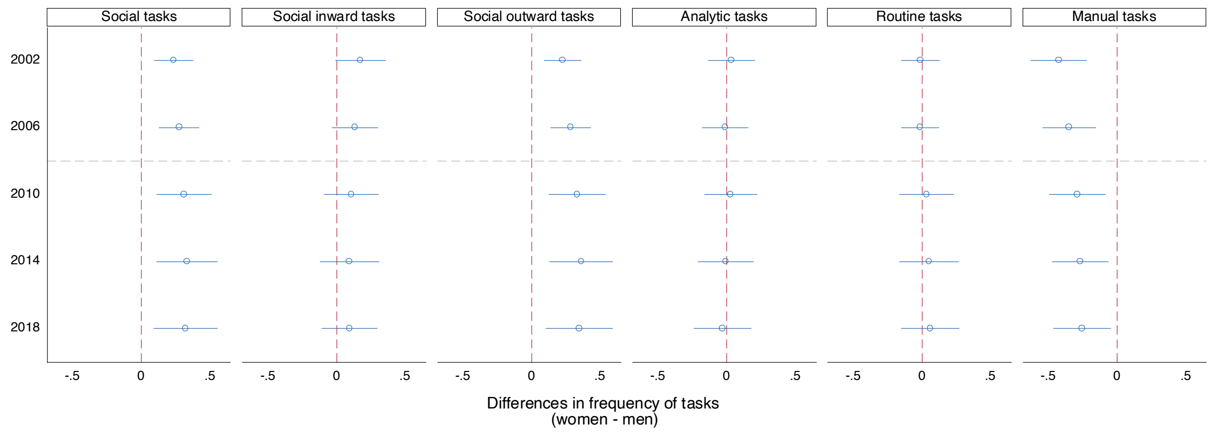
Figure 4 presents the evolution of returns to different tasks over time, while Figure 5 presents the evolution of gender differences in tasks. In both cases, remarkable stability is observed. In spite of structural transformation, there was no evidence that returns to tasks changed much over time, for men or for women. Moreover, gender differences in tasks were constant. Women performed more outward social tasks and fewer manual tasks in every sample year. No gender differences in social outward tasks and analytical tasks were found over time. In contrast to reports elsewhere in the literature, our study did not find that women performed more routine tasks in the earlier years.

Figure 4. Evolution of wage returns to tasks over time, 90% CI



Note: Countries covered: Bulgaria, Czechia, Estonia, Lithuania, Latvia, Poland and Slovakia.

Figure 5. Difference in predicted task content of occupations by gender over calendar year



Note: Countries covered: Bulgaria, Czechia, Estonia, Lithuania, Latvia, Poland and Slovakia.

6.4 Care versus managerial tasks

This study divided social tasks into outward and inward tasks in order to assess women's opportunities in the labour market. One may wonder, however, whether our conclusions would hold if the study concentrated directly on care-related and managerial tasks instead of examining the broader categories of outward and inward social tasks. In order to verify it, the models 2b, 3b and 3c were reestimated but inward social tasks were replaced with managerial tasks and outward social tasks with care tasks. The estimated coefficients for both outcome variables, gender differences in tasks and wage returns, are presented in the Appendix in Tables 5. The patterns observed earlier were even more pronounced when these narrower definitions were applied. Women more often worked in occupations requiring more "care", but less often in those requiring more "management". In terms of rewards, "care" tasks generated negative wage returns, with the penalty being stronger for men. On the other hand, lower returns were reported to "management" tasks when they were performed by women. These results confirm past findings from the US (Levanon & Grusky, 2016; Liu & Grusky, 2013).

7 Discussion

There is a body of research, largely done in the US, that argues that women will benefit from structural change in the labour market thanks to the increasing role that social tasks, occupied predominantly by women, will play, and the declining importance of manual tasks, which are more commonly done by men.

This study tests this argument in the context of EU countries, primarily by two means. The first is by extending the standard framework of the task content of occupations to account for the diversity of social tasks and occupational gender segregation. The second is through the development of measures of occupational task content based on EU-specific data on occupations and their respective skill needs, which are more suitable for analysing the continent.

In contrast to studies on the US, the present study provides only partial evidence that the structural labour market change benefits women. Women working in low- and middle-skilled occupations can indeed make inroads relative to men as they are less likely to perform occupations geared around manual tasks, and they tend to be penalised less for working in occupations dominated by routine tasks. Overall, it seems that if occupations built around routine and manual tasks are shrinking or wage returns to these tasks fall, women are less likely to suffer from these changes than men. This conclusion pertains to most of the countries analysed in this study except for Greece and Italy, the two Southern European countries and Estonia and Latvia, two Baltic countries. In these four countries women appear to be most threatened by the ongoing changes as they face stronger negative wage returns to manual tasks and, moreover, do not get less penalised than men for doing occupations intense in routine tasks.

At the same time, women working in high-skilled occupations are susceptible to losing out due to the ongoing changes in the labour market. First, in contrast to men, they do not experience positive wage returns to analytical tasks. An extreme example comes from Italy and Greece, where women are even penalised for working in occupations built around analytical tasks. Second, the findings of this study throw into question whether women will benefit from the expansion of social tasks, which clearly pay women lower wage returns than analytical tasks pay men. Furthermore, women more often work in occupations which involve outward social tasks, often resulting in wage penalties. These findings hold for most of the countries studied, apart from Czechia and Poland, where outward social tasks generate positive wage returns to women.

Overall, highly skilled women appear unlikely to benefit from the structural labour market change unless they experience an increase in wage returns to outward social tasks or analytical tasks. Theoretically, growing demand for childcare, elderly care or healthcare should increase wages in the care sector. Whether this will indeed happen is questionable, however, given that care work has been traditionally low-paid (England, 2005; England et al., 2002). It is also difficult to say whether women will experience an increase in wage returns for women doing analytical tasks as our study provides no explanation on why analytical tasks pay lower wages to women than to men. Is it because women perform different analytical tasks than men – which our data does not bear out – or that women are simply paid less for the same tasks?

Temporal changes in gender differences in wage returns to occupational tasks were also examined. Unlike in studies done on US data, no changes in returns to tasks over time were found. However, these findings should be taken with caution. The time period used in this study was much shorter than those in the American studies and our observation is blurred by changes in the occupational classification. Moreover, the estimates of time trends used here were obtained for a subset of countries for which information was available in every wave (mostly CEE countries). More research with better data—longer time series and larger country coverage—is still needed.

This study suffers from the same limitations as other studies of the task content of jobs. First, the focus is on occupational tasks but not on the actual tasks workers perform at their jobs. While occupations certainly are good proxies of what people do at work, studies have revealed substantial within-occupation heterogeneity in tasks (Autor & Handel, 2013). This study sought to overcome this problem by employing occupational data at the highest possible level of granularity. Second, the measure of task content used in this does not vary over time. As such, the analysis of changes over time should be viewed with caution. Finally, our study focuses only on wages while the structural labour market change may affect women's opportunities in the labour market in other respects—for example, the opportunity to find and maintain employment or have a high-quality job. Future research should address these aspects to obtain a more comprehensive picture of the impact of the labour market's changing structure on women's position in the labour market.

Besides these limitations, this study provides evidence that claims that women will benefit from the ongoing structural change in the labour market are overly optimistic. In fact, it is women in highly skilled occupations who may lose from these changes relative to men. These claims should be verified in a more careful analysis of wage returns that applies a gender perspective. Such analysis could, for instance, involve more detailed task categories which account for the gender heterogeneity within existing tasks. The division between inward and outward social tasks proposed in this paper is just a first step in this direction.

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Appendix

Table 1. Country coverage and sample Sizes

Country	Year				
	2002	2006	2010	2014	2018
Bulgaria	152,977	186,672	204,968	200,680	217,508
Czechia	1,030,982	1,970,864	1,981,785	2,202,636	2,434,107
Denmark					2,334,735
Estonia	78,106	126,515	119,222	122,654	154,944
France					256,600
Greece					38,987
Italy					248,783
Lithuania	145,530	131,201	38,387	44,952	43,164
Latvia	192,551	299,857	223,215	172,584	188,611
Norway					2,502,718
Poland	647,386	652,688	681,761	723,706	861,637
Slovakia	419,715	674,408	773,860	887,052	964,342
UK				175,477	

Table 2. Correlations between O*NET-based task measures (Acemoglu and Autor, 2011) with (a) our ESCO-based task measures (columns (1)-(3)), (b) PDII-based task measures from Autor and Handel (2013) (column (4)) and (c) PIAAC-based task measures from De La Rica et al., (2020) (column (5))

ESCO-based tasks	O*NET-based tasks	Pearson	Pearson (weighted)	Spearman	Autor and Handel (2013)	De La Rica et al. (2020)*
		(1)	(2)	(3)	(4)	(5)
Abstract (all)	Non-routine cognitive (average)	0.67	0.68	0.70	0.65	~0.62-0.70
- Analytical	- Non-routine cognitive analytic	0.60	0.64	0.62	-	-

- Social	- Non-routine cognitive social	0.54	0.52	0.61	-	-
Routine	Routine (avg. of manual routine and cognitive routine)	0.49	0.57	0.56	0.48	~0.20-0.49
Manual	Non-routine manual	0.72	0.72	0.81	0.63	~0.54-0.72

Note: De la Rica et al. (2020) calculate correlations for each country in the PIAAC sample, achieving the highest correlations for the US and, understandably, lower ones for all other countries. The correlations for US were 0.82, 0.53 and 0.73 for Abstract, Routine and Manual tasks, respectively. The range reported in the table refers only to the EU countries in the sample.

Table 3. Wage returns to task content of occupations. Full estimates from Models 1a, 1b, 2a, 2b

Dep. Variable: log hourly wage	Model			
	1a	1b	2a	2b
Woman=1	-0.108***	-0.108***	-0.112***	-0.114***
	[0.01]	[0.01]	[0.01]	[0.01]
Tasks:				
Social tasks	-0.017		-0.031*	
	[0.01]		[0.02]	
Social tasks: outward		-0.028**		-0.045***
		[0.01]		[0.01]
Social tasks: inward		0.026*		0.023
		[0.01]		[0.02]
Analytical tasks	0.045**	0.038**	0.066***	0.063***
	[0.02]	[0.02]	[0.02]	[0.02]
Routine tasks	-0.060***	-0.060***	-0.078***	-0.071***
	[0.02]	[0.02]	[0.02]	[0.02]
Manual tasks	-0.062***	-0.055***	-0.054**	-0.046**
	[0.02]	[0.02]	[0.02]	[0.02]
Woman=1 # Social tasks			0.029**	
			[0.01]	
Woman=1 # Social tasks: outward				0.027**
				[0.01]
Woman=1 # Social tasks: inward				0.013
				[0.01]

Woman=1 # Analytical tasks			-0.050***	-0.059***
			[0.01]	[0.01]
Woman=1 # Routine tasks			0.034***	0.022**
			[0.01]	[0.01]
Woman=1 # Manual tasks			-0.018	-0.022
			[0.02]	[0.01]
Age:				
20-29	0.132***	0.131***	0.131***	0.131***
	[0.02]	[0.02]	[0.02]	[0.02]
30-39	0.236***	0.233***	0.234***	0.232***
	[0.03]	[0.03]	[0.02]	[0.03]
40-49	0.275***	0.270***	0.273***	0.269***
	[0.03]	[0.03]	[0.03]	[0.03]
50-59	0.268***	0.263***	0.266***	0.262***
	[0.03]	[0.03]	[0.02]	[0.03]
60+	0.217***	0.211***	0.216***	0.211***
	[0.03]	[0.03]	[0.03]	[0.03]
Education level				
Upper or post-secondary	0.085***	0.084***	0.082***	0.081***
	[0.01]	[0.01]	[0.01]	[0.01]
Any tertiary	0.335***	0.337***	0.332***	0.334***
	[0.03]	[0.03]	[0.03]	[0.03]
Tenure	0.010***	0.010***	0.010***	0.009***
	[0.00]	[0.00]	[0.00]	[0.00]
Full time position	0.044**	0.046**	0.044**	0.044**
	[0.02]	[0.02]	[0.02]	[0.02]
Industry				
Construction	0.014	0.009	0.009	0.000
	[0.02]	[0.02]	[0.02]	[0.02]
Market services	-0.032	-0.035	-0.030	-0.032
	[0.02]	[0.02]	[0.02]	[0.02]
Non-market services	-0.061*	-0.065**	-0.062**	-0.067**
	[0.03]	[0.03]	[0.03]	[0.03]
Firm over 50 employees	0.135***	0.136***	0.136***	0.137***

	[0.01]	[0.02]	[0.01]	[0.02]
Share of women in occ.	-0.133*	-0.130*	-0.138*	-0.128*
	[0.07]	[0.07]	[0.07]	[0.07]
Country				
CZ	0.904***	0.905***	0.900***	0.901***
	[0.02]	[0.02]	[0.02]	[0.02]
DK	2.394***	2.395***	2.388***	2.390***
	[0.03]	[0.03]	[0.03]	[0.03]
EE	0.892***	0.893***	0.889***	0.890***
	[0.02]	[0.02]	[0.02]	[0.02]
FR	1.760***	1.759***	1.756***	1.755***
	[0.03]	[0.03]	[0.02]	[0.02]
GR	1.077***	1.079***	1.076***	1.079***
	[0.03]	[0.03]	[0.03]	[0.03]
IT	1.680***	1.679***	1.678***	1.675***
	[0.03]	[0.04]	[0.03]	[0.03]
LT	0.524***	0.523***	0.525***	0.524***
	[0.02]	[0.02]	[0.02]	[0.02]
LV	0.674***	0.668***	0.672***	0.666***
	[0.03]	[0.03]	[0.03]	[0.03]
NO	2.372***	2.370***	2.366***	2.363***
	[0.03]	[0.03]	[0.03]	[0.03]
PL	0.664***	0.664***	0.662***	0.661***
	[0.02]	[0.03]	[0.02]	[0.02]
SK	0.817***	0.819***	0.814***	0.816***
	[0.02]	[0.02]	[0.02]	[0.02]
UK	1.811***	1.812***	1.806***	1.808***
	[0.03]	[0.03]	[0.03]	[0.03]
Constant	0.498***	0.501***	0.502***	0.503***
	[0.05]	[0.05]	[0.05]	[0.05]
N	10336694	10336694	10336694	10336694
R-squared	0.809	0.810	0.810	0.811

Note: Standard errors clustered at the ISCO 3 digit level. ***, **, * indicate p-values smaller than .10, .05 and .01.

Table 4. Gender differences in occupational tasks, estimates from Models 3a-3f

Model:	3a	3b	3c	3d	3e	3f
Task:	Social	Social inward	Social outward	Analytical	Routine	Manual
Woman	0.363**	0.167	0.376**	-0.030	0.061	-0.210*
	[0.11]	[0.09]	[0.12]	[0.10]	[0.11]	[0.09]
Age:						
20-29	-0.166*	-0.097	-0.165*	-0.026	0.119	0.149
	[0.07]	[0.08]	[0.07]	[0.09]	[0.11]	[0.09]
30-39	-0.233**	-0.062	-0.251**	-0.006	0.063	0.146
	[0.08]	[0.10]	[0.08]	[0.11]	[0.13]	[0.12]
40-49	-0.225*	-0.010	-0.256**	-0.038	-0.002	0.181
	[0.09]	[0.11]	[0.10]	[0.11]	[0.14]	[0.13]
50-59	-0.267*	-0.044	-0.296**	-0.101	0.005	0.248
	[0.10]	[0.12]	[0.10]	[0.12]	[0.14]	[0.15]
60+	-0.315**	-0.046	-0.351**	-0.148	0.036	0.255
	[0.11]	[0.13]	[0.11]	[0.13]	[0.15]	[0.16]
Education level						
Upper or post-secondary	0.188**	0.219***	0.158*	0.244***	-0.046	-0.318***
	[0.07]	[0.05]	[0.07]	[0.06]	[0.06]	[0.08]
Any tertiary	0.635**	0.567**	0.580**	0.842***	-0.796***	-0.973***
	[0.20]	[0.17]	[0.21]	[0.17]	[0.19]	[0.16]
Tenure	0.010**	0.010**	0.009*	0.010***	-0.007*	-0.012***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Industry						
Construction	0.059	0.188	0.018	0.230**	0.229*	0.240
	[0.05]	[0.11]	[0.04]	[0.09]	[0.11]	[0.20]
Market services	0.401***	0.401***	0.354***	0.297*	-0.051	-0.448***
	[0.10]	[0.12]	[0.09]	[0.14]	[0.12]	[0.12]
Non-market services	1.093***	0.594***	1.097***	-0.255	-0.381	-0.358**
	[0.23]	[0.17]	[0.26]	[0.17]	[0.22]	[0.13]
Firm over 50 employees	-0.025	-0.026	-0.023	0.075	0.129	-0.031
	[0.07]	[0.09]	[0.08]	[0.05]	[0.09]	[0.03]

Full time position	-0.034	0.004	-0.041	0.144*	-0.110	-0.146*
	[0.07]	[0.06]	[0.08]	[0.07]	[0.08]	[0.07]
Country						
CZ	-0.042	-0.021	-0.042	0.155**	0.053	-0.007
	[0.05]	[0.06]	[0.05]	[0.06]	[0.05]	[0.05]
DK	0.182*	0.084	0.190	0.136	0.028	-0.069
	[0.09]	[0.07]	[0.10]	[0.08]	[0.12]	[0.06]
EE	-0.056	-0.035	-0.055	0.095	0.038	0.021
	[0.05]	[0.06]	[0.05]	[0.05]	[0.06]	[0.05]
FR	-0.178	-0.031	-0.195	0.119	0.145	0.072
	[0.10]	[0.09]	[0.10]	[0.08]	[0.10]	[0.10]
GR	0.200*	0.009	0.230	-0.118	0.253	-0.028
	[0.10]	[0.10]	[0.13]	[0.07]	[0.22]	[0.08]
IT	0.057	0.117	0.036	0.049	0.165	-0.189**
	[0.13]	[0.10]	[0.14]	[0.07]	[0.21]	[0.06]
LT	-0.046	0.012	-0.055	0.101*	-0.073	0.073
	[0.04]	[0.05]	[0.05]	[0.05]	[0.07]	[0.06]
LV	-0.075	0.161	-0.129*	0.080	-0.182	-0.016
	[0.06]	[0.19]	[0.06]	[0.05]	[0.15]	[0.05]
NO	0.270**	0.281***	0.238*	0.313***	-0.092	-0.146*
	[0.09]	[0.08]	[0.10]	[0.08]	[0.08]	[0.06]
PL	0.031	0.051	0.023	0.059	-0.109*	0.015
	[0.04]	[0.05]	[0.05]	[0.04]	[0.05]	[0.04]
SK	-0.024	-0.042	-0.016	0.093	0.026	-0.014
	[0.05]	[0.04]	[0.06]	[0.05]	[0.05]	[0.04]
UK	0.071	0.076	0.062	0.211**	-0.014	-0.145*
	[0.07]	[0.08]	[0.08]	[0.07]	[0.07]	[0.07]
Constant	-0.831***	-0.826***	-0.736***	-0.754***	0.375	0.946***
	[0.20]	[0.20]	[0.21]	[0.22]	[0.23]	[0.20]
N	10336733	10336733	10336733	10336733	10336733	10336733
R-squared	0.303	0.139	0.291	0.171	0.177	0.291

Notes: Standard errors clustered at the ISCO 3 digit level. ***, **, * indicate p-values smaller than .10, .05 and .01.

Table 5. Wage returns to task content and gender differences in occupational tasks after applying a narrower definition of social inward and outward tasks

	Wage returns	Gender differences in occupational tasks	
		management	care
Woman	-0.112***	0.1	0.313**
	[0.01]	[0.10]	[0.12]
Social tasks: management	0.003		
	[0.02]		
Woman=1 # Social tasks: management	-0.033*		
	[0.02]		
Social tasks: caring	-0.041**		
	[0.02]		
Woman=1 # Social tasks: caring	0.036***		
	[0.01]		
Analytical tasks	0.065***		
	[0.02]		
Woman=1 # Analytical tasks	-0.044***		
	[0.01]		
Routine tasks	-0.070***		
	[0.01]		
Woman=1 # Routine tasks	0.017		
	[0.01]		
Manual tasks	-0.049**		
	[0.02]		
Woman=1 # Manual tasks	-0.032**		
	[0.02]		

Notes: Standard errors clustered at the ISCO 3 digit level. ***, **, * indicate p-values smaller than .10, .05 and .01.

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