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Technology, Tasks and Social Classes in Europe

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Abstract

EGP (Erikson-Goldthorpe-Portocarero)-based occupational class schemas, rooted in industrial-age employment relations, are the standard measure of socioeconomic position in social stratification. Previous research highlighted EGP-based schemas' difficulties to keep up with changing labour markets, but few tested alternative explanations. This article explores how job tasks linked to technological change and economic inequality might confound the links between employment relations, classes, and life chances. Using the European Working Conditions Survey covering the EU-27, this article analyses over time and gender (1) the task distribution between social classes; and (2) whether tasks are predictive of class membership and life chances. Decomposition analyses suggest that tasks explain class membership and wage inequality better than employment relations. However, intellectual/routine tasks and digital tools driving income inequality are well-stratified by occupational classes. Therefore, this article does not argue for a class (schema) revolution but for fine-tuning the old instrument to portray market inequalities in the digital age.

Keywords: EGP, employment relations, ESeC, job tasks, routine biased technical change, social class, social stratification, technological change.

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Oesch, D., Contemporary Class Analysis, European Commission, Seville, 2022, JRC126506 https://joint-research-centre.ec.europa.eu/publications/contemporary-class-analysis_es

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Executive summary

- Occupational social class -Erikson-Goldthorpe-Portocarero (EGP)-based schemas as standard- is among the most widespread measures of socioeconomic position in stratification and inequality research. Occupational class models were developed during the 70s-80s, building on industrial-age employment relations. However, labour markets have experienced deep transformations since that period. This article explores how unfolding vectors of technological change in post-industrial economies -digitalisation and automation- might jeopardise the validity of (EGP-based) mainstream class models to portray socioeconomic inequalities in the digital age.

- EGP-based social class schemas rely on employment relations -reward types and time horizons offered to employees- to explain the existence of different employment contracts and social classes with unequal life chances. As an alternative explanation, considering that job tasks are the finest-grained analysis unit to capture how technological change affects employment, we test whether job task indices predict class belonging and life chances better than the theorised employment relations over time (2005-2015) and by gender. We apply mediation and decomposition methods drawing from the European Working Conditions Survey and the JRC-Eurofound task taxonomy in the EU-27.

- First, descriptive analysis shows that those job tasks that partially drive both increasing income inequality and the impact of technological change on employment -intellectual and routine tasks and ICT tools– are well stratified by (EGP-based) occupational social classes. While the work of those in the upper classes -large managers and professionals- is characterised by intensive use of intellectual tasks and ICT tools, working classes perform more physical tasks and routinary work. Moreover, this class task divide remained relatively constant between the decade spanning from 2005 to 2015. Accordingly, disadvantaged working classes at the bottom of the social structure could bear the most harmful and substitutive impact of new technologies on working conditions and life chances.

- Second, mediation analysis yields that about two-thirds of the total effect of EGP-based employment relations indicators (working conditions offered to workers) on class membership is confounded by job tasks. The job tasks most related to technology-based explanations of wage inequality -ICT tools, intellectual and routine tasks- are confounding this association most. Thus, the theoretical foundations of social class schemas based on (industrial-age) employment relations are challenged by alternative explanations like job tasks or productivity-based differences between occupations.

- Third, decomposition analysis indicates that different employment relations offered by employers explain slightly better social class differences in career stability (seniority and permanent employment) than job tasks. Hence, EGP-based employment relations are still doing a fairly job capturing the career stability dimension of life chances. By contrast, job tasks are the factor that accounts for most of the explained class wage gaps, contributing 25%-to-40% more than employment relations in relative terms. Those same tasks related to technology-based explanations of income inequality -ICT tools, intellectual and repetitive tasks- account for most wage inequality between social classes.

- Overall, these findings suggest no solid grounds for a class schema revolution but for fine-tuning the old instrument to better capture labour market inequalities in the digital age. Since workers' tasks are still reasonably well stratified by (EGP-based) occupational social classes, technological change might not be the big game-changer in cracking the building stones of the old industrial stratification system. Furthermore, even if EGP-based schemas' foundations were outdated, they operationalise classes by aggregating occupational titles. Still, tasks related to technology-based explanations of growing economic inequality better account for income inequalities between classes. Even though relying on occupational titles is still granted, direct information on job tasks could help sharpen (industrial) social class schemas to depict workplace inequalities in power and authority, gender, income, and wealth concentration in digital economies.

1 Introduction

Not long ago, occupational social class was the most widespread measure of socioeconomic position in social stratification research (Barone, Hertel and Smallenbroek, 2022), partly because occupations work well as proxies for socioeconomic status and their availability in survey data. The neo-Weberian Erikson-Goldthorpe-Portocarero (EGP) class schema and its revised European Socio-economic Classification (ESeC), based on social relations in labour markets, became the institutionalised standard (Rose and Harrison, 2010; Rose, Pevalin, and O'Reilly, 2005; Erikson and Goldthorpe, 1992). Since the late 2000s, EGP-based schemas account for about 75% of all scientific articles published in top-cited sociological journals using social class (Barone, Hertel and Smallenbroek, 2022).

The popularity of EGP-based class schemas had to do with its satisfactory criterion and construct validity when accounting for the employment relations proposed by the model or predicting life chances (Smallenbroek, Hertel and Barone, 2021; Westhoff, Bukodi and Goldthorpe, 2021; Rose and Harrison, 2010; McGovern et al., 2007; Goldthorpe and McKnight, 2006; Evans and Mills, 1998). Moreover, once a measure becomes standardised, it is more practical to keep using it for accumulating evidence and benchmarking. However, this practicality might come at the cost of unquestioning this industrial-age class measure (Lambert and Bihagen, 2014).

Income has recently replaced occupational class as the preferred indicator of social stratification scholars to measure socioeconomic inequality (Barone, Hertel and Smallenbroek, 2022). Over the last thirty years, many academics have underscored several limitations of the EGP class model when it comes to keeping up with far-reaching structural changes taking place in Western countries since the twilight of the industrial era in the 1980s (Bisello et al., 2019; González Vázquez et al., 2019; Oesch and Piccitto, 2019; Fernández-Macías and Hurley, 2017; Barbieri, 2009; McGovern et al., 2007; Oesch, 2006; Esping-Andersen, 1999; 1993): the rise of post-industrial economies at the expense of manufacturing in a context of intense global trade and offshoring, occupational and educational upgrading, women's segregated labour force incorporation, declining industrial relations, new precarious employment relations, forms of work and human resources management, and technological change.

Among these challenges, this article focuses on the digitalisation and automation of the workplace. Williams (2017) draws upon the Routine Biased Technical Change (RBTC) literature (Autor, Levy and Murnane, 2003) to consider how changing job characteristics in the form of tasks, those most connected to growing economic inequality (routine and analytical tasks) and partially driven by technological change (Acemoglu and Restrepo, 2021), might be confounding the links between employment relations and class positions derived by EGP-based schemas. RBTC posits that job tasks, not skills, can be replaced or complemented by new technologies, depending on the routine intensity of the job.

There is ample evidence showing that recent increases in income inequalities across both sides of the Atlantic—the UK, USA, and EU—can be accounted for by wage differentials between occupations—occupational-mean skills, tasks, or social classes (Goedemé et al., 2021; Albertini, Ballarino and De Luca, 2020; Williams and Bol, 2018; Zhou and Wodtke, 2019; Liu and Grusky, 2013; Goos and Manning, 2007; for alternative findings: Fernández-Macías and Arranz-Muñoz, 2020). Thus, studying the employment relations and job tasks outlined by the EGP model and the RBTC theory and their potential (and shifting) links could shed new light 'on the extent to which inequality trends may be due to shifts in the task structure related to technological change, or whether class-based changes in inequality are largely unrelated (Williams, 2017:5). ́

Suppose new productivity-enhancing technologies allow employers to redefine work tasks, roles and methods (Fernández-Macías and Bisello, 2021), altering the distribution of tasks, productivity and income across social classes. This scenario casts doubt on the validity of EGP-based social classes. The allocation of occupations into classes is neither time nor context-independent since a different form of employment relationship could regulate the same occupations in different periods and countries (Barbieri et al., 2020). Few previous research assessed whether the link between employment relations and social classes has changed over time or whether alternative explanations might confound this relationship. Thus, we do not know to what extent social classes are close relatives to the tasks emphasized by technology-based explanations or whether they account for different explanations because both approaches use occupational codes as proxies (Williams, 2017).

This article aims at answering the following research questions to map the relationship between job tasks, employment relations, and social classes:

1. How are job tasks distributed between social classes? Are social classes increasingly capturing a task divide related to technological change?
2. Are job tasks more predictive of class membership than employment relations?
3. Are job tasks more predictive of life chances than employment relations?

In answering these novel research questions, this article's contribution is to provide an integrated and interdisciplinary theoretical framework supported by new empirical evidence. First, it looks for the first time at the distribution of job tasks between occupational classes at the individual level in the EU-27 over time and by gender. Second, it tests if vectors of technological change, proxied by job tasks, might compromise the foundations of EGP-based class schemas by assessing the predictive power of employment relations and job tasks to account for social classes and life chances. Third, as jobs are bundles of tasks, this article focuses on a broader range of tasks, work methods and tools than previous literature building on the JRC-Eurofound task taxonomy designed to study technological change and employment (Fernández-Macías and Bisello, 2021).

To answer the research questions, this article pools data from three waves (2005, 2010, 2015) of the European Working Conditions Survey (EWCS) covering EU-27 countries[1]. The EWCS is the only cross-national survey including individual-level job characteristics central to EGP-based class schemas and job tasks related to technology-based explanations with a large sample.

2 Theoretical framework and previous findings

2.1 Revisiting the foundations of EGP-based class schemas

It was only in the early 2000s when Goldthorpe (2007a) outlined in a more precise (and ad-hoc) fashion the micro-foundations of the EGP class schema.[2] Then, relying on rational action theories and organizational economics, Goldthorpe (2007a) explained how employers regulate different employment contracts, generating different social classes in labour markets.

According to Goldthorpe (2007), imperfect information about prospective employees' productivity and effort at the workplace would lead employers to issue employment contracts (service relationship, mixed and labour contract) with different types of reward (specific/diffuse) and time horizons (short/long-term). Different working situations like reward types and time horizons are allocated to different jobs depending on the work type. Jobs differ inherently in their human asset specificity and

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[1] Including the UK and excluding Croatia.

[2] Initially, the EGP schema defined social classes as groups of occupations with similar market and work situations (Goldthorpe et al., 1982; Goldthorpe, 1980:40) as defined as "occupational categories whose members would appear, in the light of the available evidence, to be typically comparable, on the one hand, in terms of their sources and levels of income, their degree of economic security and chances of economic advancement [market situation]; and, on the other hand in their location within the systems of authority and control governing the processes of production in which they are engaged, and hence in their degree of autonomy in performing their work-tasks and roles [work situation]."

monitoring difficulty, and these job characteristics are perceived as contractual hazards that employers try to minimize to avoid employees' shirking.

On the one hand, monitoring difficulty relates to the capacity of employers to track workers' effort and productivity. While it is challenging to monitor professionals and managers, assembly line workers are easier to monitor due to the high intensity of routine tasks and standardised production. Thus, more diffuse reward types (company stocks; fringe benefits; performance bonus) are generally offered to higher managers and professionals involved in a service relationship (ESeC Classes 1 and 2) in comparison to working classes (Classes 7, 8 and 9) (Williams, Zhou and Zou, 2020). The latter can be compensated for discrete work units on a piece- or time-rate basis with a labour or spot contract (Rose and Harrison, 2010).

On the other hand, human asset specificity refers to expert knowledge or how difficult it is for employers to replace a worker with similar firm-specific skills and productivity. Therefore, for those jobs with high asset specificity, both employers and employees are interested in a long-term (service) relationship formalized in a permanent contract and prospective elements like salary increments and career opportunities (Goldthorpe and McKnight, 2006). By contrast, a short-term labour contract should prevail for the working classes, involving a higher risk of unemployment and more unstable careers.

Other types of workers combining elements of the service relationship and the labour contract are considered mixed or intermediated forms of employment regulation. For instance, clerical workers with low human asset specificity but difficult to monitor (Class 3), and technical workers and lower supervisors with high human asset specificity but easy to monitor (Class 6).

Due to data availability, previous research wrongly mixes employment relations indicators (reward types and time horizons) with theorised explanatory mechanisms (human asset specificity and monitoring difficulty) (Smallenbroek, Hertel and Barone, 2021). However, when assessing the criterion validity of EGP-based schemas, it is most accurate to study the relationship between employment relations indicators and social classes. The theorised mechanisms or alternative explanations can account for this relationship. Therefore, this article uses reward types and time horizons as core theoretical indicators of employment relations or work situations.

2.2 The EGP schema and its critics

Even though EGP-based schemas are the most popular measure of social class, it is an empirical fact that social class is becoming a marginal measure of socio-economic position in sociological fields—and even more so in other fields—other than social stratification (Barone, Hertel and Smallenbroek, 2022), like labour market and demography research. Meanwhile, income, wealth and distributive inequality are gaining momentum in academics (Hälsten and Thaning, 2021), public and policy discussions parallel the observed rise of economic inequalities (Oesch, 2022). Still, there is no hard evidence demonstrating the declining power of (big) social classes to capture the structure of (cross-sectional) labour market inequalities (Albertini, Ballarino and De Luca, 2020; Zhou and Wodtke, 2019). Thus, forgoing the division of labour and representing inequality with just individual education, income or wealth does not seem reassuring as of now (Barbieri et al., 2020; Weeden and Grusky, 2012).

Different alternative social class schemas were devised with the ambitious aim to replace EGP-based schemas, advocating for the central role of distinct elements such as (1) economic, social and cultural capitals (Hansen and Wiborg, 2019; Savage et al., 2013; Bourdieu, 1986); (2) horizontal work logics (Oesch, 2006); (3) management assets (i.e., power, authority and control) (Wright, 2005); (4) wealth and rent exploitation (Sørensen, 2000); (5) and industrial-post-industrial occupational divides (Esping-Andersen, 1993).

Nevertheless, these ambitious and pertinent proposals neither found comprehensive implementation in empirical research nor became a new institutionalized class-schema standard (Barone, Hertel and

Smallenbroek, 2022). That might have something to do with the lack of a direct empirical test of the accuracy of different class schemas to predict life chances or other political outcomes, along with the sizeable empirical overlap between all of them (Lambert and Bihagen, 2014). In practice, advocating for one social class scheme over another has been an arbitrary choice driven by pragmatism, ideological affiliation, or theoretical grounds to isolate mechanisms.

A second group of authors did not advocate for a class (schema) revolution but a revisionist fine-tuning of the old instrument. Instead, they support disaggregating EGP-based class schemas horizontally both at the top (higher and lower managers and professionals, or socio-cultural and technical professionals within the service class; (Guveli, Need, and de Graaf, 2007) and the bottom (routine workers vs lower-grade white-collar and blue-collar workers) to better capture observed heterogeneity in employment relations and life chances within these broad groups (Smallenbroek, Hertel and Barone, 2021). For instance, as Smallenbroek et al. (2021) observed, lower professionals sometimes have more in common with high-grade white and blue collars than with other service classes, making a case for a more granular disaggregation.

A third school of thought focused its critique on the inadequacy of big social class schemas altogether, based on aggregations of occupations like the EGP, to keep up with macro trends of increasing income inequalities or accounting for political behaviour and attitudes (Weeden and Grusky, 2005). These authors advocate for a micro-class approach based on occupations at the highest level of disaggregation as possible to better capture micro-level mechanisms of social reproduction (i.e., licenses, certifications) and action (Weeden and Grusky, 2012) since, the argument follows, occupations are the main niches of socialization and self-identification. Furthermore, recent growth in economic inequalities would be better captured by wage variation in occupations within big social classes rather than by variation between them (Weeden and Grusky, 2012; Weeden et al., 2007).

2.3 Technology, tasks, and social classes

Some authors question the conceptual foundations of EGP-based class schemas centred on employment relations by arguing that alternative explanations, like productivity-based differences between occupations, job tasks or pre-market factors like skills or educational credentials (Williams 2017; Tåhlin, 2007), might better account for the definition of social classes and life chances. In this vein, Brousse, Monso and Wolff (2010) argued that employment relations theories leave aside skill and qualification levels and the nature and organization of work. They tested the validity of the ESeC schema with rich French data using clustering methods to conclude that its class categories are more accurately ordered as a function of the cognitive content of tasks than by work monitoring difficulty.

Given that recent trends in rising income inequality can be partially explained by increasing returns to college education and analytical skills (Zhou and Wodtke, 2019; Liu and Grusky, 2013), these critiques are highly relevant, even when they did not find much echo. Instead, the Skill Biased Technical Change (SBTC) model became mainstream in accounting for trends in income inequality by linking occupations with skills and education requirements (Bekman, Bound and Machin, 1998; Violante, 2008). SBTC theories predict increasing returns to college education and wage inequalities due to advanced economies' computerisation and automation, mainly affecting low-skilled workers. As pointed out by Tåhlin (2007), educational attainment or credentials had a more considerable weight in defining different social classes in the original EGP class schema than in later theoretical tweaks.

There is nascent literature suggesting that technological change and its impact on labour markets could undermine the theoretical foundations of industrial-age class schemas (Williams, 2017). The EGP schema builds on employment relations and occupational structures that have changed dramatically in the last thirty years. These changes relate to the composition of job tasks (Fernández-Macías and Bisello, 2021), work methods and organisation, trade unions density rate (Zhou and Wodtke, 2019), labour market deregulation and flexibility (Barbieri, 2009), human resources practices to recruit and monitor employees (Moore, Upchurch, and Whittaker, 2018), and wealth accumulation dynamics (Eeckhout, 2021).

Generally, firms and employers implement production technologies and settle how work is organised. They define job tasks, how the workers will perform these tasks (i.e., autonomy, standardization, teamwork) and their monitoring. Thus, if new productivity-enhancing technologies alter the distribution of job tasks or income returns across social classes, the validity of EGP-based class schemas might be jeopardised.

Since the 1980s, two vectors of technological change, along with offshoring and international trade, have been disrupting industrial-age labour markets: digitalisation (digital tools and labour platforms) and automation (robots and artificial intelligence -AI-) (Acemoglu and Restrepo, 2021; Fernández-Macías and Bisello, 2021; Ernst, Merola, and Samaan, 2019; Pesole et al., 2018). These innovation vectors, in addition to institutional contexts (Baccaro and Howell, 2017) and trend-accelerating shocks such as the COVID-19 pandemic (Sostero et al., 2020), transform the nature of work, altering what people do and how they do it at work (Bisello et al., 2019).

Two general trends are unfolding in postindustrial labour markets. First, the vectors of digitalisation and automation are leading to a counterintuitive trend: in 2015, there were fewer routine jobs compared to the mid-1990s in the EU-15 (Oesch and Piccitto, 2019). Nevertheless, during the first decade of this period, the remaining jobs got more repetitive and standardised—standardisation as quality standards and production targets enabled by computerisation. Managers, professionals, and clerks accounted for the largest share of routinisation (Bisello et al., 2019:28). There has also been an increasing reported share of social and creative tasks in jobs in the health, education, and social care sectors (Fernández-Macías, Hurley and Bisello, 2016). Human-centred jobs involving social tasks (i.e., caring, managing, serving) and non-cognitive skills are more protected against automation risk (González Vázquez et al., 2019).

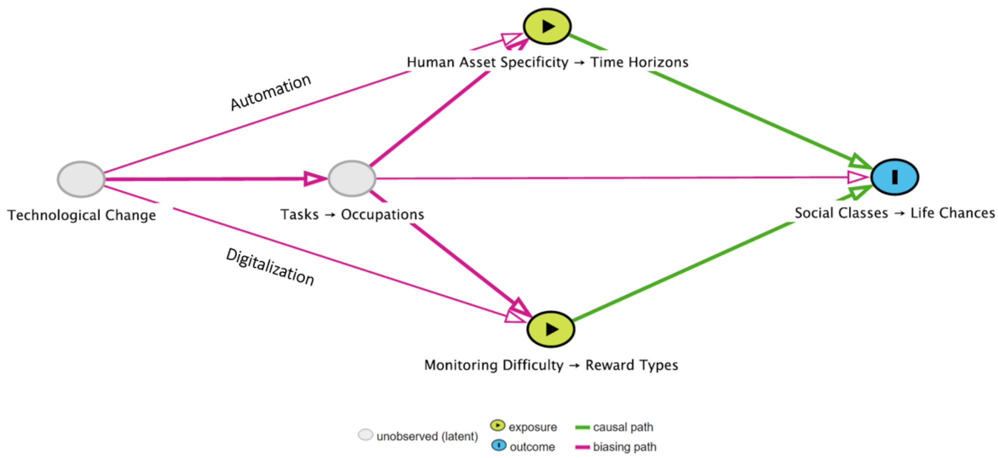
Regarding automation, rapid advances in robotization (Fernández-Macías, Klenert and Antón, 2021) and AI are increasingly able to substitute job tasks not just at the bottom of the occupational structure but also at the middle-top (Tolan et al., 2021). These new technologies replace routine tasks and codify and store knowledge more quickly and cheaply. Then, the type of job tasks and their replaceability with these new technologies might be becoming a relevant factor for firms and employers to issue employment contracts with different levels of working conditions (i.e., time horizon and reward types) over and above human asset specificity, that is, the difficulty in substituting one worker with another human worker (Williams, 2017).

Second, the new digital tracking and algorithmic management technologies increase employers' ability to monitor work (Ball, 2021). The standardization and digitalisation of work make controlling workers' output easier and cheaper (McGovern et al., 2007). Examples of work surveillance are most prominent in platform and warehouse work. If this process also permeates the office, facilitating productivity assessment in managers, professionals and clerks, variation in monitoring difficulty across social classes might decrease. Some authors argue that human resources management increasingly relies on quantitative metrics to assess workers' performance, even in jobs not traditionally evaluated on a piece- or time-rate basis (Ball, 2021; Aloisi and Gramano, 2019; Moore, Upchurch, and Whittaker, 2018).

These vectors of technological change might disrupt classic employment relations so that the distribution of employees' human asset specificity and work monitoring difficulty by social classes might be becoming more homogeneous. Figure 1 illustrates how vectors of technological change and its effects on (1) task distribution across occupations and on (2) the human asset specificity (automation) and monitoring difficulty (digitalisation) of different occupations might confound the traditional links between employment relations indicators, social classes, and life chances in EGP-based theories.

An alternative hypothesis is that new technologies and changes in work do not sizeably affect the distribution of tasks across occupations and complement the service relationship by increasing returns to analytical tasks (McGovern et al., 2007). This situation would potentially preserve or even widen the gap in employment relations and life chances compared to the mixed and, especially, labour contracts. The social classes characterised by these latter types of employment contracts could suffer the most negative impact of new technologies—digital monitoring, automation, platform work—on their working conditions.

Figure 1: The theorised causal chain between technological change, job tasks, employment relations, social classes and life chances



Still, it is unknown to what extent social classes embody the job tasks emphasised by technology-based theories or whether they represent different explanations since both approaches use occupations as proxies (Williams, 2017). Drawing from the RBTC literature (Autor, Levy, and Murnane, 2003), Williams (2017) provides evidence that technological change and job tasks—analytic/routine tasks—might confound the association between employment relations' mechanisms—human asset specificity and monitoring difficulty, social class membership and life chances. Williams (2017) found that analytical tasks substantially mediate the role of asset specificity in predicting class membership, but, at the same time, the EGP schema is still a sharp tool to capture labour market inequalities. However, this analysis only covers the United Kingdom, using limited employment relations and tasks indicators.

3 Data, variables, and methods

3.1 Data

This article relies on the EWCS survey (Eurofound, 2017). A random sample of individuals in employment during the fieldwork aged 15 or older was selected via multi-stage, stratified sampling and interviewed face to face, with an average response rate of over 50%. Data collection is harmonised across countries, including poststratification weights reflecting actual population size and the socio-demographic structure of the country. Data are pooled from three survey waves carried out in 2005, 2010 and 2015 to study EU-27 countries. Due to the small sample size of some individual countries, the EWCS is not aimed at studying each country individually. Thus, the EU-27 is analysed in the pooled dataset while controlling for country and survey fixed effects, adjusting for post-stratification weights and clustered standard errors by country and wave.

Two analytical samples for the 2005-2010-2015 and 2010-2015 waves are built, as only in the former sample trends over time can be studied and only in the latter detailed income information is available. The EWCS 2005-2015 (2010-2015) pooled dataset comprises 95,739 (70,125) observations. Several sample filters are applied by restricting the age range to 18-65, excluding self-employed individuals to study employment relations, individuals working less than 5 hours per week, and the inactive.

Unemployed individuals are kept if they report employment relations from their last occupation. For the 2005-2015 (2010-2015) pooled sample, out of the 76,649 (55,878) remaining respondents after applying the exclusion criteria, the analytical sample is left with 68,433 (40,377) observations after listwise deletion. Missing values in the filtered sample stand below 4%, except for time horizons (9%) and personal income (22%). Table 4 in the Annex displays the summary statistics of all variables by analytical samples.

3.2 Variables[3]

Social Classes. The measure of social class builds on the original 9-category ESeC schema (Rose and Harrison, 2010) using 2–3-digit ISCO-88 (International Standard Classification of Occupations) occupational codes, self-employment and number of supervised workers—excluding the unemployed as a single category (10) and the self-employed classes 4-5 (small employer and self-employed occupations): Class 1. Higher-grade professional, administrative and managerial occupations; Class 2. Lower-grade professional, administrative and managerial occupations and higher-grade technician and supervisory occupations; Class 3. Intermediate occupations; Class 6. Lower supervisory and lower technician occupations; Class 7. Lower services, sales and clerical occupations; Class 8. Lower technical occupations; Class 9. Routine occupations. The ESeC class schema can be regrouped into three forms of employment regulation—service relationship (classes 1+2), mixed/intermediate (classes 3+6), and labour contract (classes 7+8+9)—that, in some analyses, are used to test the theoretical basis of the schema.

Tasks. Job tasks are measured at the individual level relying on the JRC-Eurofound taxonomy of tasks (Bisello et al., 2021). Eleven indices available in the EWCS (2005-2015) are operationalised to measure different job tasks, work methods, and tools highlighted by technology-based explanations: (a) Tasks: intellectual [1. Information processing, 2. Problem-solving]; physical [3. Strength]; social [4. Serving]; (b) Work methods: autonomy [5. Latitude], routine [6. Repetitiveness, 7. Standardization, and 8. Certainty], and 9. Teamwork; and (c) Work tools [10. Non-digital machinery, 11. Digitally-enabled machinery]. In most cases, the values of the indices are estimated by averaging different sub-indicators. The composite indices are z-standardized by analytical sample and survey wave.

Employment Relations - Reward types. Reward types are measured with four dummy items based on questions that capture whether earnings from respondents' main job include the following type of payments: "Payments based on the performance of the company where you work?", "Payments based on the performance of your team/department?", "Income from shares in the company you work for?", and "Advantages of other nature (e.g., medical services, access to shops, etc.)?". These items were recoded so that higher scores in the composite index reflect more diffuse reward types typical of the service relationship (classes 1+2) and mixed contracts (class 3), and it is estimated as a standardised average by analytical sample and survey wave.

Employment Relations - Time horizons. Time horizons are captured with three items about respondents' agreement with two statements on a 1-to-5 scale: "I might lose my job in the next 6 months"; "My job offers good prospects for career advancement"; and whether salary in the last year was reported to have "decreased", "not changed" or "increased". The first item was reversed, so higher scores in the composite index reflect long time horizons typical of the service relationship (classes 1+2) and mixed contracts (class 6). A standardised average of the first two (2005-2015 sample) or all three items (2010-2015 sample) was estimated by analytical sample and survey wave.

[3] In Annex A, extensive information on variables' operationalisation is provided.

Permanent Contract. As a positive indicator of life chances proxying for employment security and stability over the work career, a dummy discerning between workers with temporary or fixed-term contracts (0) and permanent contracts (1) is used.

Seniority. As a second positive indicator of life chances, it is used the number of years that respondents have been working for the current organisation or company residualised of age and standardised by analytical sample and survey wave.

Income. As the third indicator of life chances in the 2010-2015 sample, the respondents' net monthly earnings in euros from the main paid job are used, adjusted by the country's purchasing power parity (PPP). This variable is transformed into its natural logarithm to adjust for the long tail and right skewness. Missing rates in personal income (22%) by social classes or gender do not vary systematically.

Controls. In all models, with some exceptions explained below, the following control variables are included: age groups (18-25; 26-35; 36-45; 46-55; 56-65); household size; migration background (both respondents and parents born in survey country=1; otherwise=0); dummies on the 1-digit sector following NACE Rev.1 (the Statistical classification of economic activities); full- (≥40 weekly working hours) or part-time (<40 weekly working hours) contracts; and country dummies.

3.3 Methods

To explore how job tasks are distributed between social classes, Ordinal Least Squares (OLS) regressions are estimated with social classes predicting each task. Interaction terms between survey wave and social classes are included to analyse change over time. Predicted marginal effects and Average Partial Effects (APE) are plotted in the figures.

The Karlson-Holm-Breen (KHB) (Breen, Karlson and Holm, 2021) decomposition method using binomial logistic specifications is applied to analyse to what extent the association between employment relations (X) and class/employment contract membership (Y) might be confounded by job tasks (Z). The KHB method relies on two nested probability models to estimate (1) the total effect of employment relations on the probability of class membership; and (2) its direct/residual effect after controlling for the confounding/mediator variable (Z=vector of tasks) residualised of X. By comparing the magnitude of the total and direct effects, KHB yields an estimation of the indirect/confounded effect by the vector Z, unaffected by rescaling or change in residual variance across models. The service relationship comprising classes 1+2 is the reference category in the binomial models predicting employment contract membership. Reward types and time horizons are included simultaneously as X in all models. In addition, all job tasks are included as mediators or confounders. Results are expressed as APE.

In order to assess the role of employment relations and tasks in accounting for class gaps in life chances, this article relies on the Blinder-Oaxaca decomposition method (Jann, 2008) for seniority and permanent contract and Recentered Influence Function (RIF)-Oaxaca decompositions for wages (Firpo, Fortin and Lemieux, 2018). The Oaxaca decomposition method compares gaps in outcomes by two groups or over time. Gaps in life chances by employment contracts between the service relationship as the reference category and mixed or labour contracts are compared and decomposed to test the core theoretical foundations of EGP-based class schemas.

Blinder-Oaxaca decomposition methods estimate the difference in the outcome distribution of two groups in terms of two components accounting for group means' differences: an explained part/composition effect due to differences in the mean (observed) characteristics of the two groups and an unexplained/structure effect part due to differences in the estimated coefficients in the groups, which cannot be accounted for by the observed factors. This residual component includes group differences in unobserved predictors (Firpo, Fortin and Lemieux, 2018). Thus, this analysis focuses on the explained part by observed predictors.

In RIF-Oaxaca regressions, coefficients can be interpreted as partial effects of a slight location shift to the right in the distribution of regressors on the unconditional (log)wage distribution. In order to decompose differences in distributional statistics of income beyond the mean, RIF-Oaxaca models with reweighting regressions (including all covariates of the model) are estimated to counterfactually evaluate what would happen to the (log)wage of mixed or labour contracts if they had the predictors' levels of the service relationship (Rios-Avila, 2020). The reweighting error yields information on the quality of the reweighting strategy and the specification error on model specification quality and the RIF approximation.

In the figures illustrating the Blinder-Oaxaca and RIF-Oaxaca decompositions, we only plot statistically significant coefficients that contribute to the explained or composition effect part as a percentage of the total raw gap between service and mixed or labour contracts in the given outcome.

All models control for country and survey fixed-effects, household size, and age groups (except when predicting seniority). Additional control for migration background is included in the 2010-2015 analytical sample, as it is only available from 2010. Models assessing and decomposing the class wage gap control for sector fixed effects and part-time contracts.

4 Results

4.1 Tasks and social classes

The first research question inquired about the distribution of job tasks between social classes at the individual level to assess whether occupational classes are (increasingly) capturing a task divide related to technological change and wage inequality. Figure 2 plots the mean standardised tasks for each social class by gender resulting from OLS (Ordinary Least Squares) models.

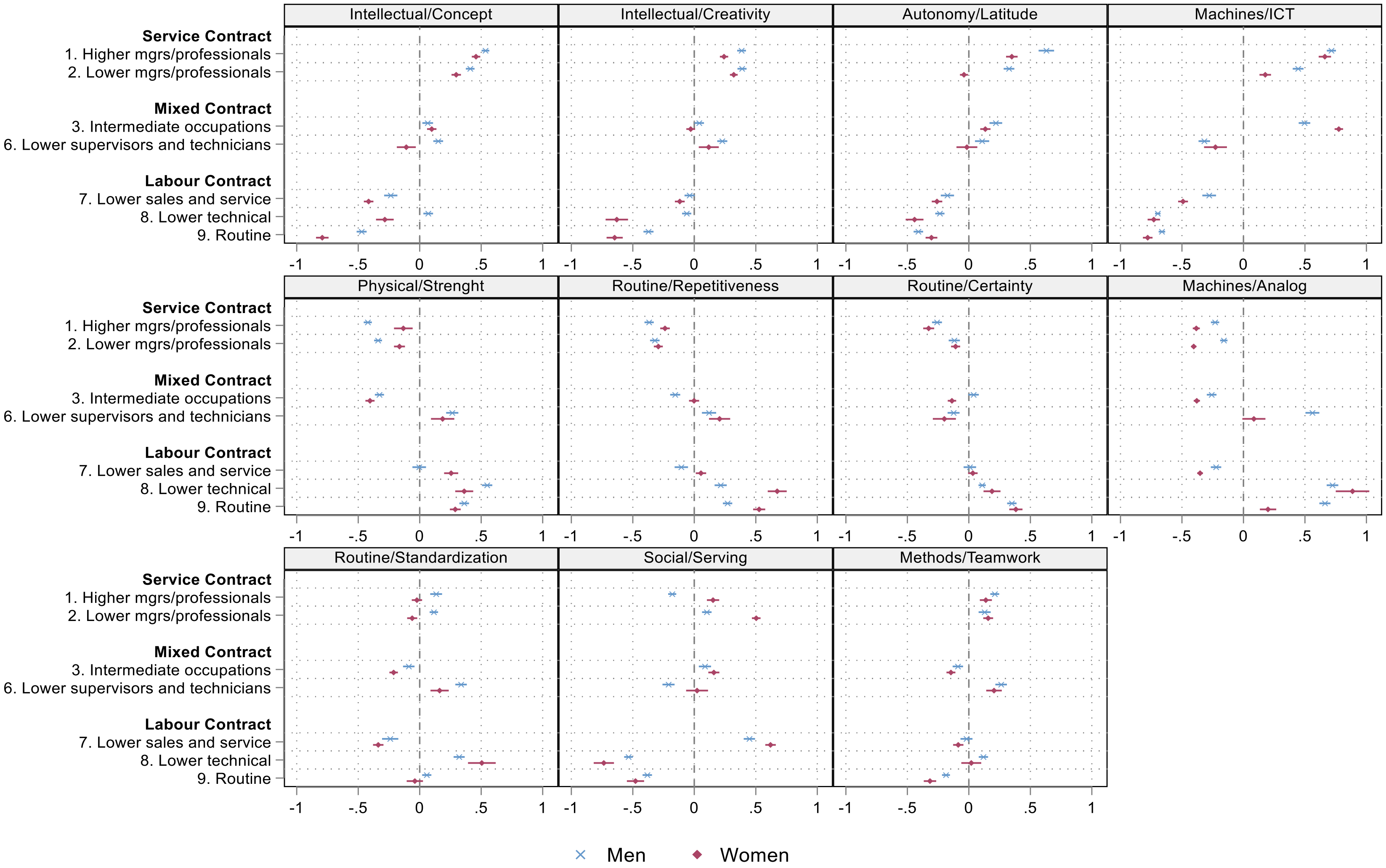
Intellectual tasks are ranked according to the expected hierarchy of human asset specificity in EGP-based theories: Classes 1 and 2 in a service relationship score the highest; mixed contracts (Classes 3 and 6) are somewhere in the middle around the mean; and labour contracts (Classes 7, 8 and 9) display the lowest intellectual intensity below the mean. It should be noted that, within mixed contracts, differences in levels of intellectual tasks between Class 3 (intermediate occupations) and Class 6 (lower supervisors and technicians) are lower than expected by the ESeC schema.

In terms of work autonomy, there is a very steep gradient across the social class hierarchy where managerial and professional classes display the highest levels of autonomy at work, followed by the mixed and labour contracts. These results mirror the hierarchy found for intellectual tasks. Note that, within those in a service relationship, men tend to enjoy a higher degree of autonomy at work than women, even within the same social classes.

The use of computing devices is one of the clearest dividing lines in work tools across non-manual and manual social classes, with higher and lower managers and professionals and intermediate occupations (clerks) displaying a very high intensity of computer use. ICT (Information and Communications Technology) use is distributed across social classes similarly to intellectual tasks and autonomy. However, there are considerable differences within mixed contract classes in this case.

The skilled and unskilled manual classes (Class 8 and 9) score high on physical strength, analogue machinery, repetitiveness, and certainty. By contrast, the prevalence of these four tasks is lower in mixed and service contracts. The index of standardisation follows a different pattern. There is no clear-cut gradient suggesting a hierarchical ranking in this case: Class 6 and 8 have the most standardised work procedures, while Class 3 and 7 are the least standardised. The largest differences are observed within types of employment contracts rather than between, especially within labour contracts, suggesting that work procedures and outputs predefined and encoded in a formalised system are independent of the logic of employment contracts.

Figure 2: Distribution of Z-tasks by social classes (ESeC) and gender (2005-2015)



Unsurprisingly, lower sales and service occupations (Class 7) have the highest score for serving and attending, understood as a form of social interaction with the public or customers. Those with less need for these social interactions are skilled and unskilled manual classes (Classes 8 and 9). With standardisation and analogue machinery, social interactions add another element to the heterogeneity within the labour contract, especially between Class 7 and Classes 8 and 9.

The first research question also asked how the distribution of job tasks between classes changed over time. According to Figure 9 in the Annex, there have not been sizeable changes concerning the task composition by social classes from 2005 to 2015. The general picture is one of stability, partly because the period analysed is likely too small to capture the effects of technological change (Bisello et al., 2019) and because those tasks (physical, intellectual), work methods (routine, autonomy) and tools (ICT, analogue) driving income inequality and proxying for technological change are well-stratified by EGP-based occupational classes.

4.2 Tasks, employment relations, and social classes

In order to address the second research question on alternative explanations challenging the theoretical foundations of EGP-based class schemas, it is assessed to what extent job tasks confound the association between employment relations indicators and social class membership.

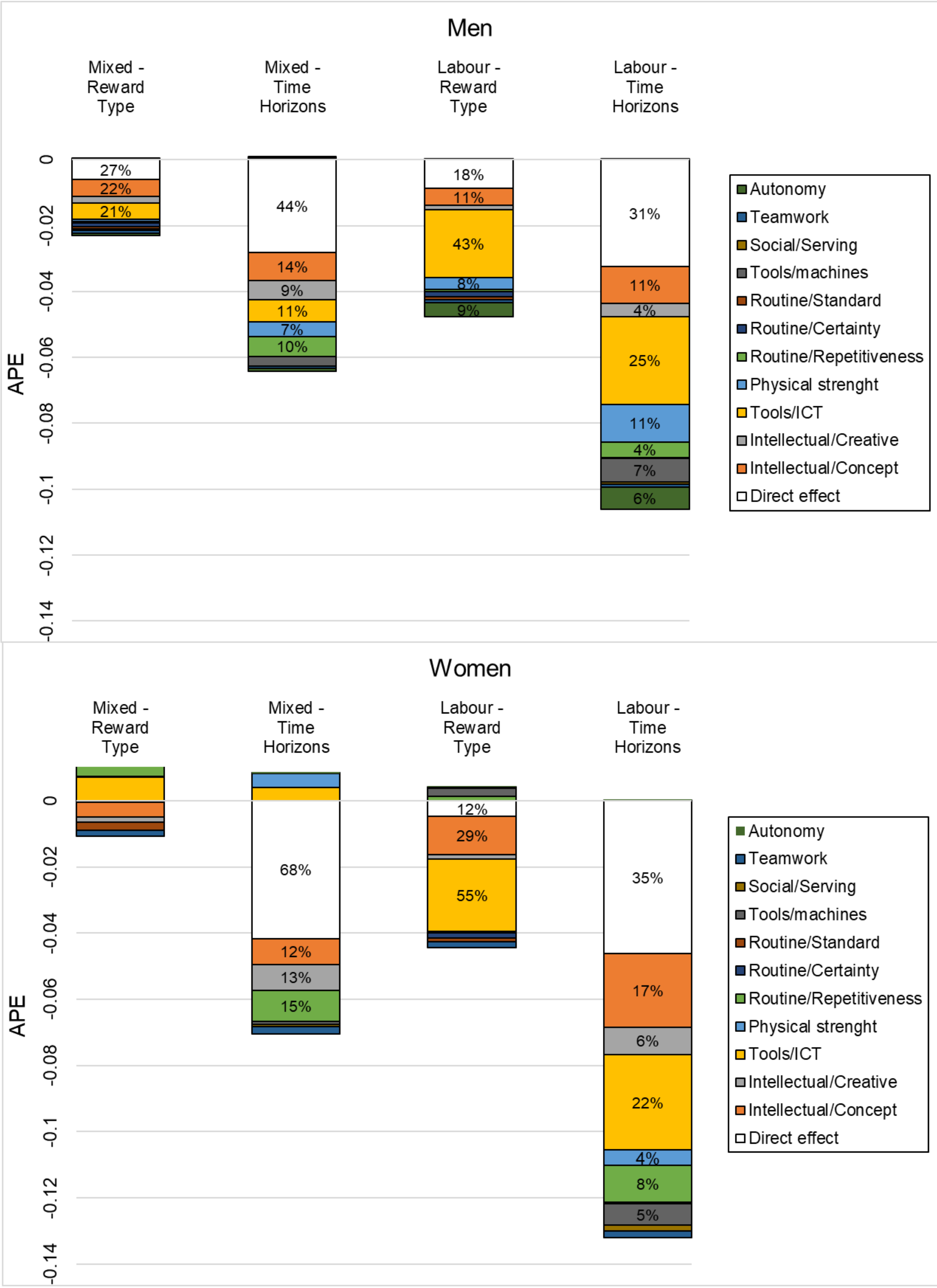
In Table 1, it is presented the KHB decomposition method with binomial logistic regressions predicting membership to mixed (ESeC Classes 3+6) or labour contracts (ESeC Classes 7+8+9), with service contracts (ESeC Classes 1+2) as the baseline. If one focuses on reward types, an SD (standard deviation) unit increase in diffuseness is associated with 2.2% (men) less probability of having a mixed contract or 4.7% (men)-4% (women) less probability of belonging to a labour contract in comparison to being employed in a service relationship. In the case of time horizons, an SD unit increase in time horizons is associated with a 6% (men and women) less probability of having a mixed contract or 10.6% (men)-13.2% (women) less probability of belonging to a labour contract in comparison to being employed in a service relationship.

Table 1. Employment relations (X), job tasks (confounder) and employment contract membership (Y) (2005-2015)

Y	**Mixed Contract**		**Labour Contract**	
APE	**Men**	**Women**	**Men**	**Women**
		Z-Reward Types		
Total effect	-0.022***	0.003	-0.047***	-0.040***
	(0.004)	(0.005)	(0.003)	(0.004)
Direct effect	-0.006	-0.001	-0.009**	-0.005
	(0.004)	(0.005)	(0.003)	(0.004)
Difference[a]	-0.016***	0.004	-0.039***	-0.035***
Confounded by Tasks	**73.01%**	116.77%	**81.56%**	**87.92%**
		Z-Time Horizons		
Total effect	-0.063***	-0.062***	-0.106***	-0.132***
	(0.005)	(0.004)	(0.003)	(0.003)
Direct effect	-0.028***	-0.042***	-0.032***	-0.046***
	(0.005)	(0.004)	(0.003)	(0.004)
Difference[a]	-0.035***	-0.020***	-0.074***	-0.085***
Confounded by Tasks	**55.55%**	**32.50%**	**69.44%**	**64.85%**
n	15,811	22,151	25,750	26,017
Pseudo R^2	0.11	0.11	0.45	0.40

Notes: Robust standard errors in parentheses; [a] Standard error of difference not known for APE method; significance levels were taken from models estimating log-odds; *p<0.05, ** p<0.01, *** p<0.001; decomposition into direct and indirect effects using the KHB method. Estimates obtained from KHB binomial logistic regressions predicting employment contracts (mixed = ESeC 3+6 or labour = EseC 7+8+9) with service contracts as reference category (EseC 1+2), survey weights and clustered standard errors by country (EU-27) and wave. Controls: age groups, country-FE, survey wave (2005-2015), and household size.

Figure 3. KHB mediation model by gender: Employment relations (X), job tasks (mediator/confounder) and employment contracts (Y) (2005-2015)



Notes: Decomposition into direct and indirect effects of Z-employment relations (reward type and time horizons) on employment contract membership using the KHB method. Coefficients as average partial effects (APE) obtained from KHB logistic regressions predicting employment contracts (mixed = ESeC 3+6; labour = ESeC 7+8+9) with service contracts as reference category (higher and lower managers and professionals' class: ESeC 1+2), survey weights and clustered standard errors by country (EU-27) and wave. Controls: age, country-FE, survey wave (2005-2015), and household size. All direct effects of employment relations and differences between total and direct effects are statistically significant (at p<0.001) except for mixed employment contracts - reward types for men and women. Sample sizes are as in Table 1 above.

Although these relationships are coherent with EGP-based theoretical foundations and previous criterion validation exercises (Smallenbroek et al., 2021), the substantive finding is that job tasks confound, on average, 66% (from 33% to 88%) of the total effect of employment relations on class membership. The confounding role of tasks is more pronounced for labour contracts (65%-88%) than for mixed contracts (33%-73%), and reward types (73%-88%) than for time horizons (33%-69%). These patterns reflect more marked differences in the nature of work and conditions between labour and service contracts than between mixed and service contracts. These patterns by employment relations suggest that time horizons are a more accurate indicator than reward types, as there is a substantially higher overlap between tasks and reward types, and its predictive power to differentiate class membership is lower than it is for time horizons. Finally, the confounding role of tasks by gender is similar except for women with mixed contracts, as there is no total effect of reward types, and tasks confound considerably less the total effect of time horizons for women (33%) than men (56%).

Figure 3 is based on Table 1 models to illustrate the contribution of each task to confound the relationship between employment relations and employment contract membership. It shows that the total effect of employment relations on class membership is larger for labour than mixed contracts and for time horizons than reward types. Concerning the share of confounding by tasks, for reward types, irrespective of gender and contract type, ICT tools (21%-51% of total confounding) and intellectual (conceptualisation) tasks (11%-29%) contribute the most. Similarly, for time horizons, ICT tools (11%-25%) and intellectual tasks (15%-26%) contribute the most to confound the relationship between time horizons and mixed/labour contract membership compared to service relationships.

These findings align with the argument that job tasks related to technological change are the primary sources of labour market stratification in post-industrial societies. While some residual effects of employment relations indicators on class membership hold, in most cases, more than half of the total effects of employment relations on class membership are confounded by job tasks. This finding suggests a considerable overlap between technology and EGP-based explanations accounting for class positions. At the same time, a 66% average confounding role of jobs tasks questions the criterion validity of EGP-based class schemas compared to alternative explanations such as the unequal distribution -and labour market returns- to tasks across social classes. As Goldthorpe (2007a) put it, “employment contracts will need to take on different forms in relation to the different kinds of work tasks and work-role that employees are engaged to perform.”

4.3 Tasks, employment relations, and life chances

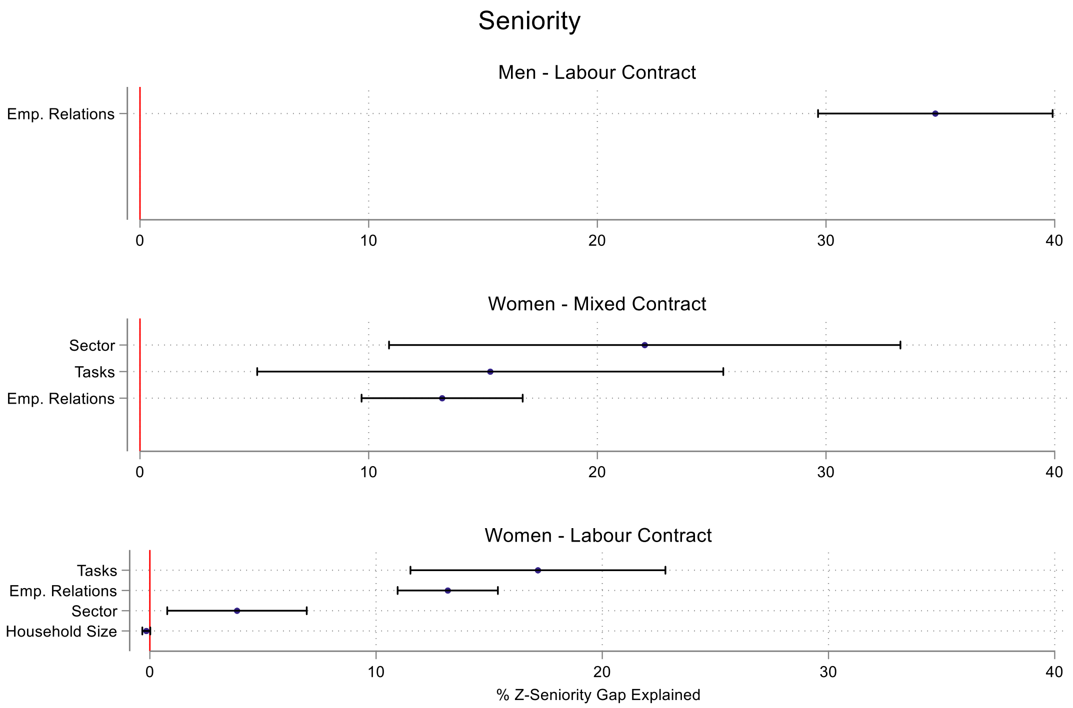
To tackle the third research question on the role of job tasks vis-à-vis employment relations in predicting life chances, the Blinder-Oaxaca and RIF-Oaxaca decomposition is estimated on three outcomes: (1) seniority residualised of age; (2) permanent contract; and (3) personal income. Firstly, as life chances’ indicators of career stability, class gaps in seniority and permanent contracts are analyzed. As shown in Table 8 (Annex), where the full results are reported, on average, women with mixed contracts have 11% SD units less seniority than women in a service relationship, while the difference for men (3% SD units) is not statistically significant. Seniority differences between labour contracts and service relationships are more substantial, with men (women) having 21% (44%) SD units less seniority than their counterparts in service relationships. Concerning class gaps in the prevalence of permanent employment, men and women with mixed contracts are 3% more likely to have a fixed contract when compared to those in a service relationship. Men (women) with a labour contract are 9% (12%) less likely to be in permanent employment than those in a service relationship.

These class gaps in career stability are consistent with previous research testing the construct validity of EGP-based schemas (McGovern et al., 2007). This article further contributes by testing whether the building stones of EGP-based schemas, employment relations indicators like reward types and time horizons, or alternative explanations, such as job tasks, better account for these observed class gaps in life chances. The complete set of explanatory and control variables fed to the Blinder-Oaxaca model account for up to 45% of the class gaps in seniority and 70% in a permanent contract.

Figure 4 summarises the groups of variables—tasks, employment relations and sector—that significantly (p-value<0.05) explain the observed class gaps in seniority. For women, tasks and employment relations explain to a similar extent (≈10%-20%) the gap in seniority among mixed or labour contracts and the service relationship. By contrast, no gap in seniority is observed for men with mixed contracts, while employment relations alone explain (over 30%) the observed gap in seniority between labour contracts and the service relationship.

Concerning class gaps in permanent employment (Figure 5), for men, job tasks and employment relations similarly account for the gap between mixed or labour contracts and the service relationship from 40% to 50%. A different picture emerges in the case of women since employment relations explain over 40% of the gap in permanent employment among those women with either mixed or labour contracts, and tasks only contribute to explaining the gap below 20% for women in a labour contract.

Figure 4. Oaxaca Decomposition of Seniority gap between service and mixed or labour contracts by gender (2005-2015)



Notes: Only statistically significant coefficients at p<0.05 and outcome differences by groups are shown in the figure.

Figure 5. Oaxaca Decomposition of permanent contract gap between service and mixed or labour contracts by gender (2005-2015)

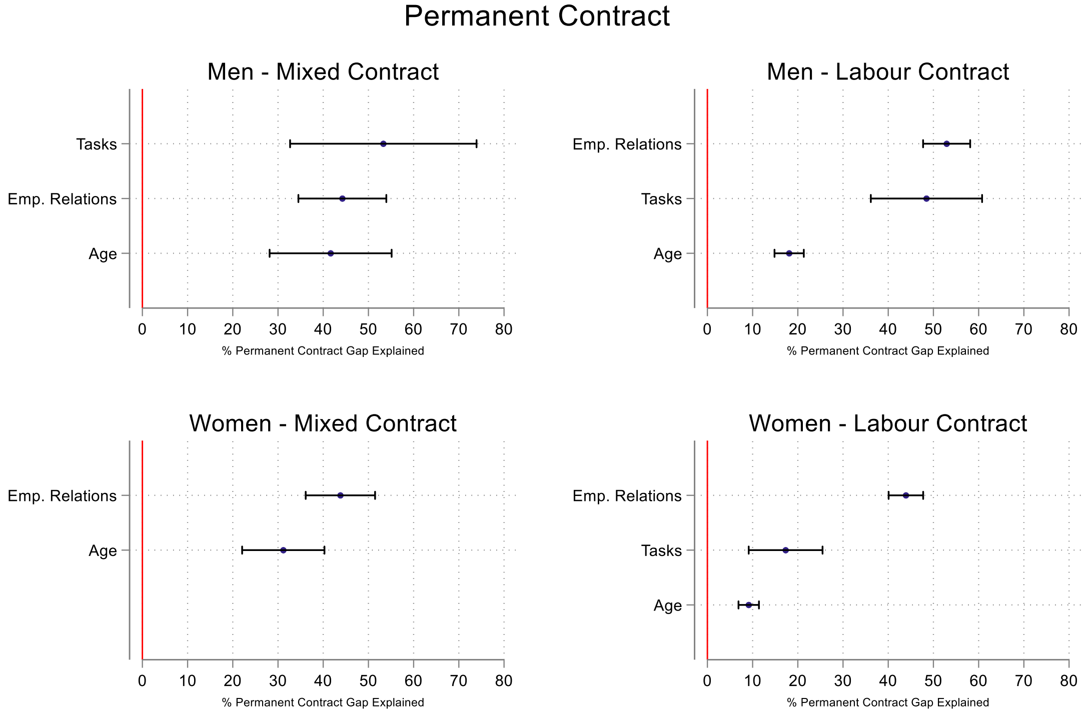
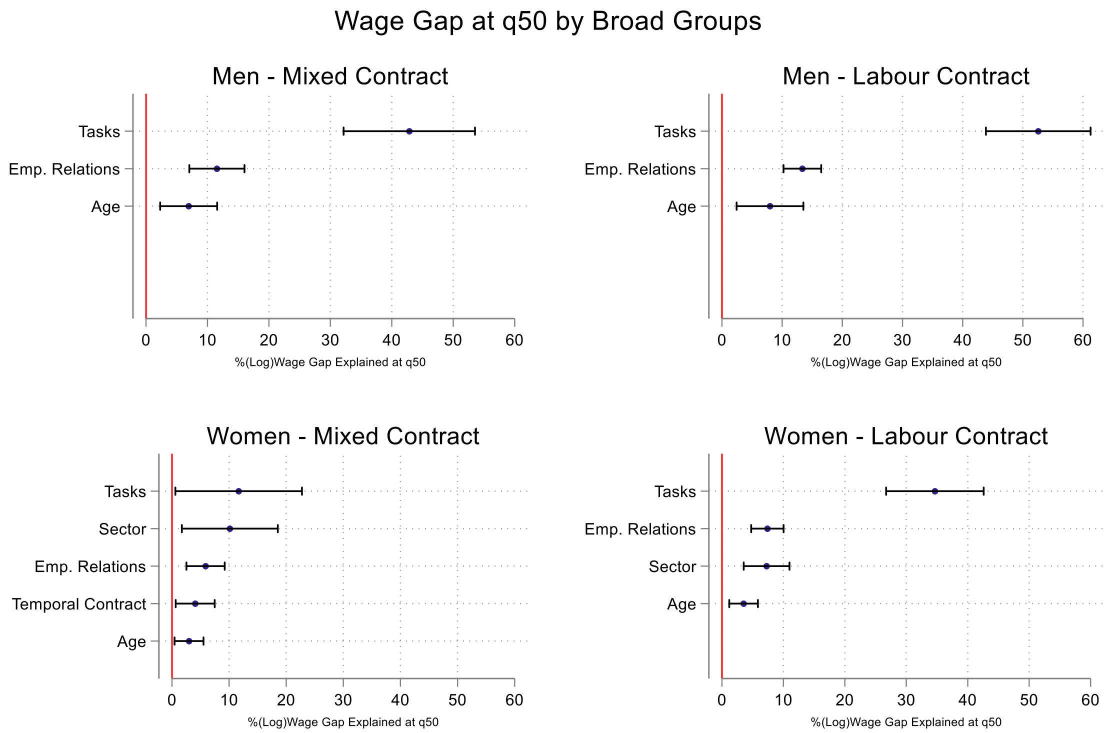
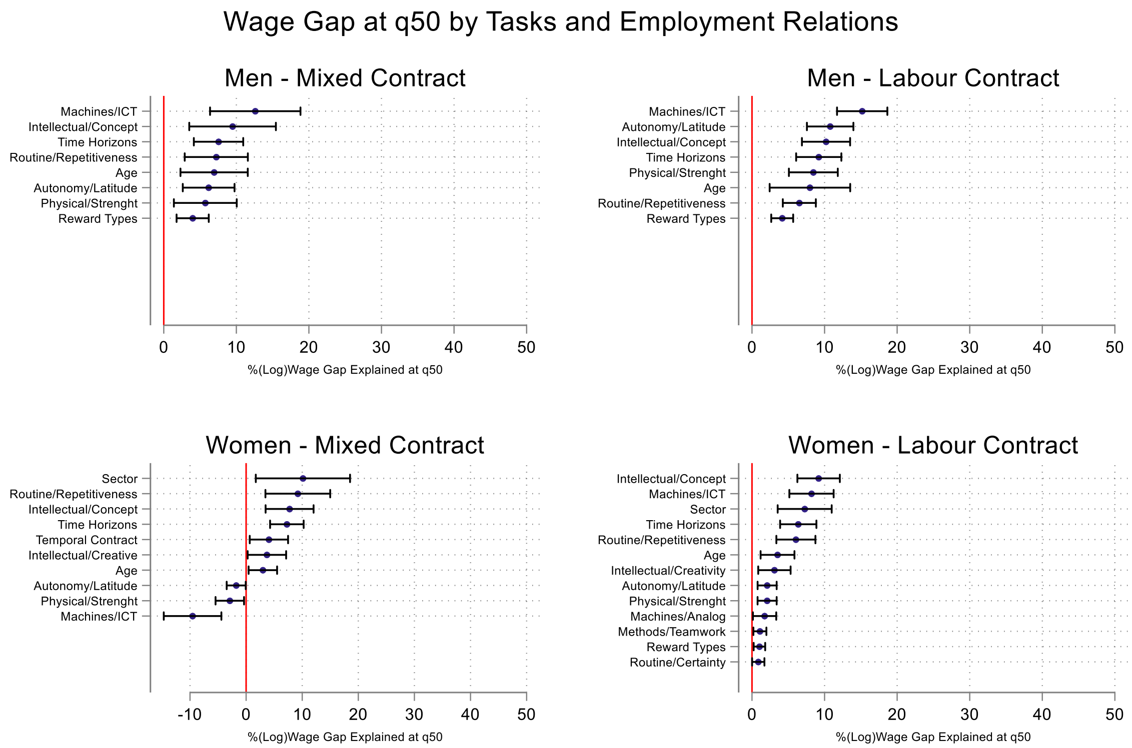


Figure 6. RIF-Oaxaca decomposition of the (log)wage gap between employment contracts by gender at q50 (2010-2015)





Notes: Only statistically significant coefficients at $p<0.05$ shown in the figure.

Secondly, to analyse the third indicator of life chances, monthly net personal income, the RIF-Oaxaca decomposition method is implemented at the median (q50) of the (log)income distribution and over quintiles (q20-q40-q60-q80). As summarised in Table 11 (Annex), reporting the full output, men and women with a mixed contract earn (log) wages about 2.5% lower than workers in a service relationship at q50. In the case of labour contracts, men (women) earn (log)wages 6.5% (9%) lower than those in a service relationship. To benchmark the effect size of these class wage gaps, the raw (log)wage gaps between labour or mixed contracts and the service relationship range from 0.18 to 0.62, and the SD of (log)wage equals 0.67.

These findings are hardly surprising and in line with EGP-based theories and previous research documenting how ESeC classes account for a substantial share of income inequalities in labour markets (Albertini, Ballarino and De Luca, 2020). Assuming no unobserved confounding, the variables in the model account for up to 57% (23%) of the men's (women's) (log)wage gap between mixed contracts and the service relationship and up to 58% of the gap for men and women between labour contracts and the service relationship at q50. If one looks at the contribution of different factors to explain class gaps over the wage distribution in Table 11 and Figure 17 (both in the Annex), no consistent differences over quintiles can be observed in the explanatory power of tasks or employment relations.

However, Figure 6 illustrates a novel finding. Job tasks are the factor that, by large and within the observed variables in the model, account for most of the explained class wage gaps from 35% to 50%, contributing 25%-to-40% more than employment relations in relative terms. An exception is women's mixed contracts, where tasks also explain the most at 10%, but their contribution is not statistically distinguishable from employment relations. In Figure 6, bottom panel, the specific contributions of each task and employment relations indicators are unpacked. Those job tasks related to technology-based explanations of income inequality account for the largest chunk of class (log)wage gaps. ICT tools, intellectual (conceptualisation) tasks and, to a lesser extent, repetitiveness and autonomy are the tasks, work methods and tools accounting for most wage differences between employment contracts or social classes as defined by EGP-based class schemas.

4.4 Robustness checks

In Annex B, several robustness checks are carried out, disaggregating the main analyses over time, gender, social classes, and income quintiles. Overall, the robustness checks are consistent with the main findings presented in the previous sections. Furthermore, additional information is provided on between-within social classes task variation (7.2.1.); the association between tasks and social classes over time and by gender (7.2.2.); the criterion validity of the ESeC schema (7.2.3.); and the relationship between tasks and employment relations (7.2.4.).

5 Conclusion and discussion

This article focuses on how unfolding vectors of technological change, workplace automation and digitalisation, might challenge the validity of mainstream industrial-age class schemas (EGP and ESeC). This article analyses over time and by gender (1) how job tasks related to technology-based explanations of growing economic inequality are distributed across social classes; (2) to what extent job tasks confound the links between employment relations and class positions; and (3) whether job tasks are more predictive of life chances than employment relations.

The article documents four findings. First, tasks (physical, intellectual), work methods (routine, autonomy) and tools (ICT, analogue) that partially drive income inequality and proxy for vectors of technological change are well-stratified by social classes. In the 2005-2015 period analyzed, the distribution of those job tasks, work methods and tools more connected to automation risk, workplace digitalisation, and wage premium remained relatively constant across occupational classes in the EU-27. Even though this decade is possibly too short an observation window to detect long-term trends in technology or occupational change (Bisello et al., 2019), and a pool of diverse countries was analyzed, the big picture is that labour market inequalities are hardwired in occupational social classes as far as they reflect stratification by tasks, productivity, and wages.

Thus, if new technologies and changes in work do not affect the distribution of tasks across occupations considerably but are just complementary to already privileged classes, (wage) stratification among occupational classes might keep constant or increase. Likewise, the more disadvantaged working classes performing more physical tasks and routinary work, including clerical jobs in intermediate classes, could bear the most significant negative and substitutive impact of new technologies on their employment relations and life chances.

Second, KHB mediation analyses yield that about two-thirds of the total effect of employment relations indicators on class membership is confounded by tasks. Job tasks, work methods and tools most related to technology-based explanations of wage inequality -ICT, intellectual and routine tasks- are confounding this association most. Thus, the criterion validity or theoretical foundations of EGP-based social class schemas is compromised by alternative explanations like job tasks or productivity-based differences between occupations. Even though employment relations still explain the class membership net of tasks, the observed extensive overlap between technology- and EGP-based explanations when predicting class positions suggests that the latter needs further theoretical refinements to keep up with inequality drivers in the digital age (Williams, 2017). It certainly seems that the nature of work (job tasks) "determines the contractual hazards faced by employers and influences the contractual solutions that they will choose (McGovern et al., 2007:24)." Paradoxically, even if EGP-based schemas' foundations were outdated, they could still account for contemporary labour market inequalities as they build on occupational titles and aggregations.

Third, Blinder-Oaxaca decomposition analyses indicate that job tasks account for class differences in career stability (life chances) worse than employment relations. Different employment relations offered by employers, reward types and time horizons better explain differences by social classes in seniority and permanent employment than job tasks. Hence, EGP-based employment relations are still doing a fair job capturing the career stability dimension of life chances.

Fourth, RIF-Oaxaca wage decompositions by social classes suggest that job tasks are the factor that, by large and within the observed variables, account for most of the explained class wage gaps up to over 50%, contributing 25%-to-40% more than employment relations in relative terms. ICT tools, intellectual, repetitiveness, and autonomy are the tasks, work methods and tools accounting for most wage differences between employment contracts. Thus, those same tasks related to technology-based explanations of income inequality account for the biggest chunk of class wage gaps.

What is the bottom line of these findings to (re)define social classes in the digital age? This article does not argue for a class (schema) revolution but for fine-tuning the old instrument to better capture labour market inequalities. The distribution (and overtime change) of workers' skills, job tasks, productivity, wage inequality, poverty and unemployment risk are still reasonably well stratified by occupational classes (Albertini, Ballarino and De Luca, 2020). Thus, technological change might not be the big game-changer in cracking the building stones of the old industrial stratification system, while other national and international institutional factors might have stronger impact. Job tasks related to technology-based explanations of growing economic inequality better account for income inequalities between occupational classes, but relying on occupational titles seems more pragmatic than directly measuring job tasks or employment relations.

Still, there are three promising future research pathways for improving class measurement to keep up with changing labour markets and inequality dynamics. Firstly, further vertical disaggregation in EGP-based class schemas would be necessary to depict more fine-grained differences in employment relations and life chances (Smallenbroek et al., 2021), for instance, between higher and lower managers and professionals and higher and lower blue-collar workers. Second, to describe the nature of work, an additional horizontal axis to the vertical axis structuring EGP-based schemas, like the work logics proposed by the Oesch class schema (Oesch, 2006), could better account for inequalities in power and authority at the workplace, gender, and income. Third, future schemas could better represent wealth concentration dynamics in digital economies by integrating labour and capital sources of economic inequality not captured by occupational classes (Eeckhout, 2021).

Even though EGP-based class schemas are still doing a decent job in capturing employment relations and inequalities in contemporary labour markets (Smallenbroek, Hertel and Barone, 2021; Willams, 2017), a task-based approach to study occupational class stratification in working conditions and wage inequality, among other indicators of life chances, is a promising avenue of research to portray the rapid change in technology and labour markets in the digital age (Bol and Williams, 2018).

This investigation has two main limitations related to data constraints to be addressed in future research. First, analyses with country fixed effects prevented from depicting institutional particularities that might drive country-specific deviations. Still, this article provided a novel interdisciplinary theoretical and analytical framework that future research on single country cases might apply. Second, this article covered a short period (2005-2015) when the bulk of the analogue-to-digital transition had taken place, while innovations in AI were still burgeoning. Future studies might cover a longer-term period to identify technological changes and their effects on labour market inequalities.

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7 Annexes

7.1 Annex A: variables and summary statistics

7.1.1 Jobs tasks

Tasks are discrete units of work that produce outputs in terms of goods and services (Acemoglu and Autor, 2011). This concept is related to but different from skills, which can be understood as the worker's stock of capabilities for performing various tasks (Autor, 2013). Workers do not perform one single task, even in low-skilled jobs or the jobs that are more standardised and routinised. Instead, they perform a variety. That is why jobs and occupations are conceived as bundles of tasks (Fernández-Macías and Bisello, 2021).

Tasks indices have some advantages compared to educational or occupational measures. For example, social scientists have often relied on the skill level of workers to analyse labour market dynamics and the links between training, education and employment. However, by simply classifying jobs by their skill level (low, mid or high-skilled jobs), it is more difficult to disentangle some of the processes that better explain how technology and other factors shape labour markets. That is why some researchers proposed to analyse the task content of jobs (Autor et al. 2003), finding that technological developments, including artificial intelligence, robotics, and advancements in ICT, have made possible the replacement of workers performing routine tasks (irrespective of their skill level) by machines.

The RBTC hypothesis, a reformulation of SBTC, highlights that there Is heterogeneity even within the same group of jobs, as defined by their skill level. Some low-skilled workers perform activities challenging to automate (i.e., personal services requiring human interactions and hand-eye coordination) (Brynjolfsson and McAfee, 2014), while others perform jobs at high risk of automation (i.e., routine and repetitive tasks). Similarly, tasks offer more detailed information than sectors, occupations, and other variables. Since tasks are the smallest unit of work involved in an economic process, they are among the best measures to highlight the heterogeneity within broader categories.

However, the task-based approach also has some limitations. The main one is that information on tasks is fragmented, and we lack comparative and comprehensive data to measure what workers do at work. Although several sources provide information on worker' activities, they contain partial information. Apart from this, the different surveys and occupational databases have been conducted in different years and countries and, in some cases, use different classifications to identify key variables. These features compromise the comparability of the different sources and indicators across countries and over time.

This limitation has been partially overcome by the JRC-Eurofound taxonomy of tasks (Bisello et al. 2021), which was devised to be relatively comparable across countries and over time, an advantage concerning previous inconsistent tasks measures. This taxonomy extracts information on worker' activities from different EU countries and links this information with standard classifications of occupations and sectors using different sources, like ICP, PIAAC and EWCS. As a result, this database defines indices measuring (1) the material content of work (what people do at work) reflecting the technical nature of the production process; (2) its organisational form (how people coordinate their work); and (3) the tools used at work. Its main advantages are two. First, it covers an extensive range of job tasks, a significant advantage considering that surveys focus on one or few types of activities at work. Second, it is also intended to assess the impact of technology on employment by including the dimension of work methods, which assumes that specific jobs can be performed differently depending on work organisation and production technologies. This article relies on the JRC-Eurofound taxonomy of tasks indices to measure job tasks at the individual level (Bisello et al., 2021) and analyse the task content of different social classes in the EU using tasks as proxies of technological change.

Table 2 describes the tasks indices used in this article according to Fernandez-Macías and Bisello (2021) and the variables available in the EWCS to operationalise them. All variables comprising each index are standardised to be fully comparable, with ''0'' meaning that the worker never has to perform the task and ''1'' that the job is only focused on that task. In most cases, the values of the indices are estimated by averaging different sub-indicators, but for some of them, there is only one variable associated with a task dimension. The composite indices are z-standardized by analytical sample and survey wave. More details on operationalization and reliability in Fernandez-Macías et al. (2016) and Bisello et al. (2021). Table 3 plots the correlation matrix of all job tasks.

From all the dimensions detailed in table 2, routine activities have been repeatedly identified as the ones more susceptible to being automated (Autor et al. 2003; Goos and Manning 2007; Acemoglu and Autor 2011; Goos et al. 2014; Autor 2015; Brynjolfsson and Mitchell 2017; Górka et al. 2017; Gregory et al. 2019; de Vries et al. 2020) and offshored (Blinder 2009; Becker et al., 2013; Blinder and Krueger, 2013). For that reason, the indices measuring routine at work have become the most commonly used in labour market research.

Table 2. Description and variables used from the EWCS to construct tasks indices (2005-2015)

Task indices	Description	Variables used	Categories
Physical tasks: strength	**Physical tasks** encompass the types of activities that the literature sometimes refers to as "manual". More specifically, **strength** refers to the pure exertion of muscular power (lifting people and heavy loads).	*Q30a: Does your main paid job involve painful or tiring positions?* *Q30b: Does your main paid job involve lifting or moving people?* *Q30c: Does your main paid job involve carrying or moving heavy loads?*	*1 - All of the time* *2 - Almost all of the time* *3 - Around ¾ of the time* *4 - Around half of the time* *5 - Around ¼ of the time* *6 - Almost never* *7 - Never*
Intellectual tasks: conceptualisation, learning and abstraction	**Intellectual tasks** are similar to the concept of cognitive tasks (Martínez-Matute and Villanueva 2020). More specifically, **conceptualisation, learning and abstraction** are activities focused on the gathering and evaluation of information. They can be conceived as problem-solving tasks.	*Q53e: Does your main paid job involve complex tasks?* *Q53f: Does your main paid job involve learning new things?*	*1 - Yes* *2 - No*
Intellectual tasks: creativity	**Intellectual tasks** are similar to the concept of cognitive tasks (Martínez-Matute and Villanueva 2020). More specifically, **creativity** is a problem-solving task that refers to the creativity required for finding a solution.	*Q53c: Does your main paid job involve solving unforeseen problems on your own?* *Q61i: For each of the following statements, please select the response which best describes your work situation. [You are able to apply your own ideas in your work].*	*1 - Yes* *2 - No* *1 - Always* *2 - Most of the time* *3 - Sometimes* *4 - Rarely* *5 - Never*
Social tasks: serving/ attending	**Social tasks** are those aimed at the interaction with other people. More specifically, **serving/ attending** refers to responding directly to demands from public or customers.	*Q30f: Does your main paid job involve [dealing directly with people who are not employees at your workplace such as customers, passengers, pupils, patients…]?*	*1 - All of the time* *2 - Almost all of the time* *3 - Around ¾ of the time* *4 - Around half of the time* *5 - Around ¼ of the time* *6 - Almost never* *7 - Never*
Autonomy: latitude	**Autonomy** refers to the degree of **latitude** of workers for carrying out their tasks: the ability to decide working time, task order, methods and speed.	*Q42: How are your working time arrangements set?* *Q54a: Are you able to choose or change your order of tasks?* *Q54b: Are you able to choose or change your methods of work?* *Q54c: Are you able to choose or change your speed or rate of work?* *Q61f: For each of the following statements, please select the response which best describes your work situation. [You can take a break when you wish].*	*1 - They are set by the company / organisation with no possibility for changes* *2 - You can choose between several fixed working schedules determined by the company/organisation* *3 - You can adapt your working hours within certain limits (eg flexytime)* *4 - Your working hours are entirely determined by yourself* *1 - Yes* *2 – No* *1 - Always* *2 - Most of the time* *3 - Sometimes* *4 - Rarely* *5 - Never*

Teamwork	**Teamwork** refers to the extent to which the worker has to collaborate and coordinate his/ her actions with other workers.	*Q58: Do you work in a group or team that has common tasks and can plan its work?* *Q60a: For the team in which you work mostly, do the members decide by themselves on the division of tasks?* *Q60b: For the team in which you work mostly, do the members decide by themselves who will be head of the team?*	*1 - Yes* *2 - No*
Routine: repetitiveness	**Repetitiveness**: the extent to which the worker has to repeat the same procedures.	*Q30e: Does your main paid job involve repetitive hand or arm movements?* *Q48a: Please tell me, does your job involve short repetitive tasks of less than 1 minute?* *Q48b: Please tell me, does your job involve short repetitive tasks of less than 10 minutes?* *Q53d: Generally, does your main paid job involve monotonous tasks?*	*1 - All of the time* *2 - Almost all of the time* *3 - Around ¾ of the time* *4 - Around half of the time* *5 - Around ¼ of the time* *6 - Almost never* *7 - Never* *1 - Yes* *2 - No*
Routine: Standardisation	**Standardisation**: the extent to which work procedures and outputs are predefined and encoded in a formalized system.	*Q50c: On the whole, is your pace of work dependent, or not, on numerical production targets or performance targets?* *Q53a: Does your main paid job involve meeting precise quality standards?*	*1 - Yes* *2 - No*
Routine: certainty	**Certainty:** the extent to which the worker doesn't have to respond to unforeseen situations.	*Q51: How often do you have to interrupt a task you are doing in order to take on an unforeseen task?*	*1 - Very often* *2 - Fairly often* *3 - Occasionally* *4 - Never*
Tools: analogue machinery	**Analog machinery** refers to the use of analogue mechanical devices.	*Q50d: On the whole, is your pace of work dependent, or not, on automatic speed of a machine or movement of a product?* *Q29a: Are you exposed at work to vibrations from hand tools, machinery, etc?*	*1 - Yes* *2 - No* *1 - All of the time* *2 - Almost all of the time* *3 - Around ¾ of the time* *4 - Around half of the time* *5 - Around ¼ of the time* *6 - Almost never* *7 - Never*
Tools: computing devices	**Computing devices:** the use of not autonomous digitally-enabled machinery (or ICT technologies).	*Q30i: Does your main paid job involve working with computers (PCs, network, mainframe)?*	*1 - All of the time* *2 - Almost all of the time* *3 - Around ¾ of the time* *4 - Around half of the time* *5 - Around ¼ of the time* *6 - Almost never* *7 - Never*

Source: own elaboration based on Fernández-Macías and Bisello (2021). Notes: All items within tasks available except for autonomy (Work-life balance - take short time off) and teamwork (Team autonomy - timetable) in 2005.

Physical tasks have been on a decline for an extended period. This transformation is not recent but started to be consolidated with mechanization in the 19th Century. Physical tasks are still at a clear risk of being replaced by analogue machines (for instance, in agriculture) and robots (in the industry, transport and logistics). This is especially the case for physical strength and, to a lesser extent, dexterity and navigation. That is why the average EU worker today scores low when measuring the physical effort required at work (Bisello et al., 2021). Jobs that involve many physical tasks tend to involve less intellectual and social tasks, and vice versa. On the other hand, physical tasks tend to be associated with less autonomy, more routine (particularly in terms of repetitiveness), high use of analogue machinery and less use of computing devices (ICT tools).

However, this is not the only relevant dimension one can consider: cognitive or intellectual tasks, social tasks and others, such as autonomy or the use of ICT tools, have been identified in the specialised literature as activities that are susceptible to channel or discriminate the impact that different economic and social transformations have on the labour market.

Intellectual tasks require conscious thinking, manipulating and transforming information, and active problem-solving. These are not so easy to codify and standardise, imply some degree of uncertainty and thus are less likely to be replaced by technology. Intellectual tasks require more skills and human asset specificity and better complement new technologies, a reason why they are often associated with wage premiums and better employment conditions (Liu and Grusky, 2013; Martínez-Matute and Villanueva 2020; Fernández-Macías and Bisello 2021).

Deming (2017) classifies social tasks as those requiring cooperation and interaction with colleagues and/or dependants. They are not automatable because the object of the task is a social relationship. Considering this, only the most advanced machines (those that can satisfactorily act like humans) would be able to perform social tasks. For that reason, in the last decades, the jobs requiring social interactions expanded relative to the rest (Bisello et al., 2019). This is in line with existing literature, which suggests that social tasks tend to grow because they are neither easy to automate nor offshore and are thus relatively protected from RBTC and globalisation (Blinder, 2009; Goos and Manning, 2014).

Autonomy is a form of work organisation. Routinised and standardised jobs do not leave much space for the workers to make autonomous decisions since the order of the tasks, the pace of work and other key features are more likely to be predefined. By contrast, other jobs, such as those with a creative component and/or are more focused on problem solving or analytical tasks, are not easy to standardise and monitor. These workers' activities are not easy to predefine and control, but their performance is assessed by objectives instead. Consequently, workers in these cases have more room to define themselves when and how to do their duties. Autonomy is highly and positively correlated with intellectual tasks and negatively correlated with physical and routine tasks (see Table 3 below). Usually, jobs with more autonomy require more skills and are more difficult to be automated, such as the scientists, professionals and managers (Cetrulo et al. 2020; Bisello et al. 2021). That is also why autonomy is positively correlated with higher wages (Fernández-Macías and Bisello, 2021). Autonomy is also a dimension related to power and the hierarchical position of workers inside organisations, being key to analyzing how inequalities are structured in the labour market (Cetrulo et al., 2020).

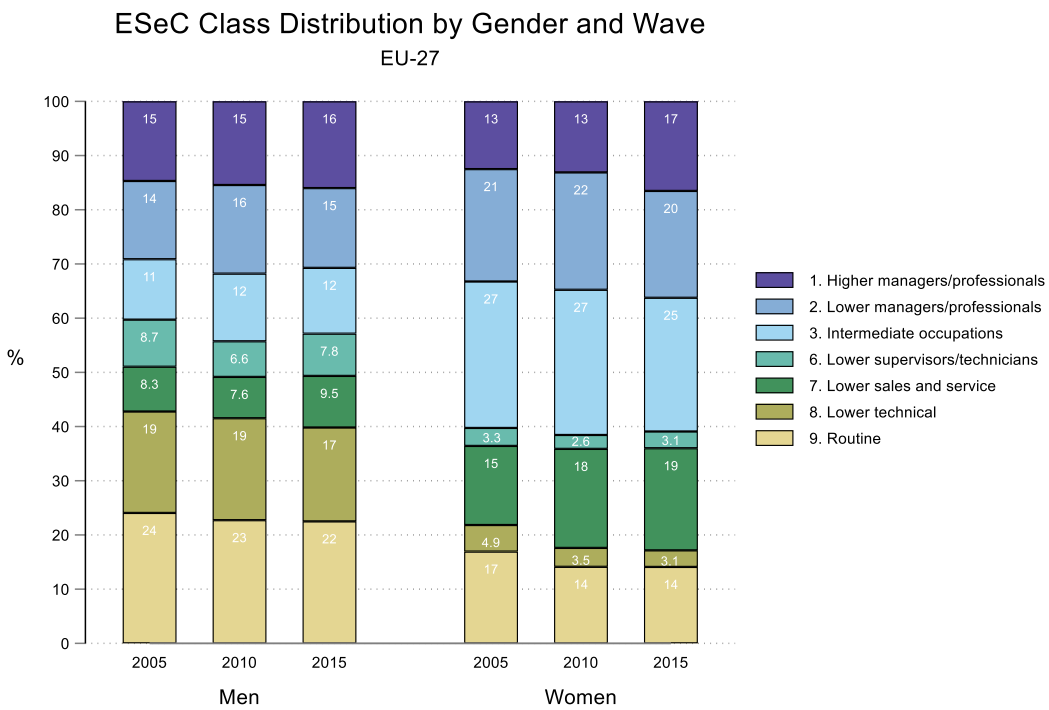
With intellectual and non-cognitive tasks, proficiency in ICT tools is associated with a wage premium (De la Rica, Gortazar and Lewandowski, 2020; González Vazquez et al., 2019). These tools play a crucial role because they transform workplaces: from clerk offices to industries getting more digitalised or the desks of different qualified professionals. Advancements in ICT have made possible the replacement of workers performing routine tasks, while these technologies complement the work of more qualified workers. The intensity of ICT use at work tends to be positively correlated with analytical work (because they complement jobs oriented towards intellectual tasks), but also with autonomy.

7.1.2 Social class

To build the ESeC-class schema, one just needs to rely on two-to-three core pieces of information commonly available in general-purpose surveys: (1) occupational titles proxying for skill requirements (i.e., ISCO); (2) ownership of means of production (employer, self-employed or employee); and (3) supervision.

The measure of social class builds on the original 9-category ESeC schema (Rose and Harrison, 2010). Regarding occupations, in the 2005-2015 pooled sample, we use 2-digit (in 2005, only 2-digit codes were available) ISCO-88(COM), the European Union variant of the ISCO-88, adapting the operationalization into nine classes proposed by the GESIS Institute[4]. A cross-tab of the 2- and 3-digit based ESeC schema in 2010-2015 shows an overall level of agreement at 81.4%. To reclassify observations into the service or higher-grade blue-collar classes with supervisory roles, we use the following question to differentiate managers: "How many people work under your supervision, for whom pay increases, bonuses or promotion depend directly on you?". In 2005-2015 we used a dummy distinguishing between less or more than ten supervisees, while in 2010-2015 we used a metric version. Table 4 displays the ESeC class distribution in the analytical samples and Figure 7 illustrates its distribution by gender and by survey waves in the 2005-2015 sample.

Figure 7. ESeC class distribution by gender and wave (2005-2015) excluding self-employed



7.1.3 Employment relations

We replicate the operationalization of employment relations, time horizons and reward types, as theorised by EGP-based class schemas and implemented by Smallenbroek et al. (2021) for comparability and benchmarking. See Smallenbroek et al. (2021) for extensive measurement details. Table 3 plots the correlation matrix of employment relations indicators and tasks.

Reward types. We measure reward types, proxying for monitoring difficulty, with four dummy items asking if earnings from respondents' main job include the following type of payments: "Payments based on the performance of the company where you work?", "Payments based on the performance of your team/department?", "Income from shares in the company you work for?", and "Advantages of

[4] The do-files were developed by Anika Herter and Heike Wirth for the EU-SILC and can be downloaded from https://www.gesis.org/en/gml/european-microdata/eu-silc/ (last consulted 18 February 2022). For the 2010-2015 sample, we rely on 3-digit ISCO-88(COM) using the 'iscogen' Stata package (Jann, 2019).

other nature (e.g., medical services, access to shops, etc.)?". We recoded these items so that higher scores in the composite index reflect more diffuse reward types typical of the service relationship (classes 1+2) and mixed contracts (class 3) and estimated a standardised average (α = 0.44) by analytical sample and survey wave. Principal Components Analysis (PCA) using tetrachoric correlations on our four dichotomous indicators yields the first PC with an Eigenvalue at 2.32, accounting for 58% of the variance. Only 3% of cases on both analytical samples after applying exclusion filters report missing values in at least one of the items. The distribution of the reward types index is highly skewed to the left because most workers are paid with fixed salaries, not with diffuse payments (the prevalence of the items stands from 3% to 20% in the 2005-2015 sample). However, as shown in Figure 14, there is substantial variation in the index by job tasks and, as shown in Figures 12-13, by social classes.

Time horizons. We capture time horizons, proxying for human asset specificity, with two items about respondents' agreement with two statements in a 1-to-5 scale: "I might lose my job in the next 6 months" and "My job offers good prospects for career advancement". Additionally, in the 2010-2015 sample, we also rely on a third item asking workers about changes in their salary in the last year: "decreased", “not changed” or “increased”. We reversed the first item so that higher scores in the composite index reflect long time horizons typical of the service relationship (classes 1+2) and mixed contracts (class 6). We estimated a standardised average of the first two (2005-2015) or all three items (2010-2015) by analytical sample and survey wave. Principal Components Analysis (PCA) on these indicators yields the first PC with an Eigenvalue at 1.33, accounting for 44% of the variance and α = 0.38. Only 9% of cases of the analytical sample after applying exclusion filters report missing values in at least one of the items in the 2005-2015 sample and 10.8% in the 2010-2015 sample comprising all three items.

In addition to these indices, we also operationalised seven indicators accounting for employment relations’ mechanisms on monitoring difficulty (4 items on piece-work and over-time earnings, pace of work dependent on boss control, and self-quality control) and human asset specificity (3 items on skills’ mismatch, on-the-job training, and training paid by employers) to replicate the main empirical analyses and results hold.

Table 3. Correlation matrix between tasks and employment relations for men and women (2005-2015)

		Tasks				Work Methods					Tools		Emp. Relations	
		Strenght	Concept	Creative	Serving	Autonomy	Teamwork	Repetitive	Standard	Certainty	Machines	ICT	Reward Types	Time Horizons
Tasks	Strenght	1												
	Concept	-0.06	1											
	Creative	-0.10	0.40	1										
	Serving	0.02	0.06	0.17	1									
	Autonomy	-0.21	0.25	0.42	0.04	1								
	Teamwork	0.06	0.21	0.14	0.02	0.06	1							
	Repetitive	0.30	-0.08	-0.14	-0.06	-0.18	0.02	1						
	Standard	0.12	0.21	0.06	-0.10	-0.06	0.13	0.19	1					
	Certainty	-0.05	-0.27	-0.21	-0.13	-0.19	-0.16	-0.02	-0.09	1				
	Machines	0.31	-0.03	-0.14	-0.24	-0.22	0.05	0.31	0.29	0.04	1			
	ICT	-0.30	0.33	0.24	0.14	0.33	0.07	-0.13	0.03	-0.26	-0.24	1		
ER	RT	-0.07	0.15	0.12	-0.01	0.17	0.09	-0.02	0.10	-0.10	0.01	0.18	1	
	TH	-0.18	0.23	0.25	0.09	0.24	0.10	-0.16	0.02	-0.07	-0.13	0.24	0.17	1

Notes: n=68,433; weighted figures; all correlations statistically significant at p<0.001

7.1.4 Income

As the third indicator of life chances in the 2010-2015 sample, we use the respondents’ net monthly earnings in euros from the main paid job. If respondents were unable or refused to answer with a precise estimation, they provided their income range in 12 categories, and EWCS assigned the band midpoint to these observations. We have adjusted income by country’s purchasing power parity (PPP), relying on the World Bank Development Indicators deflators (PPP conversion factor, private consumption) and the European Central Bank Euro foreign exchange reference rates for those countries out of the Eurozone.

Table 4. Summary Statistics with weighted figures

	2005-2015 (n = 68,433)				2010-2015 (n = 40,377)			
	Mean	**Std. dev.**	**Min**	**Max**	**Mean**	**Std. dev.**	**Min**	**Max**
Wave								
2005	26.06%							
2010	37.11%				44.13%			
2015	36.83%				55.87%			
Age	40.58	11.19	18	65	41	11.30	18	65
18-25	10.26%				9.68%			
26-35	25.55%				25.16%			
36-45	28.10%				27.27%			
46-55	25.67%				26.41%			
56-65	10.42%				11.48%			
Women	48.10%				49.35%			
Household Members								
1	10.36%				11.24%			
2	26.27%				27.38%			
3	25.54%				25.42%			
4	25.62%				24.69%			
5	8.74%				8.18%			
6 or more	3.47%				3.08%			
Migrant					14.36%			
Tasks								
Z-Physical Strenght	0.00	1.00	-0.89	3.94	0.00	1.00	-0.92	3.94
Z-Intellectual/Concept	0.00	1.00	-1.76	0.88	0.00	1.00	-1.77	0.88
Z-Intellectual/Creative	0.00	1.00	-2.58	0.98	0.00	1.00	-2.60	0.98
Z-Social/Serving	0.00	1.00	-1.23	1.21	0.00	1.00	-1.21	1.14
Z-Autonomy/Latitude	0.00	1.00	-1.77	2.08	0.00	1.00	-1.77	2.07
Z-Methods/Teamwork	0.00	1.00	-1.33	1.20	0.00	1.00	-1.32	1.19
Z-Routine/Repetitive	0.00	1.00	-1.28	1.93	0.00	1.00	-1.28	1.88
Z-Routine/Standard	0.00	1.00	-1.57	1.18	0.00	1.00	-1.57	1.17
Z-Routine/Certainty	0.00	1.00	-1.89	1.39	0.00	1.00	-1.87	1.40
Z-Machines/Analog	0.00	1.00	-0.63	3.00	0.00	1.00	-0.61	3.00
Z-Machines/ICT	0.00	1.00	-1.08	1.54	0.00	1.00	-1.07	1.38
Employment Relations								
Z-Reward Types	0.00	1.00	-0.74	4.33	0.00	1.00	-0.74	4.29
Z-Time Horizons	0.00	1.00	-2.35	1.85	0.00	1.00	-2.86	2.07
Weekly Working Hours	38.02	1.00	5	168	37.61	9.93	5	148
Permanent Contract	59.74%				57.70%			
Z-Seniority	0.00	1.00	-2.60	6.77	0.00	1.00	-2.57	6.73
Full-Time Contract	81.10%				81.85%			
ESeC Classes								
1	14.87%				11.58%			
2	17.87%				21.11%			
3	18.75%				11.95%			
6	5.35%				5.94%			
7	12.84%				15.23%			
8	11.24%				12.00%			
9	19.07%				22.20%			
Employment Contract								
Service	32.74%				32.69%			
Mixed	24.10%				17.88%			
Labour	43.15%				49.43%			
Personal Net Monthly Income Adjusted by PPP (q50)					1,501.54	1,846.57	0.83	229,845
(Log)Personal Net Monthly Income Adjusted by PPP (q50)					7.31	0.67	-0.19	12.35

7.2 Annex B. Additional analyses and robustness checks

7.2.1 Tasks variance between and within classes: overtime and comparative analyses

To decompose the variation in each task between and within social classes (and by gender and overtime), we rely on the Intraclass Correlation (ICC), expressing the ratio of the between-class variance to the total variance in each task accounted for social classes. It is obtained through multilevel regressions where the dependent variable is each of the tasks and the second-level variable is the social class (or the corresponding cluster variable), with individual-level weights. In Table 5, we benchmark the variation in each task explained by social classes compared to other factors like occupational titles, sectors, and countries.

Figure 8 shows the intraclass correlation coefficient (ICC) over time, which is essentially the percentage of the variance for each task due to the differences across social classes. For instance, around 14 % of the variance in intellectual conceptualisation tasks is due to differences across social classes, while 37 % to ICT use at work. Surprisingly, routine measures are amongst those that least explain the overall variance due to differences between social classes, while the use of machinery is the largest and increasing over time, especially for ICT. Overall, there are no considerable changes over the period, suggesting that the role of occupational classes accounting for task divides remains relatively constant.

It is also worth considering the variance explained in tasks due to differences across social classes compared to other clusters such as countries, sectors, or occupations (see Table 5). For example, countries only explain between 3 to 9 % of the variance on the one end. On the other end, the ISCO-88 codes at two digits explain between 5 and 48 % of the variance. The differences between the variance explained by ISCO and social classes or types of employment contracts are not significant, suggesting that the ESeC occupational aggregation performs well to capture task divides.

Figure 8. Tasks variance explained between EseC social classes (ICC) over time for men and women (2005-2015)

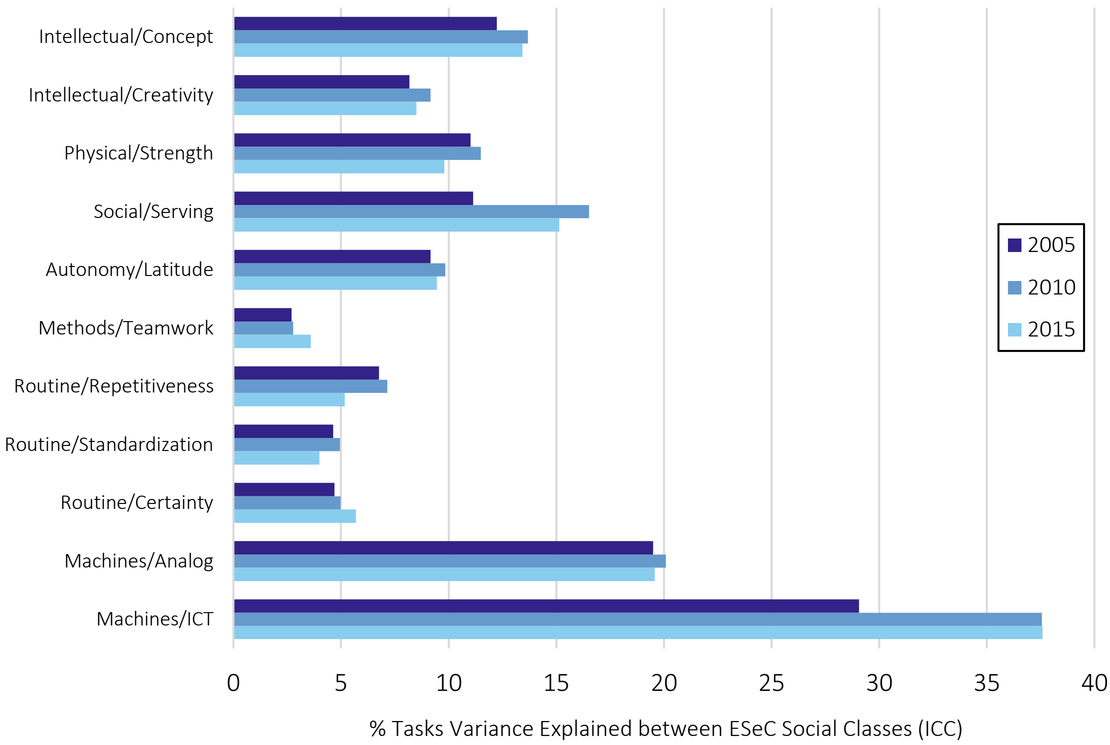


Table 5. % Variance explained (ICC) by selected variables by gender in 2005-2015

Tasks	ESeC Social Classes		Employment Contracts		Occupations (2-digit ISCO-88)		Sector (1-digit NACE)		Country (EU-27)	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Intellectual/Concept	11.60	16.74	9.29	15.11	18.06	20.97	9.11	12.93	3.95	4.46
Intellectual/Creativity	8.23	14.07	7.50	8.18	15.10	25.67	3.45	5.28	6.04	6.36
Physical/Strength	13.32	7.00	10.08	6.73	24.23	19.82	10.69	8.61	2.97	2.51
Social/Serving	10.80	20.47	2.04	1.85	31.71	37.90	17.10	16.80	3.47	2.04
Autonomy/Latitude	12.90	8.42	12.04	4.90	26.51	29.71	5.92	7.41	9.77	7.41
Methods/Teamwork	2.44	3.46	0.96	2.30	5.21	5.85	2.23	6.84	2.14	3.82
Routine/Repetitiveness	5.65	11.21	5.00	5.95	14.80	19.43	6.12	5.04	3.58	3.72
Routine/Standardization	3.65	5.61	0.01	0.28	11.77	13.99	5.11	5.79	3.23	2.66
Routine/Certainty	4.75	6.63	3.93	3.57	10.70	12.40	4.19	4.20	6.62	8.89
Machines/Analog	16.05	26.24	8.23	4.77	35.45	55.49	13.97	11.06	2.22	1.70
Machines/ICT	34.51	36.38	29.11	31.42	48.94	54.55	22.12	26.70	6.39	3.23

7.2.2 Job tasks and social classes over time and by gender

The second part of the first research question asked how the distribution of job tasks between and within classes changed over time between 2005 and 2015 and whether social classes are increasingly capturing a task divide related to technology-based explanations of income inequality trends. According to Figure 9, which displays the APE of each wave compared to 2005, there have not been many significant changes concerning the task composition of the different social classes from 2005 to 2015. The general over-time picture is one of stability. Only a few cases deserve our attention.

It is worth noting that no statistically significant change can be observed for the service classes for any of the periods. The same applies to mixed contracts with one notable exception: the increase of repetitiveness in 2015 compared to 2005 for intermediate occupations (Class 3) and its decrease for lower supervisors and technicians (Class 6). Finally, changes in labour contracts are heterogeneous. On the one hand, the level of ICT use at work declines for all three classes (7, 8 and 9). On the other hand, the lower sales and service class (class 7) displays higher physical strength, teamwork and social serving, while the opposite is true, or there is no significant effect for routine and lower technical occupations (classes 8 and 9). Overall, the changes over time are inconspicuous, which might be because the period analyzed is too small to capture the significant disruptive effects of technological change compared to longer-term periods (Bisello et al., 2019). Figures 10 and 11 disaggregate the association between social classes and job tasks over time and gender.

Figure 9. Distribution of Z-tasks by social classes (ESeC) over time (2005-2015) for men and women. APE over time with survey wave 2005 as reference category (0)

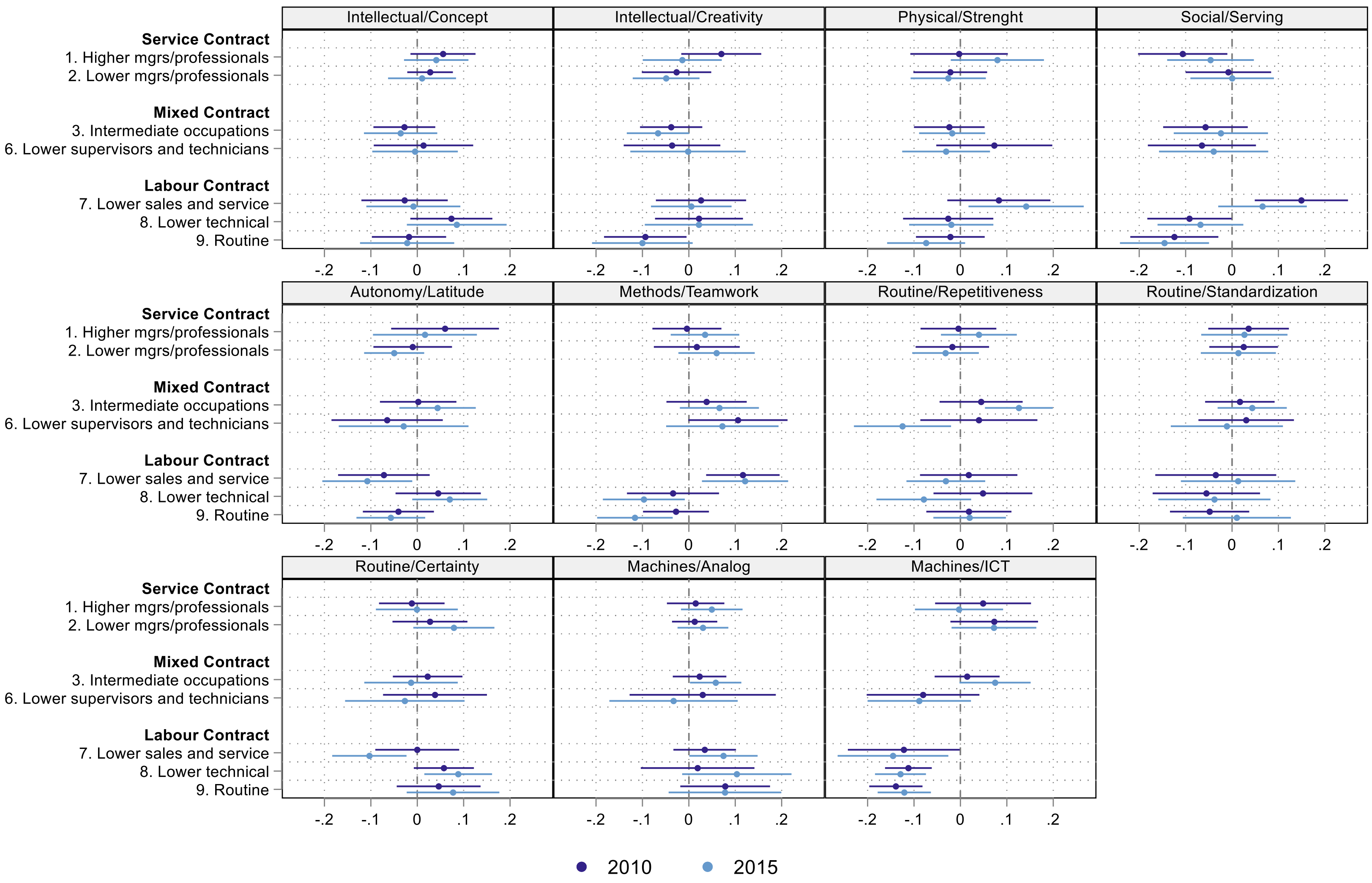


Figure 10. Distribution of tasks by social classes (ESeC) over time (2005-2015) for men

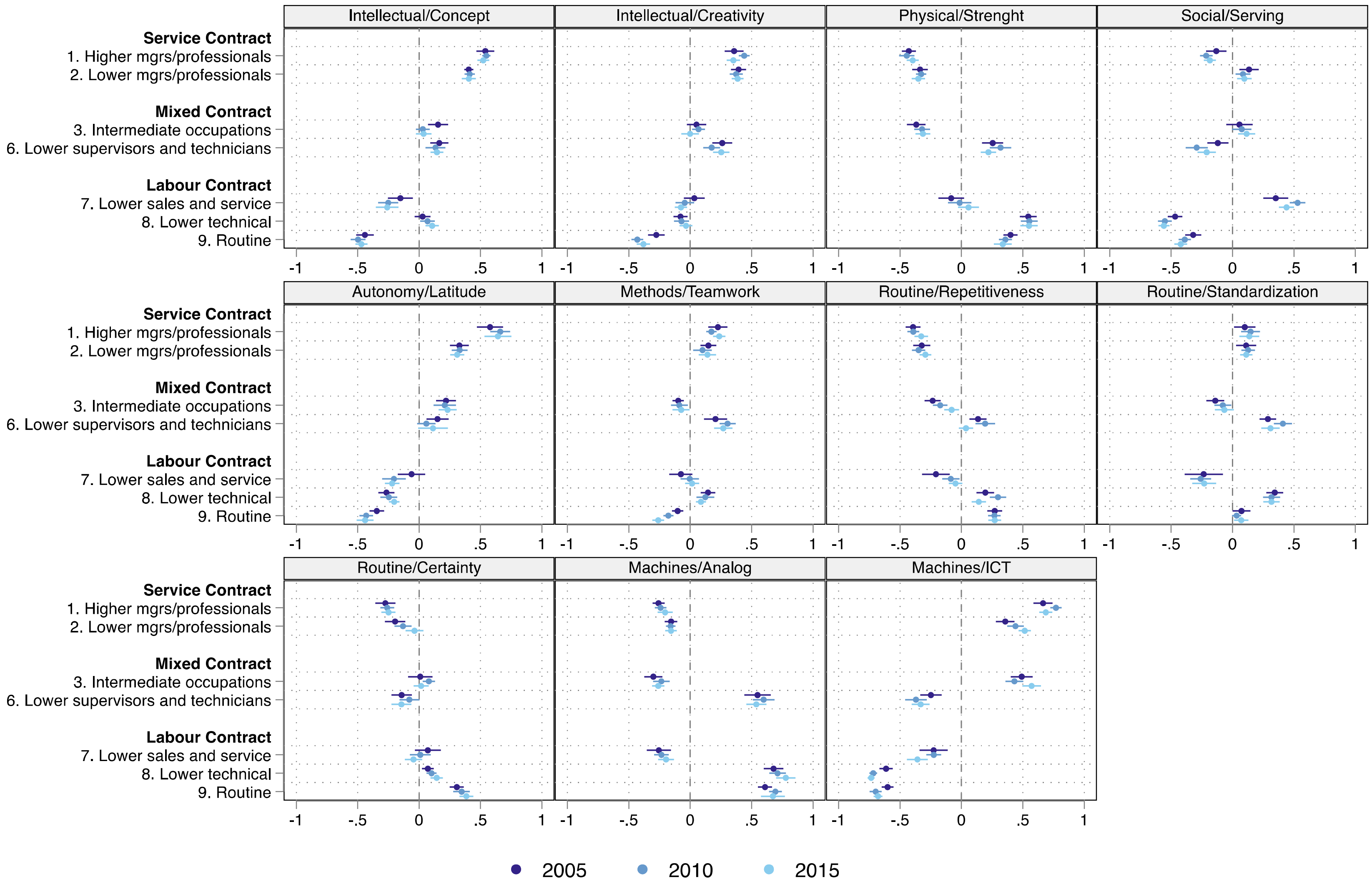
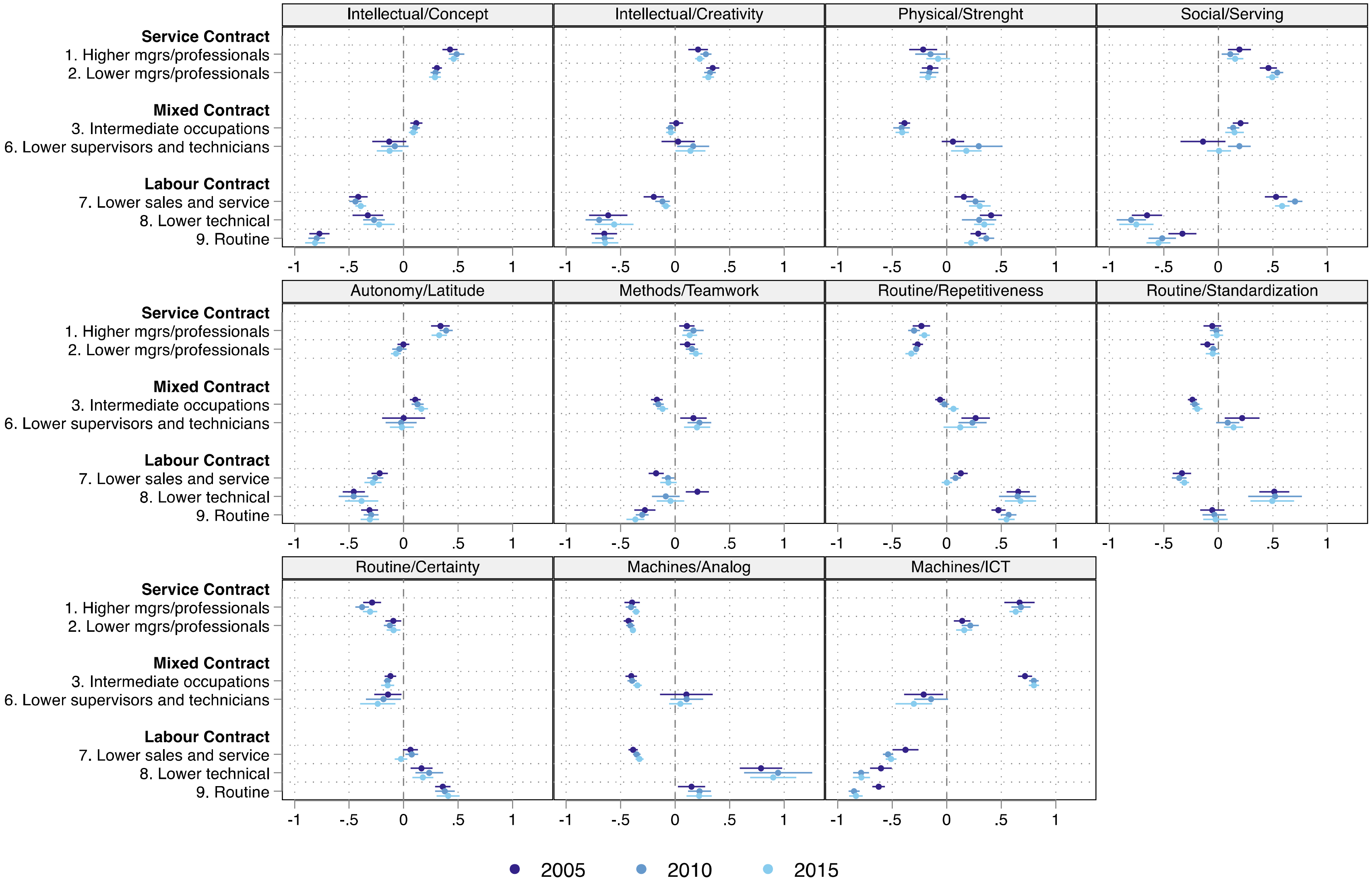


Figure 11. Distribution of tasks by social classes (ESeC) over time (2005-2015) for women



7.2.3 Social classes and employment relations: ESeC criterion validity

To explore how employment relations are distributed between social classes, we run multivariate OLS regressions with social classes predicting each indicator of employment relations (reward types or time horizons) in the 2005-2015 analytical sample. Furthermore, we predict employment relations indicators as outcomes with interaction terms between survey wave and social classes to analyse change over time. Finally, we plot predicted marginal effects in the figures.

Here we provide a test of the criterion validity of the ESeC class schema over time and by gender according to its theorised indicators on reward types and time horizons. As already documented by Smallenbroek et al. (2021) and illustrated in figure 12 and 13, the ESeC class schema and derived employment contracts account relatively well for the underlying mechanisms outlined by the theory, and they do not change considerably over time (Figure 13). However, in the case of women, employment relations indicators do not discriminate as well social classes as they do for men.

Figure 12. Social classes and employment relations by gender (2005-2015)

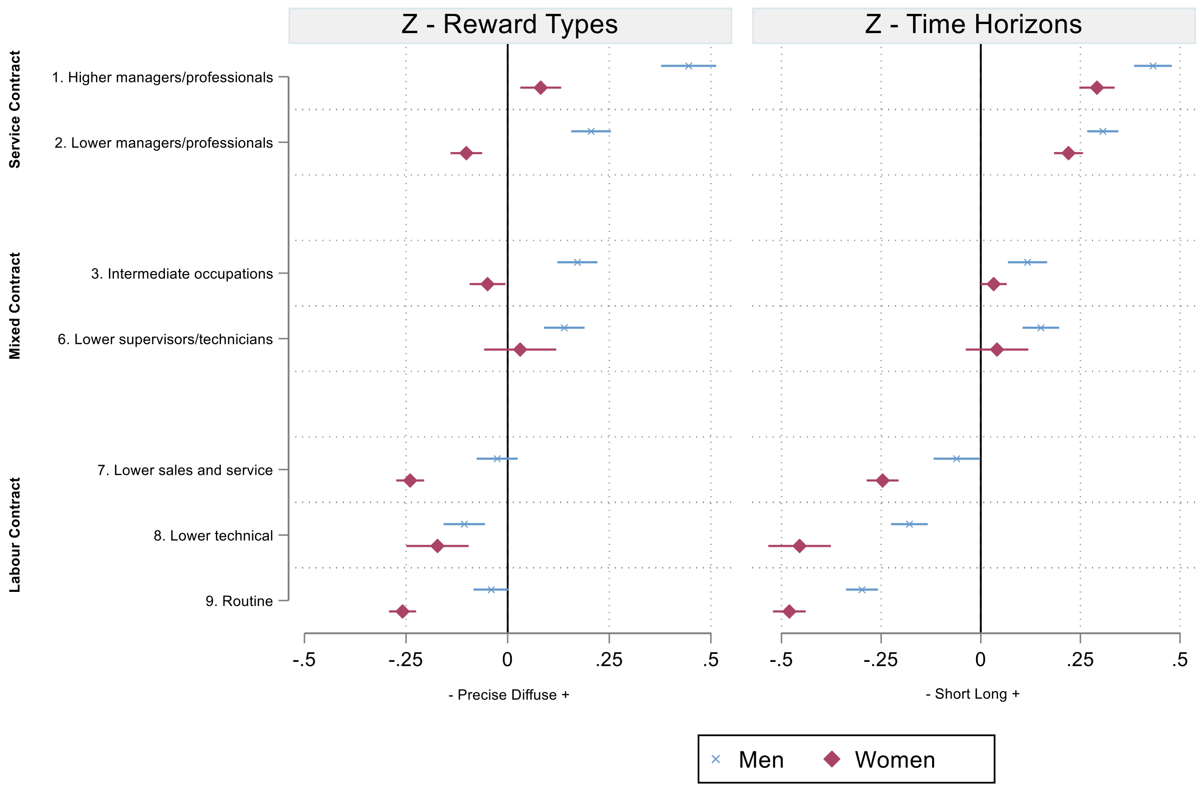


Figure 13. Social classes and employment relations by gender and survey wave (2005-2015)

7.2.4 *Tasks and employment relations*

To assess how job tasks are distributed between social classes, we run multivariate OLS regressions with social classes predicting each task indicator in the 2005-2015 analytical sample. Furthermore, we predict job tasks as outcomes with interaction terms between survey wave and social classes to analyse change over time. Finally, we plot predicted marginal effects and APE in the figures.

Figure 14 plots the standardized coefficients of each task on standardized reward types and time horizons by gender for the period 2005-2015. Concerning reward types, theorized to be more precise (fixed salary) or diffuse (team performance payments, company stocks) as a result of different levels of work monitoring difficulty, it seems that, controlling for the remaining tasks and covariates, ICT tools (βmen = 14% SD [p<0.001]; βwomen = 9% SD [p<0.001]), autonomy (βmen = 11% [p<0.001]; βwomen = 6% SD [p<0.001]), standardization (βmen = 7% [p<0.001]; βwomen = 5% SD [p<0.001]), teamwork (βmen = 5% [p<0.001]; βwomen = 5% SD [p<0.001]), intellectual/conceptualization tasks (βmen = 4% [p<0.001]; βwomen = 2% SD [p<0.001]) and analog machinery (β = 4% SD for men and women [p<0.001]) are positively associated with more diffuse types of payments. On the contrary, we found that men reporting higher levels of muscular strength (physical strength) (βmen = -5% SD [p<0.001]), but only for men, and certainty (βmen = -3% SD [p<0.001]; βwomen = -2% SD [p<0.001]) in their jobs receive more fixed payments (i.e., piecewise payments). That is, physical strength and certainty are negatively associated with diffuse reward types.

Differences in the effect of tasks on reward types by gender are statistically significant for physical strength tasks (βmen-women = -4% SD [p<0.001]), autonomy (βmen-women = 5% SD [p<0.001]), routine/standardization (βmen-women = 3% SD [p<0.05]) and ICT tools (βmen-women = 6% SD [p<0.001]).

Apart from the positive associations of analogue machinery and standardisation on diffuse reward types, the ranking and direction of the task's coefficients are highly in line with the theoretical foundations of EGP-based class schemas. Those jobs involving more intense use of computers, higher levels of latitude to decide the working time, task order, methods and speed, and more abstract intellectual tasks are more difficult to monitor so that workers receive more diffuse types of payments. These workers are typically managers and professionals involved in a service relationship, as we saw above. The contrary applies to workers reporting higher levels of physical strength and certainty to take unforeseen tasks, being easier to monitor and getting paid in a more piecewise way.

Concerning time horizons, assumed to be a function of jobs involving different degrees of human asset specificity or replaceability, intellectual tasks like conceptualization (β = 11% SD for men and women [p<0.001]) and creativity (βmen = 11% SD [p<0.001]; βwomen = 13% SD [p<0.001]), ICT tools (β = 10% SD for men and women [p<0.001]), autonomy (βmen = 9% SD; βwomen = 8% SD [p<0.001]), certainty (βmen = 7% SD [p<0.001]; βwomen = 6% SD [p<0.001]) and teamwork (βmen = 4% SD; βwomen = 7% SD [p<0.001]) are positively associated with longer time horizons. The positive association between the intensity in the use of this tasks at work and the probability of having long time horizons is stronger for intellectual tasks, the use of ICT at work and autonomy. In other words, long time horizons are generally offered to the workers performing intellectual tasks, using computers, and enjoying a high degree of autonomy at work. Differences by gender are non-significant in all cases. Conversely, physical tasks (βmen = -11% SD [p<0.001]; βwomen = -7% SD [p<0.001]) and repetitiveness (βmen = -7% SD [p<0.001]; βwomen = -8% SD [p<0.001]) are negatively associated with the probability of having long time horizons at work. That is, workers reporting physical and repetitive tasks at work tend to have shorter time horizons. Differences in the effect of tasks on time horizons by gender are only statistically significant for physical strength tasks (βmen-women = -4% SD [p<0.001]) and teamwork (βmen-women = -3% SD [p<0.001]).

Except for the positive effect of certainty on longer time horizons, the ranking and magnitude of the coefficients expressing the relationship between tasks and time horizons are generally in line with theoretical expectations of EGP-based class schemas. Those jobs with higher contents of intellectual tasks, autonomy and ICT tools are generally highly qualified, requiring a college education, being more difficult to replace and with higher levels of human asset specificity. Thus, workers ranking higher in these tasks, work methods and tools tend to get longer time horizons than workers whose jobs are more intense in muscular power, repetitive movements and monotonous tasks, as other workers can more easily replace the latter with similar productivity.

If we look at the relationship between tasks and employment relations over time between 2005 and 2015 (Figure 15) by adding interaction terms between tasks and survey waves, the overall picture is of stability, meaning that tasks have similar predictive power over the whole period.

Figure 14. Tasks and employment relations by gender (2005-2015)

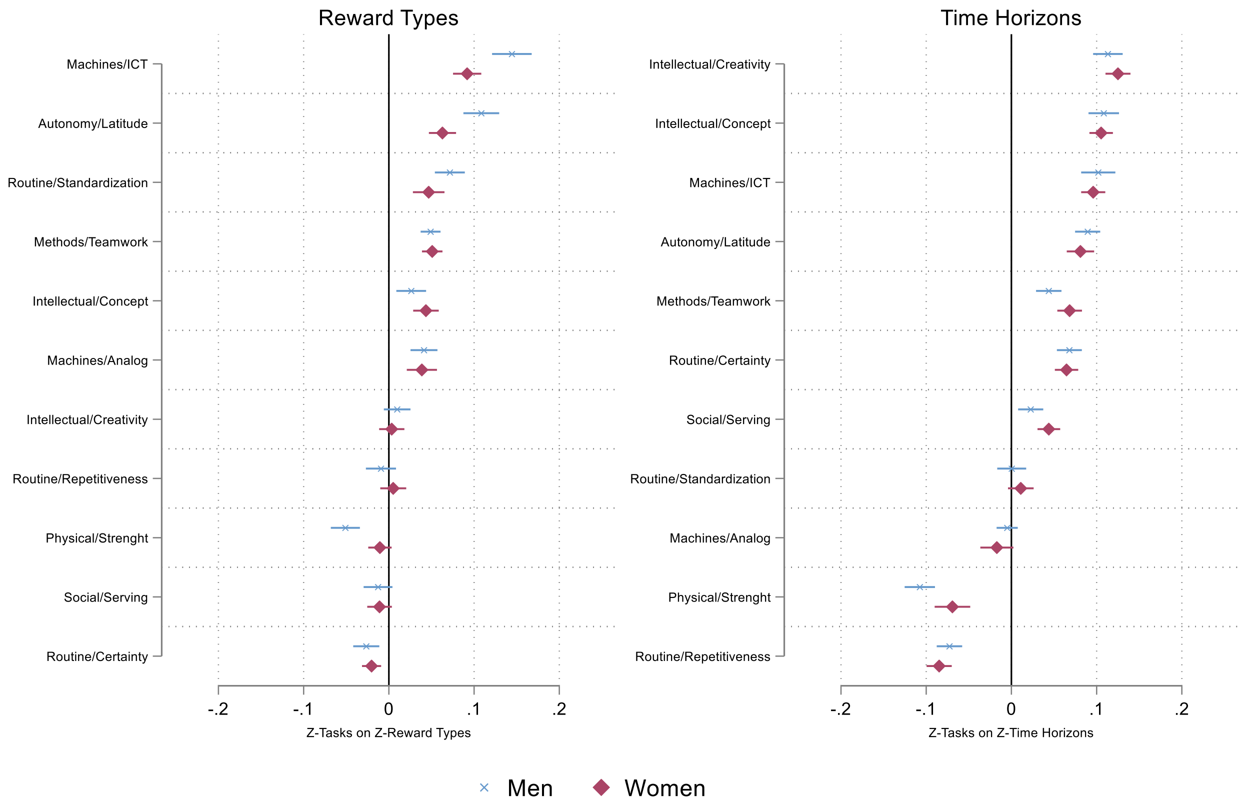
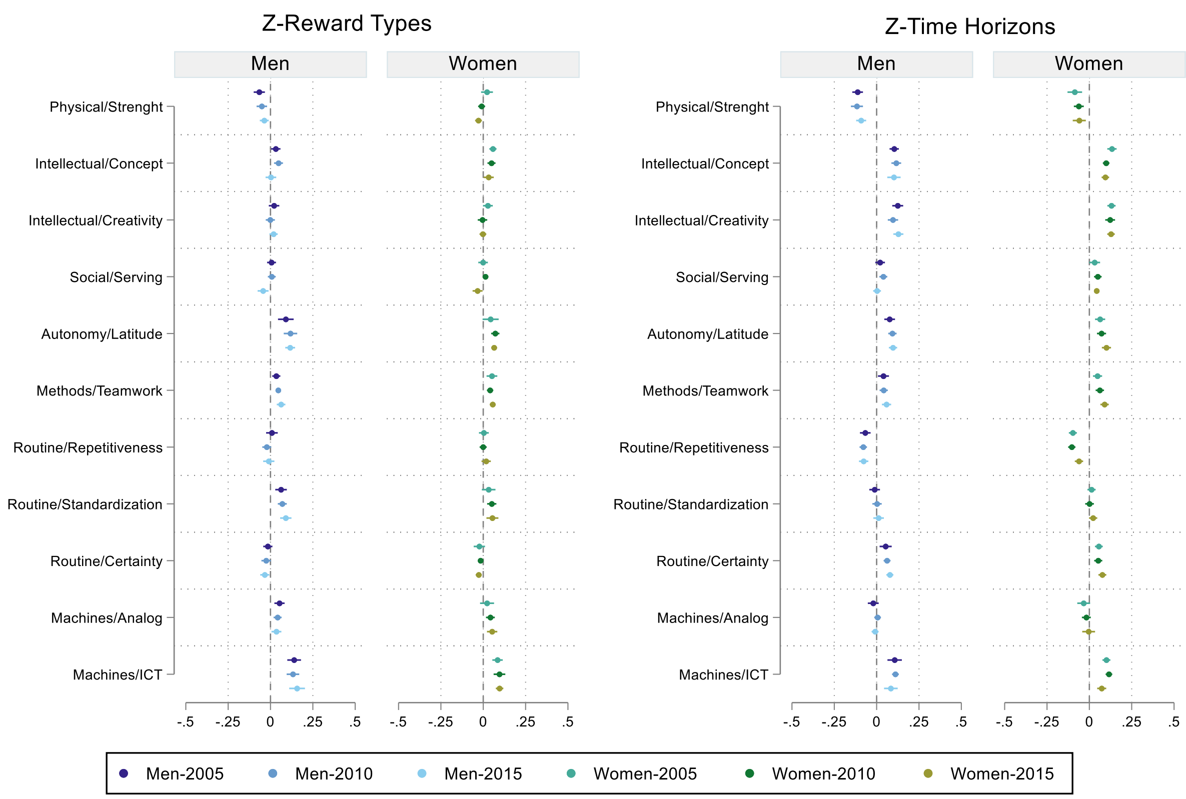


Figure 15. Tasks and employment relations over time (2005-2015) and by gender



7.2.5 Tasks, employment relations, and social classes: overtime analysis & ESeC classes

To further address our second research question on alternative explanations that might challenge the theoretical foundations of EGP-based class schemas or their criterion validity, we assess how job tasks confound the association between employment relations indicators (reward types and time horizons) and social class membership. We run multinomial models predicting each social class membership, ESeC class 1 is always the reference category. Results are expressed as log-odds.

We find similar patterns as in the article's main results (Table 1) predicting employment contracts' membership when we perform the same analysis over time (Table 7) or use disaggregated EseC social classes as dependent variables (Table 6). First, regarding the analysis over time across survey waves 2005, 2010 and 2015, we find that the mediating or confounding role of job tasks in employment contract membership is highly stable in most cases or even increasing in some.

Second, concerning the disaggregated analyses by EseC social classes, the more diffuse the reward types or, the longer the time horizons, the lower the probability of belonging to any social class different from Class 1 (higher managers and professionals). As with aggregated employment contracts, tasks explain a big and statistically significant chunk of the effect of reward types (Class 2: 47% (men) – 54% (women); Class 3: 72%-50%; Class 6: 72% (men); Class 7: 73%-69%; Class 8: 60%-73%; Class 9: 83%-76%) or time horizons (Class 2: 46% (men) – 54% (women); Class 3: 46%-32%; Class 6: 88%-78%; Class 7: 62%-57%; Class 8: 71%-65%; Class 9: 68%-66%) on class membership. Furthermore, sensitivity checks using only those tasks more related to technology-based explanations (physical and intellectual tasks, routine work methods and analogue and ICT machines) and excluding work autonomy, which could account for variation in reward types and monitoring difficulty, yield highly consistent results.

Table 6. Employment relations, job tasks (mediator/confounder) and ESeC class membership (2005-2015)

	Class 2 Lower managers/ professionals		**Class 3 Intermediate occupations**		**Class 6 Lower supervisors/ technicians**		**Class 7 Lower sales/ service**		**Class 8 Lower technical**		**Class 9 Routine**	
Log odds	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
						Reward Types						
Total effect	-0.184***	-0.216***	-0.194***	-0.116***	-0.287***	-0.0634	-0.408***	-0.434***	-0.584***	-0.328***	-0.490***	-0.448***
	(0.0246)	(0.0338)	(0.0251)	(0.0229)	(0.0331)	(0.0498)	(0.0369)	(0.0306)	(0.0349)	(0.0642)	(0.0375)	(0.0350)
Direct effect	-0.0981***	-0.0996**	-0.0543*	-0.0580*	-0.0794*	0.0806	-0.111**	-0.135***	-0.232***	-0.0888	-0.0830*	-0.106**
	(0.0240)	(0.0350)	(0.0256)	(0.0239)	(0.0313)	(0.0488)	(0.0344)	(0.0299)	(0.0335)	(0.0621)	(0.0380)	(0.0343)
Difference	-0.0856***	-0.117***	-0.140***	-0.0576***	-0.208***	-0.144***	-0.297***	-0.300***	-0.352***	-0.240***	-0.407***	-0.342***
	(0.0120)	(0.0140)	(0.0158)	(0.0131)	(0.0285)	(0.0272)	(0.0288)	(0.0301)	(0.0380)	(0.0423)	(0.0411)	(0.0413)
Confounded by Tasks %	**46.61**	**53.96**	**72.06**	**49.83**	**72.35**	227.1	**72.89**	**69.03**	**60.29**	**72.98**	**83.04**	**76.31**
						Time Horizons						
Total effect	-0.191***	-0.107***	-0.463***	-0.360***	-0.542***	-0.512***	-0.693***	-0.791***	-0.982***	-1.101***	-1.135***	-1.197***
	(0.0276)	(0.0261)	(0.0375)	(0.0262)	(0.0454)	(0.0529)	(0.0433)	(0.0330)	(0.0493)	(0.0652)	(0.0566)	(0.0445)
Direct effect	-0.103***	-0.0488	-0.248***	-0.245***	-0.0638	-0.113*	-0.265***	-0.342***	-0.284***	-0.383***	-0.368***	-0.410***
	(0.0256)	(0.0275)	(0.0346)	(0.0272)	(0.0392)	(0.0562)	(0.0435)	(0.0342)	(0.0412)	(0.0521)	(0.0430)	(0.0363)
Difference	-0.0876***	-0.0584**	-0.214***	-0.115***	-0.478***	-0.399***	-0.428***	-0.449***	-0.698***	-0.718***	-0.767***	-0.787***
	(0.0191)	(0.0191)	(0.0224)	(0.0191)	(0.0343)	(0.0393)	(0.0350)	(0.0355)	(0.0429)	(0.0560)	(0.0461)	(0.0489)
Confounded by Tasks %	**45.97**	**54.46**	**46.30**	**31.97**	**88.21**	**77.89**	**61.76**	**56.81**	**71.09**	**65.20**	**67.56**	**65.77**
n	32158	36275	32158	36275	32158	36275	32158	36275	32158	36275	32158	36275

Notes: robust standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001; decomposition into direct and indirect effects using the KHB method (Karlson et al., 2020). Estimates obtained from KHB multinomial logistic regressions predicting ESeC social classes with Class 1 (higher managers/professionals) as the reference category, survey weights and clustered standard errors by country (EU-27) and wave. Controls: age, country-FE, survey wave (2005-2015), and household size.

Table 7. Employment relations, job tasks (mediator/confounder) and employment contracts over time (2005-2015)

	Men						**Women**					
	Mixed Contract			**Labour Contract**			**Mixed Contract**			**Labour Contract**		
Log odds	**2005**	**2010**	**2015**	**2005**	**2010**	**2015**	**2005**	**2010**	**2015**	**2005**	**2010**	**2015**
						Reward Types						
Total effect	-0.136**	-0.160***	-0.144***	-0.390***	-0.370***	-0.475***	-0.0809	-0.0324	0.119***	-0.341***	-0.362***	-0.258***
	(0.0453)	(0.0323)	(0.0289)	(0.0546)	(0.0380)	(0.0369)	(0.0446)	(0.0328)	(0.0281)	(0.0528)	(0.0431)	(0.0336)
Direct effect	-0.0432	-0.0163	-0.0125	-0.136**	-0.0168	-0.130***	-0.0494	-0.0388	0.0778**	-0.152**	-0.0891*	-0.0131
	(0.0434)	(0.0332)	(0.0306)	(0.0489)	(0.0355)	(0.0350)	(0.0444)	(0.0319)	(0.0292)	(0.0477)	(0.0406)	(0.0328)
Difference	-0.0930***	-0.144***	-0.131***	-0.255***	-0.353***	-0.345***	-0.0315	0.00643	0.0411	-0.189***	-0.272***	-0.245***
	(0.0237)	(0.0266)	(0.0268)	(0.0526)	(0.0527)	(0.0549)	(0.0165)	(0.0212)	(0.0269)	(0.0429)	(0.0472)	(0.0460)
Confounded by Tasks	**68.29**	**89.80**	**91.33**	**65.26**	**95.46**	**72.58**	38.90	-19.87	**34.56**	**55.53**	**75.35**	**94.94**
						Time Horizons						
Total effect	-0.385***	-0.482***	-0.374***	-0.945***	-1.020***	-0.761***	-0.320***	-0.358***	-0.299***	-0.941***	-1.052***	-0.785***
	(0.0484)	(0.0519)	(0.0409)	(0.0747)	(0.0786)	(0.0395)	(0.0522)	(0.0317)	(0.0306)	(0.0704)	(0.0589)	(0.0405)
Direct effect	-0.120**	-0.166***	-0.0827	-0.358***	-0.335***	-0.161***	-0.192***	-0.247***	-0.179***	-0.325***	-0.418***	-0.299***
	(0.0464)	(0.0412)	(0.0423)	(0.0599)	(0.0562)	(0.0431)	(0.0438)	(0.0267)	(0.0348)	(0.0507)	(0.0497)	(0.0426)
Difference	-0.265***	-0.316***	-0.291***	-0.587***	-0.685***	-0.600***	-0.128***	-0.111***	-0.121***	-0.617***	-0.634***	-0.486***
	(0.0316)	(0.0341)	(0.0353)	(0.0607)	(0.0603)	(0.0574)	(0.0358)	(0.0246)	(0.0293)	(0.0617)	(0.0521)	(0.0487)
Confounded by Tasks	**68.90**	**65.54**	**77.87**	**62.15**	**67.13**	**78.83**	**39.92**	**31.03**	**40.33**	**65.52**	**60.29**	**61.94**
n	8445	12028	11685	8445	12028	11685	9663	13409	13203	9663	13409	13203

Notes: robust standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001; decomposition into direct and indirect effects using the KHB method (Karlson et al., 2020). Estimates obtained from KHB multinomial logistic regressions predicting employment contracts (mixed = ESeC 3+6; labour = ESeC 7+8+9) with service contracts as reference category (higher and lower managers and professionals' class: ESeC 1+2), survey weights and clustered standard errors by country (EU-27). Controls: age, country-FE, and household size.

Table 8. Oaxaca decomposition of seniority and permanent contract by class and gender (2005-2015)

Group 1	Z-Seniority Residualised of Age				Permanent Contract			
	Mixed Contract		Labour Contract		Mixed Contract		Labour Contract	
	Men	Women	Men	Women	Men	Women	Men	Women
Overall								
Group 1	0.174***	0.0240*	-0.0619***	-0.299***	0.841***	0.826***	0.779***	0.734***
	(0.0143)	(0.0108)	(0.00881)	(0.00891)	(0.00536)	(0.00436)	(0.00378)	(0.00436)
Group 2: Service	0.149***	0.138***	0.149***	0.138***	0.866***	0.857***	0.866***	0.857***
	(0.0117)	(0.0100)	(0.0117)	(0.0100)	(0.00409)	(0.00376)	(0.00409)	(0.00376)
Diff. (1-2)	0.0255	-0.114***	-0.211***	-0.437***	-0.0256***	-0.0317***	-0.0871***	-0.123***
	(0.0185)	(0.0147)	(0.0147)	(0.0134)	(0.00674)	(0.00576)	(0.00556)	(0.00576)
Explained	0.0152	-0.0519***	-0.0912***	-0.147***	-0.0285***	-0.0209***	-0.0929***	-0.0870***
	(0.00993)	(0.00825)	(0.0155)	(0.0140)	(0.00405)	(0.00363)	(0.00605)	(0.00615)
Unexplained	0.0103	-0.0621***	-0.120***	-0.290***	0.00296	-0.0108	0.00580	-0.0363***
	(0.0195)	(0.0161)	(0.0208)	(0.0189)	(0.00695)	(0.00607)	(0.00744)	(0.00767)
Explained / Composition Effects								
Tasks	-0.00223	-0.0175**	-0.00356	-0.0750***	-0.0136***	-0.00294	-0.0422***	-0.0213***
	(0.00723)	(0.00593)	(0.0146)	(0.0126)	(0.00269)	(0.00228)	(0.00547)	(0.00514)
Emp. relations	-0.0202***	-0.0151***	-0.0733***	-0.0576***	-0.0113***	-0.0139***	-0.0461***	-0.0541***
	(0.00309)	(0.00205)	(0.00552)	(0.00495)	(0.00127)	(0.00124)	(0.00232)	(0.00240)
Survey waves	0.00124	-0.00125*	0.000540	-0.0000162	-0.000551	-0.000724**	-0.000523*	-0.000378*
	(0.000687)	(0.000591)	(0.000391)	(0.000298)	(0.000330)	(0.000261)	(0.000212)	(0.000180)
Country-FE	0.0249***	0.00654*	-0.0207***	0.00181	-0.000536	-0.00630***	0.00554**	-0.00617***
	(0.00420)	(0.00310)	(0.00389)	(0.00285)	(0.00177)	(0.00145)	(0.00182)	(0.00167)
Household size	-0.000583	0.000488	0.000547	0.000687	-0.000165	0.00000800	0.0000452	-0.000143
	(0.000511)	(0.000329)	(0.000458)	(0.000394)	(0.000152)	(0.0000968)	(0.0000607)	(0.000159)
Sector	0.0121*	-0.0252***	0.00526	-0.0168*	0.00831***	0.0128***	0.00610*	0.00640*
	(0.00589)	(0.00650)	(0.00738)	(0.00688)	(0.00187)	(0.00239)	(0.00271)	(0.00290)
Age					-0.0107***	-0.00988***	-0.0158***	-0.0113***
					(0.00176)	(0.00147)	(0.00144)	(0.00142)
Unexplained / Structure Effects								
Tasks	0.0503***	0.000371	0.0119	-0.0162	0.000870	0.00598	0.00595	0.00529
	(0.0118)	(0.0139)	(0.00803)	(0.00896)	(0.00451)	(0.00534)	(0.00309)	(0.00366)
Emp. relations	-0.000641	0.000861	0.0115***	-0.00113	-0.00114	0.000977	0.00848***	-0.00160
	(0.00584)	(0.00254)	(0.00339)	(0.00269)	(0.00223)	(0.00103)	(0.00133)	(0.00106)
Survey waves	0.0506*	-0.00643	0.0711***	0.0171	0.000644	-0.00531	0.0143*	-0.00470
	(0.0237)	(0.0187)	(0.0189)	(0.0167)	(0.00839)	(0.00690)	(0.00689)	(0.00667)
Country-FE	0.229**	0.0120	0.0704	-0.0805	0.0277	0.00152	0.0262	0.00103
	(0.0861)	(0.0605)	(0.0631)	(0.0581)	(0.0321)	(0.0241)	(0.0245)	(0.0263)
Household size	0.0462	-0.0634	0.0496	0.0800*	-0.0315*	0.00642	-0.0378**	-0.00341
	(0.0436)	(0.0355)	(0.0338)	(0.0324)	(0.0160)	(0.0145)	(0.0128)	(0.0144)
Sector	0.113**	0.127***	0.106**	0.124***	0.0131	0.0113	-0.0203	-0.00401
	(0.0431)	(0.0207)	(0.0357)	(0.0171)	(0.0171)	(0.00798)	(0.0145)	(0.00703)
Age					0.00150	-0.0106	0.0119	0.0190
					(0.0152)	(0.0142)	(0.0129)	(0.0145)
Constant	-0.478***	-0.133	-0.440***	-0.413***	-0.00825	-0.0212	-0.00292	-0.0478
	(0.103)	(0.0775)	(0.0809)	(0.0726)	(0.0408)	(0.0309)	(0.0329)	(0.0323)
n	15811	22151	25750	26017	15811	22151	25750	26017

Notes: robust standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001; service contracts as group 2 or reference category (higher and lower managers and professionals' class: ESeC 1+2), and survey weights.

Table 9. Oaxaca decomposition of seniority and permanent contract by employment contracts and survey waves (2005-2015) for men

Men												
	Z-Residual Seniority						**Permanent Contract**					
Group 1	**Mixed**			**Labour**			**Mixed**			**Labour**		
	2005	**2010**	**2015**	**2005**	**2010**	**2015**	**2005**	**2010**	**2015**	**2005**	**2010**	**2015**
Group 1	0.200***	0.181***	0.148***	-0.0474**	-0.0448**	-0.0914***	0.805***	0.855***	0.853***	0.762***	0.790***	0.781***
	(0.0273)	(0.0238)	(0.0235)	(0.0174)	(0.0143)	(0.0145)	(0.0112)	(0.00841)	(0.00850)	(0.00769)	(0.00597)	(0.00616)
Groups 2: Service	0.160***	0.118***	0.174***	0.160***	0.118***	0.174***	0.842***	0.873***	0.876***	0.842***	0.873***	0.876***
	(0.0253)	(0.0184)	(0.0187)	(0.0253)	(0.0184)	(0.0187)	(0.00882)	(0.00645)	(0.00643)	(0.00882)	(0.00645)	(0.00643)
Difference (1-2)	0.0403	0.0623*	-0.0259	-0.207***	-0.163***	-0.266***	-0.0370**	-0.0184	-0.0228*	-0.0802***	-0.0836***	-0.0944***
	(0.0373)	(0.0300)	(0.0300)	(0.0307)	(0.0232)	(0.0237)	(0.0143)	(0.0106)	(0.0107)	(0.0117)	(0.00879)	(0.00890)
Explained	0.0116	0.00390	0.0325	-0.0857**	-0.0983***	-0.0991***	-0.0323***	-0.0181**	-0.0299***	-0.0926***	-0.0873***	-0.0929***
	(0.0203)	(0.0167)	(0.0169)	(0.0304)	(0.0257)	(0.0256)	(0.00868)	(0.00634)	(0.00706)	(0.0121)	(0.00962)	(0.0102)
Unexplained	0.0288	0.0584	-0.0584	-0.122**	-0.0649*	-0.167***	-0.00465	-0.000280	0.00711	0.0123	0.00373	-0.00154
	(0.0388)	(0.0319)	(0.0316)	(0.0423)	(0.0330)	(0.0344)	(0.0143)	(0.0110)	(0.0111)	(0.0152)	(0.0115)	(0.0124)
Explained / Composition Effects												
Tasks	0.00624	-0.00287	-0.00191	0.0347	-0.00848	-0.0281	-0.0173**	-0.00805	-0.0157***	-0.0465***	-0.0338***	-0.0464***
	(0.0141)	(0.0123)	(0.0122)	(0.0270)	(0.0246)	(0.0249)	(0.00541)	(0.00423)	(0.00461)	(0.0108)	(0.00864)	(0.00920)
Emp. Relations	-0.0171**	-0.0295***	-0.0142**	-0.0759***	-0.0856***	-0.0650***	-0.00746**	-0.0151***	-0.0110***	-0.0463***	-0.0516***	-0.0393***
	(0.00596)	(0.00544)	(0.00504)	(0.0119)	(0.00955)	(0.00826)	(0.00229)	(0.00229)	(0.00202)	(0.00506)	(0.00399)	(0.00336)
Country-FE	0.0215	0.0235***	0.0288***	-0.0419***	-0.0156**	-0.00974	0.00509	0.0000966	-0.00228	0.0155***	0.00398	0.00237
	(0.0116)	(0.00615)	(0.00765)	(0.00986)	(0.00563)	(0.00661)	(0.00481)	(0.00288)	(0.00269)	(0.00450)	(0.00273)	(0.00297)
Household size	0.00174	-0.000501	-0.00305	0.00148	0.00164	-0.00259*	0.000424	-0.000243	-0.000791	0.0000159	0.000221	-0.000219
	(0.00155)	(0.000652)	(0.00160)	(0.00112)	(0.000901)	(0.00116)	(0.000500)	(0.000273)	(0.000500)	(0.000357)	(0.000278)	(0.000310)
Sector	-0.000779	0.0132	0.0229*	-0.00415	0.00979	0.00634	0.00657	0.0101***	0.00995**	0.00567	0.00797	0.00399
	(0.0110)	(0.00953)	(0.0106)	(0.0159)	(0.0113)	(0.0122)	(0.00350)	(0.00286)	(0.00348)	(0.00569)	(0.00421)	(0.00443)
Age							-0.0196***	-0.00492*	-0.0101**	-0.0209***	-0.0141***	-0.0134***
							(0.00402)	(0.00233)	(0.00328)	(0.00304)	(0.00230)	(0.00244)
Unexplained / Structure Effects												
Tasks	0.0699**	0.0595**	0.0328	0.0249	0.00333	0.0141	-0.00536	-0.00123	0.00627	0.0107	0.00658	0.00163
	(0.0244)	(0.0184)	(0.0211)	(0.0179)	(0.0128)	(0.0141)	(0.00951)	(0.00647)	(0.00809)	(0.00699)	(0.00466)	(0.00545)
Emp. Relations	0.00297	-0.000346	-0.00722	0.0182*	0.00413	0.0148**	-0.000680	0.00355	-0.00637*	0.0124***	0.00812***	0.00460*
	(0.0136)	(0.00957)	(0.00877)	(0.00802)	(0.00515)	(0.00545)	(0.00533)	(0.00355)	(0.00317)	(0.00319)	(0.00207)	(0.00205)
Country-FE	0.245	-0.0416	0.458***	0.155	-0.0234	0.113	0.185*	-0.0455	-0.0175	0.156**	-0.0152	-0.0115
	(0.212)	(0.136)	(0.116)	(0.150)	(0.0984)	(0.0954)	(0.0770)	(0.0492)	(0.0407)	(0.0563)	(0.0412)	(0.0340)
Household size	0.101	-0.0443	0.103	0.0634	0.0191	0.0646	-0.0932**	-0.0164	-0.00215	-0.0859**	-0.0173	-0.0273
	(0.0901)	(0.0718)	(0.0668)	(0.0733)	(0.0543)	(0.0516)	(0.0335)	(0.0260)	(0.0241)	(0.0278)	(0.0205)	(0.0198)
Sector	0.0557	0.0605	0.237**	0.0886	0.0922	0.154*	-0.00443	-0.00234	0.0410	-0.0648*	-0.000894	-0.0172
	(0.0828)	(0.0685)	(0.0744)	(0.0727)	(0.0551)	(0.0607)	(0.0303)	(0.0266)	(0.0316)	(0.0289)	(0.0229)	(0.0237)
Age							0.00170	-0.0199	0.0342	0.0104	-0.0365	0.0560**
							(0.0372)	(0.0241)	(0.0216)	(0.0318)	(0.0208)	(0.0178)
Constant	-0.446	0.0245	-0.883***	-0.472**	-0.160	-0.528***	-0.0874	0.0816	-0.0483	-0.0270	0.0589	-0.00779
	(0.234)	(0.163)	(0.151)	(0.177)	(0.127)	(0.124)	(0.0932)	(0.0641)	(0.0572)	(0.0737)	(0.0537)	(0.0480)
n	8445	12028	11708	8445	12028	11708	8445	12028	11708	8445	12028	11708

Note: robust standard errors in parentheses; *p<0.05, **p<0.01, ***p<0.001; service contracts as group 2 or reference category (higher and lower managers and professionals' class: ESeC 1+2), and survey weights

Table 10. Oaxaca decomposition of seniority and permanent contract by employment contracts and survey waves (2005-2015) for women

						Women						
			Z-Residual Seniority							**Permanent Contract**		
Group 1		**Mixed**			**Labour**			**Mixed**			**Labour**	
	2005	**2010**	**2015**	**2005**	**2010**	**2015**	**2005**	**2010**	**2015**	**2005**	**2010**	**2015**
Group 1	-0.0200	0.0222	0.0576**	-0.280***	-0.308***	-0.304***	0.799***	0.830***	0.840***	0.720***	0.730***	0.747***
	(0.0207)	(0.0172)	(0.0183)	(0.0184)	(0.0137)	(0.0148)	(0.00870)	(0.00699)	(0.00715)	(0.00902)	(0.00696)	(0.00702)
Groups 2: Service	0.111***	0.139***	0.153***	0.111***	0.139***	0.153***	0.831***	0.869***	0.862***	0.831***	0.869***	0.862***
	(0.0192)	(0.0166)	(0.0164)	(0.0192)	(0.0166)	(0.0164)	(0.00808)	(0.00595)	(0.00594)	(0.00808)	(0.00595)	(0.00594)
Difference (1-2)	-0.132***	-0.117***	-0.0957***	-0.392***	-0.447***	-0.457***	-0.0321**	-0.0387***	-0.0224*	-0.111***	-0.139***	-0.116***
	(0.0282)	(0.0239)	(0.0246)	(0.0266)	(0.0216)	(0.0221)	(0.0119)	(0.00918)	(0.00930)	(0.0121)	(0.00916)	(0.00920)
Explained	-0.0327*	-0.0517***	-0.0577***	-0.0826**	-0.158***	-0.177***	-0.0217**	-0.0169**	-0.0230***	-0.0861***	-0.0810***	-0.0838***
	(0.0156)	(0.0140)	(0.0146)	(0.0270)	(0.0239)	(0.0226)	(0.00753)	(0.00591)	(0.00610)	(0.0124)	(0.0107)	(0.00962)
Unexplained	-0.0988**	-0.0648*	-0.0381	-0.309***	-0.289***	-0.280***	-0.0103	-0.0218*	0.000538	-0.0248	-0.0576***	-0.0318**
	(0.0304)	(0.0265)	(0.0268)	(0.0365)	(0.0320)	(0.0304)	(0.0125)	(0.00969)	(0.00954)	(0.0156)	(0.0129)	(0.0120)
						Explained / Composition Effects						
Tasks	-0.00284	-0.0274**	-0.0127	-0.0335	-0.0790***	-0.0971***	0.00122	-0.00216	-0.00575	-0.0120	-0.0171	-0.0258**
	(0.0105)	(0.0100)	(0.0104)	(0.0238)	(0.0212)	(0.0205)	(0.00426)	(0.00363)	(0.00395)	(0.00966)	(0.00892)	(0.00820)
Emp. Relations	-0.0124***	-0.0164***	-0.0200***	-0.0583***	-0.0644***	-0.0569***	-0.0123***	-0.0135***	-0.0152***	-0.0622***	-0.0551***	-0.0481***
	(0.00352)	(0.00358)	(0.00398)	(0.0105)	(0.00891)	(0.00720)	(0.00229)	(0.00195)	(0.00223)	(0.00536)	(0.00414)	(0.00351)
Country-FE	0.00441	-0.00668	0.0224***	-0.00196	-0.00382	0.00972	-0.0137***	-0.00594*	-0.00396	-0.00286	-0.00864**	-0.00394
	(0.00694)	(0.00512)	(0.00646)	(0.00653)	(0.00474)	(0.00525)	(0.00368)	(0.00245)	(0.00239)	(0.00387)	(0.00270)	(0.00285)
Household size	0.000656	0.000414	0.000328	0.000506	0.000713	0.000424	0.000417	-0.000264	0.0000675	-0.0000206	-0.000108	-0.000245
	(0.00105)	(0.000516)	(0.000627)	(0.000672)	(0.000708)	(0.000511)	(0.000483)	(0.000248)	(0.000141)	(0.000266)	(0.000297)	(0.000241)
Sector	-0.0225	-0.00157	-0.0477***	0.0107	-0.0114	-0.0330**	0.0153**	0.0148***	0.00928*	0.00234	0.0131**	0.00343
	(0.0119)	(0.0109)	(0.0112)	(0.0159)	(0.0108)	(0.0105)	(0.00472)	(0.00391)	(0.00393)	(0.00678)	(0.00461)	(0.00434)
Age							-0.0128***	-0.00987***	-0.00740**	-0.0114***	-0.0131***	-0.00915***
							(0.00308)	(0.00230)	(0.00246)	(0.00285)	(0.00236)	(0.00231)
						Unexplained / Structure Effects						
Tasks	-0.00208	0.0186	0.00113	-0.0158	-0.0320	0.00161	-0.0139	0.0170	0.0155	0.00741	0.00851	0.000757
	(0.0265)	(0.0249)	(0.0216)	(0.0168)	(0.0171)	(0.0139)	(0.00992)	(0.00929)	(0.00865)	(0.00707)	(0.00660)	(0.00574)
Emp. Relations	0.00611	0.00301	-0.00140	-0.00247	0.00306	-0.00186	0.000620	0.00272	0.000390	-0.00266	-0.00316	0.00172
	(0.00553)	(0.00469)	(0.00335)	(0.00502)	(0.00470)	(0.00451)	(0.00244)	(0.00198)	(0.00121)	(0.00202)	(0.00194)	(0.00179)
Country-FE	0.0930	-0.0632	0.0700	0.0564	-0.0534	-0.161	0.0166	-0.0171	-0.000208	0.0296	-0.00387	-0.0268
	(0.114)	(0.0947)	(0.103)	(0.119)	(0.0892)	(0.0941)	(0.0572)	(0.0376)	(0.0350)	(0.0651)	(0.0397)	(0.0381)
Household size	-0.109	-0.00311	-0.0857	0.0183	0.101	0.0855	-0.0000683	0.0261	-0.0212	0.0247	-0.0128	-0.0197
	(0.0699)	(0.0590)	(0.0569)	(0.0658)	(0.0529)	(0.0510)	(0.0303)	(0.0230)	(0.0230)	(0.0300)	(0.0236)	(0.0221)
Sector	0.108**	0.0884**	0.167***	0.173***	0.0525	0.153***	0.0427**	-0.0108	0.0123	0.00592	-0.0113	-0.00459
							(0.0155)	(0.0121)	(0.0138)	(0.0147)	(0.0110)	(0.0114)
Age							0.0158	-0.0243	-0.0158	0.0241	-0.000811	0.0224
							(0.0344)	(0.0254)	(0.0189)	(0.0364)	(0.0247)	(0.0201)
Constant	-0.195	-0.109	-0.189	-0.539***	-0.360**	-0.357**	-0.0721	-0.0155	0.00956	-0.114	-0.0341	-0.00555
	(0.145)	(0.119)	(0.125)	(0.144)	(0.112)	(0.112)	(0.0724)	(0.0483)	(0.0446)	(0.0784)	(0.0507)	(0.0457)
n	9663	13409	13209	9663	13409	13209	9663	13409	13209	9663	13409	13209

Note: robust standard errors in parentheses; *p<0.05, **p<0.01, ***p<0.001; service contracts as group 2 or reference category (higher and lower managers and professionals' class: ESeC 1+2), and survey weights

Table 11. RIF-Oaxaca decomposition of the (log)wage gap (q50) between employment contracts by gender (2010-2015)

Explained / Composition Effects												
	Men						**Women**					
(Log)Income q50	**Mixed Contract**			**Labour Contract**			**Mixed Contract**			**Labour Contract**		
	Coeff.	Robust SE	P>z	Coeff.	Robust SE	P>z	Coeff.	Robust SE	P>z	Coeff.	Robust SE	P>z
Overall												
Group 1: x1*b1	7.545	0.041	0.000	7.258	0.070	0.000	7.272	0.046	0.000	6.834	0.083	0.000
Counterfactual: x1*b2	7.621	0.041	0.000	7.460	0.060	0.000	7.408	0.047	0.000	7.100	0.105	0.000
Group 2 (Service): x2*b2	7.731	0.041	0.000	7.731	0.041	0.000	7.450	0.055	0.000	7.450	0.055	0.000
Difference (1-2)	-0.187	0.024	0.000	-0.473	0.043	0.000	-0.178	0.025	0.000	-0.615	0.042	0.000
Total explained	-0.110	0.018	0.000	-0.272	0.048	0.000	-0.041	0.021	0.049	-0.349	0.075	0.000
Total unexplained	-0.076	0.025	0.002	-0.201	0.053	0.000	-0.137	0.023	0.000	-0.266	0.077	0.001
Explained / Composition Effects												
Total	-0.110	0.018	0.000	-0.272	0.048	0.000	-0.041	0.021	0.049	-0.349	0.075	0.000
Pure	-0.114	0.018	0.000	-0.411	0.031	0.000	-0.028	0.020	0.162	-0.345	0.050	0.000
Specification error	0.004	0.019	0.843	0.139	0.049	0.004	-0.013	0.014	0.333	-0.004	0.061	0.949
Z - Tasks												
Routine/Repetitiveness	-0.014	0.004	0.001	-0.031	0.005	0.000	-0.016	0.005	0.002	-0.037	0.008	0.000
Routine/Standard	0.000	0.000	0.921	0.000	0.000	0.630	-0.001	0.001	0.266	0.000	0.001	0.764
Routine/Certainty	0.000	0.001	0.899	0.000	0.002	0.779	0.001	0.001	0.234	-0.005	0.003	0.046
Intellectual/Concept	-0.018	0.006	0.002	-0.048	0.008	0.000	-0.014	0.004	0.000	-0.056	0.009	0.000
Intellectual/Creative	-0.003	0.004	0.552	-0.009	0.007	0.208	-0.007	0.003	0.034	-0.019	0.007	0.007
Physical strenght	-0.011	0.004	0.010	-0.040	0.008	0.000	0.005	0.002	0.025	-0.013	0.004	0.002
Social/Serving	0.000	0.000	0.524	0.003	0.002	0.159	-0.003	0.003	0.374	-0.002	0.002	0.278
Autonomy	-0.012	0.003	0.001	-0.051	0.008	0.000	0.003	0.002	0.042	-0.013	0.004	0.002
Teamwork	-0.001	0.001	0.620	-0.001	0.001	0.370	-0.005	0.003	0.095	-0.007	0.003	0.017
Tools/machines	0.000	0.005	0.979	0.000	0.007	0.952	-0.001	0.001	0.127	-0.011	0.005	0.035
Tools/ICT	-0.024	0.006	0.000	-0.072	0.008	0.000	0.017	0.005	0.000	-0.050	0.010	0.000
Z - Employment Relations												
Reward types	-0.007	0.002	0.000	-0.020	0.004	0.000	0.002	0.001	0.058	-0.006	0.002	0.011
Time horizons	-0.014	0.003	0.000	-0.043	0.008	0.000	-0.013	0.003	0.000	-0.039	0.008	0.000
Others												
Survey waves	-0.001	0.003	0.859	-0.004	0.007	0.590	-0.005	0.003	0.180	0.007	0.006	0.246
Age	-0.013	0.004	0.003	-0.038	0.013	0.005	-0.005	0.002	0.021	-0.022	0.007	0.003
Household size	-0.002	0.001	0.125	-0.002	0.001	0.144	-0.001	0.001	0.163	-0.002	0.002	0.272
Migrant	0.000	0.000	0.993	0.000	0.000	0.659	0.000	0.000	0.458	-0.001	0.001	0.328
Country-FE	0.008	0.011	0.486	-0.042	0.033	0.198	0.039	0.019	0.040	-0.026	0.039	0.505
Sector	-0.002	0.007	0.811	-0.011	0.006	0.055	-0.018	0.008	0.018	-0.045	0.012	0.000
Full-time	-0.003	0.002	0.091	-0.002	0.007	0.789	-0.007	0.003	0.020	0.002	0.006	0.710
Constant	-0.498	0.186	0.007	-0.738	0.393	0.061	0.202	0.161	0.210	-0.676	0.535	0.206
n		8116			16103			11377			17299	

Table 11. Continuation

(Log)Income q50	Men						Women					
	Mixed Contract			Labour Contract			Mixed Contract			Labour Contract		
	Coeff.	Robust SE	P>z	Coeff.	Robust SE	P>z	Coeff.	Robust SE	P>z	Coeff.	Robust SE	P>z
Overall												
Group 1: x1*b1	7.545	0.041	0.000	7.258	0.070	0.000	7.272	0.046	0.000	6.834	0.083	0.000
Counterfactual: x1*b2	7.621	0.041	0.000	7.460	0.060	0.000	7.408	0.047	0.000	7.100	0.105	0.000
Group 2 (Service): x2*b2	7.731	0.041	0.000	7.731	0.041	0.000	7.450	0.055	0.000	7.450	0.055	0.000
Difference (1-2)	-0.187	0.024	0.000	-0.473	0.043	0.000	-0.178	0.025	0.000	-0.615	0.042	0.000
Total explained	-0.110	0.018	0.000	-0.272	0.048	0.000	-0.041	0.021	0.049	-0.349	0.075	0.000
Total unexplained	-0.076	0.025	0.002	-0.201	0.053	0.000	-0.137	0.023	0.000	-0.266	0.077	0.001
Unexplained / Structure Effects												
Total	-0.076	0.025	0.002	-0.201	0.053	0.000	-0.137	0.023	0.000	-0.266	0.077	0.001
Pure	-0.087	0.022	0.000	-0.173	0.041	0.000	-0.148	0.016	0.000	-0.285	0.039	0.000
Reweighting error	0.010	0.014	0.447	-0.028	0.042	0.497	0.011	0.014	0.428	0.019	0.062	0.766
Z - Tasks												
Routine/Repetitiveness	0.000	0.001	0.843	-0.001	0.005	0.895	-0.001	0.001	0.658	-0.008	0.009	0.368
Routine/Standard	0.001	0.003	0.696	0.002	0.002	0.328	-0.001	0.002	0.772	-0.004	0.006	0.541
Routine/Certainty	0.000	0.002	0.898	0.005	0.008	0.524	-0.001	0.003	0.737	-0.006	0.007	0.334
Intellectual/Concept	0.001	0.004	0.856	-0.002	0.009	0.858	-0.007	0.003	0.036	-0.009	0.020	0.638
Intellectual/Creative	-0.007	0.006	0.211	-0.006	0.009	0.481	-0.002	0.002	0.314	0.004	0.012	0.718
Physical strenght	-0.003	0.003	0.299	0.000	0.008	0.986	-0.008	0.008	0.278	0.012	0.008	0.128
Social/Serving	-0.001	0.001	0.444	0.013	0.007	0.076	-0.001	0.001	0.474	0.000	0.003	0.910
Autonomy	0.001	0.006	0.870	-0.012	0.012	0.318	0.001	0.005	0.847	0.001	0.014	0.970
Teamwork	0.002	0.002	0.201	0.000	0.002	0.861	0.000	0.002	0.939	0.004	0.008	0.566
Tools/machines	-0.001	0.001	0.671	0.009	0.011	0.431	-0.005	0.009	0.620	-0.003	0.003	0.342
Tools/ICT	0.000	0.005	0.966	-0.017	0.018	0.356	-0.023	0.016	0.152	-0.016	0.016	0.322
Z - Employment Relations												
Reward types	-0.004	0.005	0.358	0.001	0.002	0.528	0.000	0.000	0.965	0.001	0.009	0.887
Time horizons	0.000	0.003	0.947	-0.004	0.008	0.655	-0.001	0.001	0.474	-0.019	0.011	0.069
Others												
Survey waves	0.044	0.131	0.736	-0.243	0.272	0.372	-0.389	0.114	0.001	0.119	0.407	0.770
Age	0.061	0.041	0.140	-0.017	0.049	0.726	0.024	0.049	0.623	0.036	0.071	0.613
Household size	0.008	0.039	0.834	0.047	0.064	0.465	-0.071	0.039	0.068	-0.090	0.074	0.226
Migrant	0.048	0.057	0.400	0.317	0.129	0.014	-0.013	0.045	0.782	0.040	0.084	0.633
Country-FE	0.180	0.032	0.000	0.342	0.142	0.016	0.032	0.032	0.318	0.260	0.244	0.286
Sector	0.087	0.044	0.051	0.042	0.079	0.599	0.091	0.026	0.001	0.017	0.066	0.795
Full-time	-0.006	0.037	0.871	0.088	0.037	0.017	0.024	0.015	0.120	0.052	0.055	0.344
Constant	-0.498	0.186	0.007	-0.738	0.393	0.061	0.202	0.161	0.210	-0.676	0.535	0.206
n	8116			16103			11377			17299		

Note: Service contracts as group 2 or reference category (Class: ESeC 1+2), and survey weights.

7.2.6 Tasks, employment relations, and career stability: over time analysis

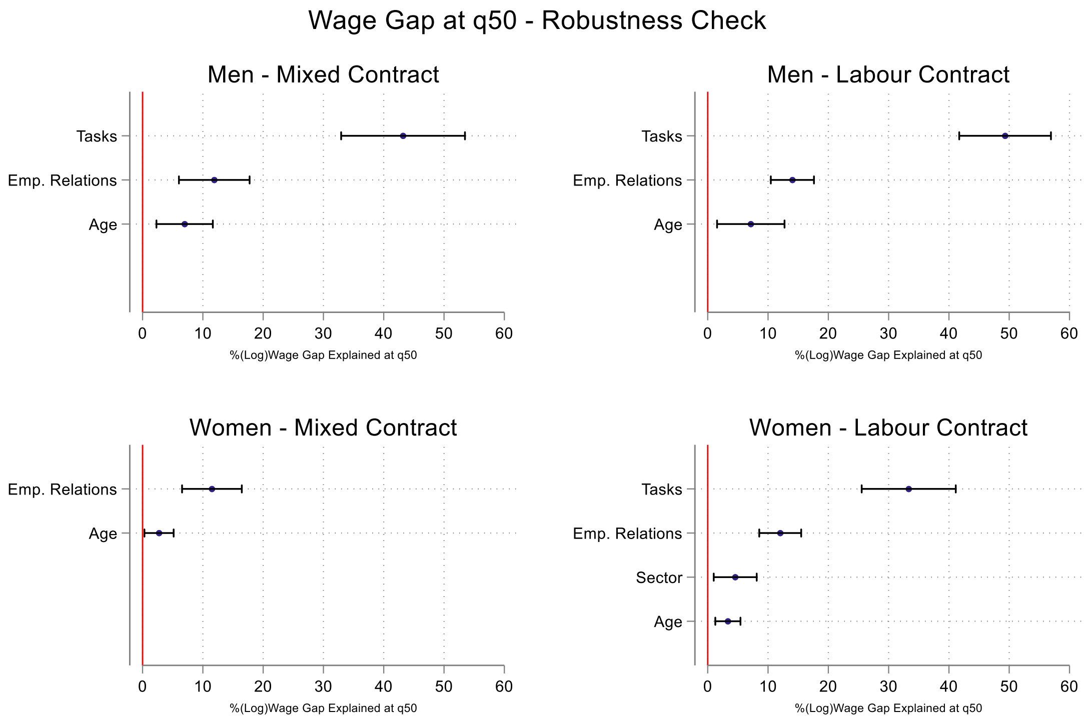
In Tables 9-10, we run the same Blinder-Oaxaca decomposition models as in the article's main findings section, reported in Table 8, for seniority and permanent contracts over time and by gender. Results are stable, and no consistent trends over time in the role played by job tasks or employment relations in explaining class gaps in life-chances could be detected with enough statistical certainty.

7.2.7 Tasks, employment relations, and income: robustness checks

One could argue that, as shown in Figure 6 and Table 11, a horse race between eleven composite indexes of tasks and two composite indexes of employment relations is not a fair comparison in terms of their potential to account for variation. Furthermore, within the task indexes, we included autonomy, which some authors consider a mechanism proxying for monitoring difficulty and explaining reward types or an outcome of life chances.

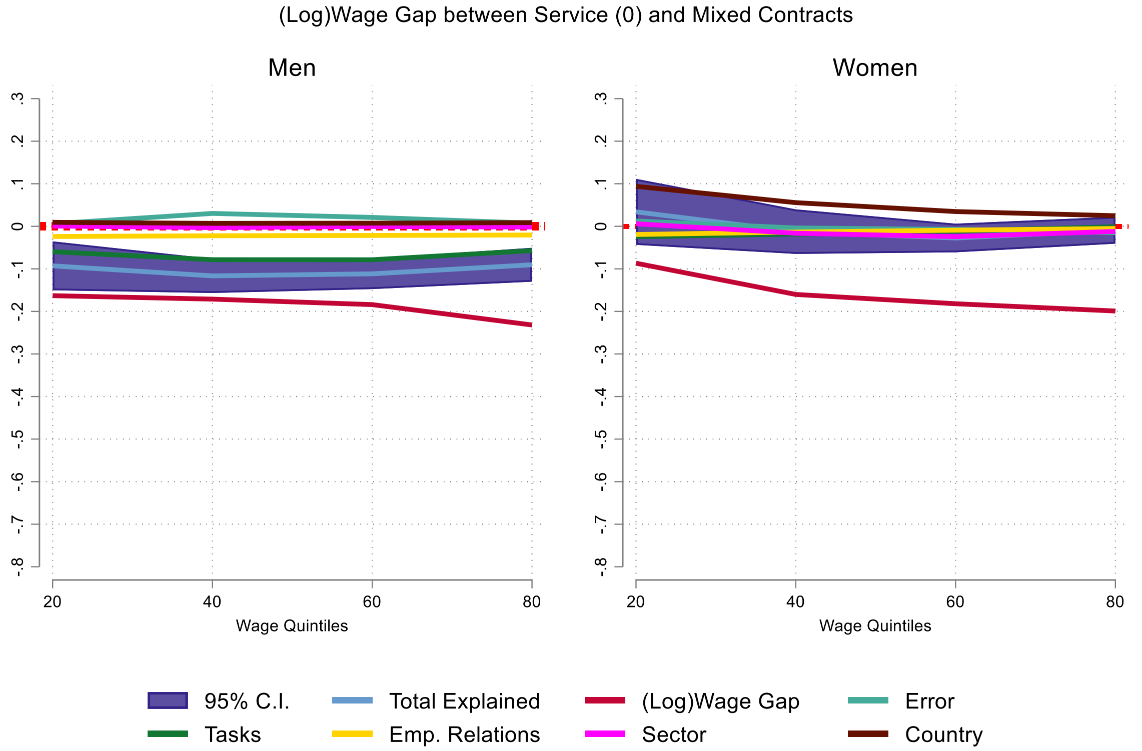
To tackle these concerns, we carried out a sensitivity check analysis replicating the main RIF-Oaxaca models at q50 (again, illustrated in Figure 6 and Table 11) by (1) keeping only those tasks, work methods and tools more directly related to technology-based explanations—ICT and analogue tools, physical strength, intellectual (conceptualisation and creativity), and routine (repetitiveness, standardisation and certainty) tasks; (2) including several additional items to proxy for employment relations mechanisms like human asset specificity—3 items on skills' mismatch, on-the-job training, and training paid by employers—and monitoring difficulty—4 items on piece-work and over-time earnings, the pace of work dependent on boss control, and self-quality control; (3) and dropping the dummy on full-time contracts as it could mediate the effect of time horizons. Human asset specificity and monitoring difficulty are the theorised mechanism behind the leading employment relations indicators: time horizons and reward types. As shown in Figure 16, the results are virtually identical to those displayed in Figure 6, except for women's mixed contracts, where tasks do not significantly explain the (log) wage gap anymore.

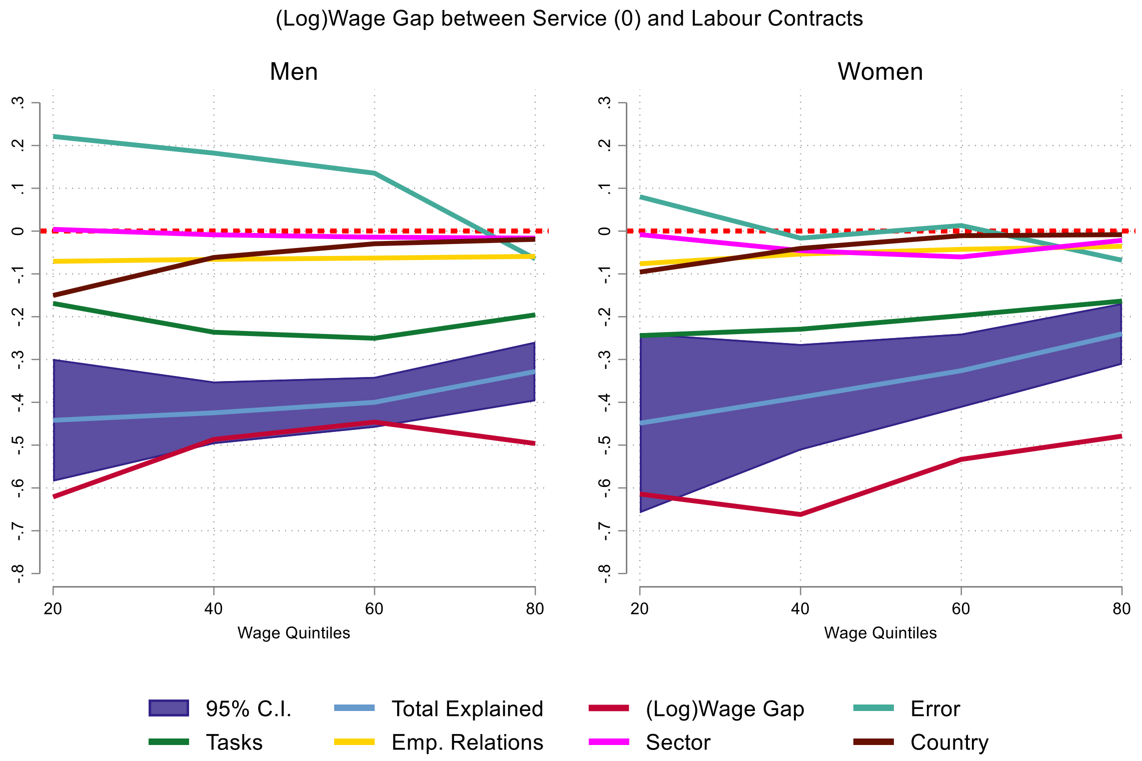
Figure 16. RIF-Oaxaca decomposition of the (log)wage gap between employment contracts by gender at q50 (2010-2015)



Note: robustness checks only including routine, physical and intellectual tasks and analog and ICT machines; and adding indicators of human asset specificity and monitoring difficulty. No control for autonomy or temporary contracts.

Figure 17. RIF-Oaxaca decomposition of the (log)wage gap between employment contracts (mixed above and labour below) by gender and by wage quintiles (2010-2015)





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