



Gendered wage returns to changes in non-routine job tasks: Evidence from Germany

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ABSTRACT

The labor market exhibits persistent occupational segregation by gender, with women and men performing distinct job tasks within their occupations. Prior research suggests that non-routine job tasks generally lead to higher wages, especially in digitally advancing contexts. However, these findings are largely based on cross-sectional data and neglect gender as a relevant dimension of inequality. We analyze three-wave panel data over nine years from the German National Educational Panel Study to explore the relationship between changes in non-routine job tasks and wages by gender. Given the constrained wage-setting opportunities within German firms, we further examine whether the association between task changes and wages differs for employees with and without job changes, both within and across occupational segments. Our fixed-effect regression analyses reveal gender-specific associations between changes in non-routine job tasks and wage increases. Men benefit from performing more complex and autonomous tasks, with additional gains when an inter-segmental job change accompanies the increase in complex job tasks. Conversely, women do not see wage benefits from enhancements in either complex or autonomous job tasks. These findings underscore the gendered patterns of wage increases associated with advancements in non-routine job tasks, with men profiting intra-individually from shifts towards more non-routine job tasks.

1. Introduction

Gender segregation in the labor market remains a persistent and pervasive feature of modern societies, significantly influencing employment outcomes and perpetuating gender inequalities (England, 2005b; Scarborough, 2020). While some countries have experienced a decline in occupational segregation over time (Blau et al., 2013), achieving gender parity in occupational distribution remains a distant goal. For instance, in the United States, it is estimated that over 40 % of the workforce would need to switch occupations to reach gender parity in occupational distribution (England et al., 2020). However, the category of occupation may be too broad to adequately capture the nuances of gender segregation (Levanon & Grusky, 2016). There are significant gender-specific task differences within occupations related to disparities in working hours, career trajectories, job satisfaction, and wage returns (Arntz et al., 2017; Autor & Handel, 2013).

Previous research on wage returns to specific job tasks has mostly

focused on cross-sectional data sources and paid no or very little attention to gender differences (e.g., Böhm, 2020; De La Rica et al., 2020; Mihaylov, 2021; Autor & Handel, 2013). These studies highlighted wage penalties for routine tasks and wage premiums for non-routine tasks. To date, there is limited empirical evidence of whether wage returns to non-routine job tasks are gender specific. Casabianca et al. (2020) found stronger positive correlations between wages and cognitive tasks for women than men, while men benefited more from managerial tasks than did women. Rohrbach-Schmidt et al. (2023) found positive correlations between wages and interactive or analytic tasks for both men and women, with men also benefiting from non-manual routine tasks. However, both papers relied on cross-sectional data sources and did not systematically address gender-specific wage returns.

In this paper, we adopt a longitudinal perspective and focus on gender-specific wage returns to non-routine job tasks. We examine the intra-individual wage developments of female and male employees after

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changing their task profile in a given job. Modeling these associations with fixed-effects regressions allows us to account for time-constant variables, which are known to affect gender-specific task profiles and wages, such as personality traits (Rohrbach-Schmidt et al., 2023) or previous task assignments (De Pater et al., 2010). This longitudinal approach allows us to narrow down potential selection biases to time-variant factors, such as employee motivation, internal job reassignments, or job changes within or between occupational segments that may affect the remuneration of women and men.

Our study focuses on Germany, a country characterized by high labor market participation rates for women, high rates of part-time employment for women and an above-average gender pay gap, compared to other OECD countries (OECD, 2023). At the same time, Germany has strong labor market regulations. The prevailing collective bargaining system for occupations and occupational segments limits employers in their flexibility to set wages. It is therefore important to consider job changes within and between occupational segments when assessing gendered differences in wage returns to job task modifications. Given its strict labor market regulations, Germany may serve as a conservative test case for assessing the gender inequalities stemming from differential wage returns to changing job tasks.

For our empirical analyses, we employ unique large-scale panel data with repeated measures of job tasks. With this data set, we can 1) assess individual wage returns to changes in individual non-routine job tasks; 2) highlight gender differences in these individual wage returns to non-routine task changes; and 3) assess the role of non-routine task changes in the context of routine-biased technological change for gendered wage returns.

2. Theorizing and previous research

2.1. Job tasks and wages

According to Autor and Handel (2013), job tasks can be defined as a set of main activities an individual performs on the job. Several scholars have employed the task-based approach to investigate the relationship between technological change, task composition, and changes in the wage structure of the labor force (Acemoglu & Restrepo, 2018; Spit-Z-Oener, 2006). Autor et al. (2003) classify job tasks in two dimensions: routine vs. non-routine and manual vs. cognitive (i.e., analytic and interactive tasks). By combining these two dimensions, they identify five types of job tasks: (1) non-routine analytic, (2) non-routine interactive, (3) non-routine manual, (4) routine cognitive, and (5) routine manual.

Autor et al. (2003) argue that changes in the availability and use of digital technologies lead to a decline in jobs with routine-intensive manual or cognitive tasks, as these lend themselves to automation, while the number of jobs with non-routine analytic or interactive tasks will increase. This is because digital technologies can be utilized as complements rather than as substitutes for the latter type of tasks. This line of reasoning, mainly based on the work of Autor et al. (2003), has become known as routine-biased technological change theory (RBTC). While the central focus of RBTC lies in the evolving structure of labor markets and the demand for specific skills and tasks, we adopt its classification of job tasks for our intra-individual analyses. Consistent with Autor et al. (2003), we argue that non-routine tasks play a crucial role in the course of digital transformation and will pay off monetarily for employees.

This assumption aligns with human capital theory (Becker, 1964; Rosen, 1976), which proposes that wage levels are determined by the level of human capital possessed by a worker. Since non-routine tasks are typically more complex and demand a higher level of human capital than routine tasks – and are considered by employers to be more valuable to the company – workers who carry out non-routine tasks generally earn more than those who carry out routine tasks. Additionally, Acemoglu and Autor (2011) contend that the higher level of skills and knowledge required for non-routine tasks means that employees

performing them are more productive than those performing routine tasks. It follows that an increase in non-routine job tasks should result in individual wage increases.

A growing body of research has examined the relationship between job tasks and individual wages but is almost exclusively limited to cross-sectional or repeated cross-sectional data. Using repeated cross-sectional data for the US, Autor and Handel (2013) found that an increase in non-routine abstract (analytic and interpersonal) tasks is associated with a wage premium, while an increase in routine manual tasks is associated with a wage penalty. Similarly, Böhm's study (2020) based on cross-sectional data for the US found a relative wage premium for non-routine abstract tasks and a relative wage decrease for routine tasks for male workers. Further research by De La Rica et al. (2020), using the first wave of the PIAAC data, found that workers who perform non-routine tasks earn higher wages than workers who perform routine tasks in 19 developed countries. This relationship was also found by Mihaylov (2021) in Germany and by Cassidy (2017) with a sample of West German workers. Using more recent German data, Rohrbach-Schmidt et al. (2023) confirmed that for male workers, non-routine manual, interactive, or analytic tasks yield economically meaningful wage returns compared to routine manual tasks. The authors of these studies applied different strategies to correct for the non-random assignment of workers into occupations and tasks, such as the inclusion of broad sets of control variables, occupation-fixed effects, a Roy (1951) selection model, propensity regression methods, and instrumental variable approaches.

Ross (2017) in the UK and Dastory (2019) in Sweden are among the very few studies providing longitudinal evidence that the wage premium for routine tasks has declined, while the wage premium for abstract (non-routine) tasks has increased. While the main findings align with cross-sectional studies, panel data outperforms cross-sectional data in assessing the association between job tasks and wages. By allowing for variation in task measures across and within occupations and by observing the same workers over time, panel data enables researchers to control for time-constant unobserved factors. This approach ensures that observed changes in wages are attributed to task content rather than to confounding factors. Moreover, while new hirings and the establishment of new companies account for a substantial part of (gendered) wage differentials (Cortes & Salvatori, 2019), in the following we argue for the significance of intra-individual gendered wage returns after a person changes their job task profile.

2.2. Gendered wage returns to job tasks

While many of the above-mentioned studies on wage returns to tasks have focused only on men, Autor and Handel (2013) (for the US) and De La Rica et al. (2020) (for 19 European countries) analyzed men and women together, using gender as a control variable. Casabianca et al. (2020) analyzed the association between job tasks and wages between and within occupations and found substantial heterogeneity in the correlation between wages and tasks across genders in the US. By including interaction terms between gender and job tasks, they moreover showed that the positive relationship between cognitive tasks and wages between and within occupations is stronger for women, and the negative relationship between manual tasks and wages is stronger for men. In addition, they found interactive job tasks to be positively related to male wages but negatively to female wages.

Autor et al. (2003) (for the US) and Rohrbach-Schmidt et al. (2023) (for Germany) provide separate analyses by gender. While the former reported similar results for both genders, the latter found meaningful gender differences. Rohrbach-Schmidt et al. (2023) differentiated between routine manual, non-routine manual, interactive, and analytic tasks and found that more non-routine manual, interactive, and analytic tasks are associated with higher wages for men, and more interactive and analytic tasks correlate with higher wages for women. While more analytic tasks were found to result in similar wage levels across gender,

men were found to profit more than ten times as much from more interactive job tasks than do women. All five studies mentioned here rely on cross-sectional data. The two longitudinal studies by Ross (2017) and Dastory (2019) did not differentiate by gender in their analyses.

Individual returns to changes in job tasks may differ by gender for a set of reasons. The (self-)selection of women and men into different occupations and jobs with specific task bundles and task trajectories, as well as discrimination and gender differences in pay expectations and non-cognitive skills are likely to play a role here.

Discriminatory practices. Employers may pay women less than men due to perceived lower productivity, the potential of career interruptions, or different leadership styles (Bertrand et al., 2010; pp. 2; England, 2005a; Feldberg, 2022). Also, employers may evaluate women's performance on non-routine tasks more critically than they do men's (Bowen et al., 2000; Wynn & Carian, 2023). This bias can lead to lower performance evaluations for women. In addition, employers may unintentionally engage in discriminatory pay practices by relying on prior salary histories during the hiring process and when setting pay levels, which may perpetuate discriminatory pay rates across job transitions (Altonji & Pierret, 2001; Hansen & McNichols, 2020; Lange, 2007). This may lead to a further devaluation of women's work and lower wage premiums for non-routine tasks performed by women. Our intra-individual approach accounts for previous pay levels and career patterns.

Gender differences in pay expectations and non-cognitive skills. Women may have lower pay expectations than men, even when they perform similar tasks. This may stem from a general perception of wage disadvantage (Manzi et al., 2023) and a tendency to accept lower wages in return for non-monetary benefits (Goldin, 2014). Additionally, gender differences in non-cognitive skills, such as negotiation skills, competitiveness, and risk aversion (Charness & Gneezy, 2012; Hernandez-Arenaz & Iriberrí, 2019; Niederle & Vesterlund, 2007) have been shown to affect the gender wage gap (Collischon, 2021; Nyhus & Pons, 2012). Again, these gender-specific differences may mainly result in differential wage returns between persons. But some of the mechanisms (e.g., pay expectations) may moderate gender-specific intra-individual wage returns.

Self-selection and gender differences in job changes. Women and men tend to self-select into different occupations and tasks, with women often favoring occupations with more social tasks and placing less importance on the monetary aspects of an occupation than men do (Grove et al., 2011; Krueger & Schkade, 2008). These choices are often influenced by societal expectations concerning gender-appropriate skills (Eagly et al., 2020) and behaviors consistent with gender roles and stereotypes (Young & Schieman, 2018). The latter includes the fact that women, especially mothers, still bear more responsibility for the family than men do (Domínguez-Folgueras, 2013) and, in general, are the ones who adjust their careers to family obligations when young children are present in the household (Young & Schieman, 2018). Women value job attributes that make careers more compatible with domestic responsibilities, including flexible work schedules and shorter commutes (Petrongolo & Ronchi, 2020), although these gendered differences in the evaluation of job attributes have decreased over time (Konrad et al., 2000). While self-selection is certainly most relevant for between-variation in occupations and tasks, self-selection may still contribute to within-variations in the wage returns to task changes due to the gender-specific willingness and motivation to pursue or accept more non-routine tasks with longer working hours and less flexibility for family obligations.

Given these gendered preferences, job changes may improve the individual job situation in a different way for women than they do for men. In the U.S., men change jobs more often than women, although voluntary job changes are observed more often among women than among men (Kronberg, 2014). Moreover, if women change jobs in the US, this is less likely to lead to wage growth than it is for male job changers (Pearlman, 2018). Similar to the U.S., women in Germany tend

to turn down attractive job offers (in terms of additional earnings or career options) that would require them to commute further distances for the sake of their family, while men are less likely to do so (Abraham et al., 2019). Since men and women show different job changing patterns, we include job changes in our analyses. We need to differentiate between job changes within one occupational segment and between occupational segments to account for occupational gender segregation in the labor market.

3. The German context

3.1. Gender-segregation in the German labor market

Male and female employment rates are comparatively high in Germany. In 2021, the female employment rate among 20–64 year-olds (~76 %) was about eight percentage points above the EU-27 average (~68 %), and only about six percentage points below the male employment rate in Germany (~83 %) (Labor Force Survey (LFS), 2022). However, similar to other Western societies, these figures mask fundamental differences in male and female employment patterns (Charles & Grusky, 2004). These include typical male and female jobs, women's underrepresentation in higher management, a high part-time employment rate for women, and a considerable gender pay gap (Ahrens & Scheele, 2022). Females are more likely to work in female-typical jobs, usually in the retail and care sector, with lower prestige, limited income prospects, and few meaningful career opportunities (Ahrens & Scheele, 2022; Hausmann et al., 2015). While horizontal gender segregation, i.e., the segregation into typical male and female jobs, is a strong driver of vertical gender inequality, such as lower wages in female-dominated occupations, including in Germany, there are considerable within-occupation (and even within-job) gender wage differences (Penner et al., 2022).

3.2. The highly regulated German labor market

Although the German labor market has been rendered more flexible over the past two decades (most importantly by the Hartz reforms in 2003–05, Engbom et al., 2015), it remains highly regulated compared to other developed economies. This is due to strict employment protection legislation, which includes extensive labor laws regulating working hours, hiring and firing procedures, and working conditions. Trade unions and works councils play a significant role in the German labor market (Latzke et al., 2016; Schneider & Rinne, 2019). This institutional framework strongly limits the leeway companies have to set salaries (Schnabel, 2005). Collective bargaining agreements tend to be negotiated at the industry level or between unions and large companies (e.g., railway companies). Individual union membership, however, does not tend to affect individual wages (Fitzenberger et al., 2013)¹.

The number of companies and workers tied to collective bargaining agreements has declined significantly in recent decades (Ellguth & Kohaut, 2013), primarily due to a shift in employment from the manufacturing sector to the service sector (Lübker & Schulten, 2023) and the exit of many enterprises from collective bargaining schemes. This has created some additional flexibility for employers to set wages, but the overall wage structure remains highly restrictive. Thus, the

¹ Due to the constitutional right not to associate, collective bargaining agreements usually do not include specific premiums for union members. In recent years, unions have tried to a small extent to incorporate some additional premiums for their members. Bonaccolto-Töpfer and Schnabel (2023) claim to be the first authors to find an individual union membership bonus of almost two percent. However, their data come from an employee survey that fails to include some important information about the companies, such as whether they participate in or adopt collective bargaining agreements. These variables are very relevant to the role of individual union membership.

likelihood of a wage change due to a change of tasks can be expected to be relatively low in Germany. It may be somewhat higher if task changes are associated with job changes within or between occupational segments, as previous research on occupational mobility suggests (Reichelt & Abraham, 2017).

4. The present study

Our study adopts a gender perspective on the relationship between non-routine job tasks and wage premiums. We contribute to the literature in three ways: first, while previous research on the association between individual-level job tasks and individual-level wages is scarce and primarily based on (repeated) cross-sectional data, we use three-wave panel data from the German National Education Panel Study (NEPS) covering nine years, and analyze changes in job tasks and wages using fixed-effects (FE) regressions to provide a comprehensive picture of changes over time. This method avoids biased associations arising from time-constant factors that lead to self-selection into different occupations, which are fundamentally gender-segregated in the German context. Second, we explicitly differentiate the relationship between job tasks and wages for men and women, taking gender as a relevant dimension of inequality for the association between changing job tasks and changing wages, which has so far been neglected in the literature. Third, we focus on gendered wage returns to non-routine task changes, highlighting the role of routine-biased technological change for task changes and its gendered association with wages.

Drawing on our theoretical framework and consistent with prior mostly cross-sectional studies, we anticipate that an increase in an individual's non-routine job tasks will result in a wage premium. We build on the operationalization of job tasks developed by Matthes et al. (2014), which is based on the work of Spitz-Oener (2006), who applied the task-based approach of Autor et al. (2003) to the German context. While Autor et al. (2003) differentiate between routine vs. non-routine and manual vs. cognitive tasks and combine these two dimensions into five different task types, Matthes et al. (2014) slightly deviate from this approach. First, they consider non-routine, cognitive, and manual tasks as separate task dimensions; and second, they define routine "ex negative," that is, by asking respondents whether their job tasks are in some ways non-routine. Non-routine tasks comprise (1) complex tasks and (2) autonomous tasks. We focus on complex and autonomous tasks as these are the only dimensions that measure task (non)routinization. For details on the measurement of job tasks, including the other dimensions, see our variables Section (5.2).

Given the profound level of gender segregation prevalent in the German labor market and the finding of within-occupation gender gaps (Penner et al., 2022), we anticipate observing a wage increase following an increase in non-routine job tasks, especially among male workers. Among females, we expect to find a comparatively smaller wage increase following an increase in non-routine job tasks. The (non-testable) mechanisms underlying this phenomenon may include gender-based discrimination by employers, variations in pay expectations or self-selection into specific job settings driven by gendered disparities in motives, values, and individual decision-making.

Due to the high rigidity of the German labor market, especially as concerns wages, we expect that the wage returns to non-routine job tasks will be greater among individuals who also change their jobs as compared to job stayers. We anticipate that the impact of a change in job tasks coupled with a job change will be less pronounced among females than among males. This expectation is grounded in the presence of analogous (non-testable) mechanisms, previously outlined in the context of reduced wage returns to changes in job tasks alone.

Like selection into different gender-specific occupations and occupational profiles, job changes during our observation period were also subject to time-varying unobserved factors. We therefore control for job changes and correlate task changes and job changes in our models. We allow for two kinds of job changes: those happening within similar

occupational segments and those between occupational segments. Job changes within an occupational segment may minimize confounding effects related to specific segments, e.g., segment-specific wages or more favorable compensation for non-routine tasks. Job changes between segments may contribute to more heterogeneity in the wage returns of changing job tasks.

In summary, we expect to find the following:

Hypothesis 1. Male workers who increase their share of non-routine job tasks (complex and autonomous tasks) experience a wage increase.

Hypothesis 2. Female workers who increase their share of non-routine job tasks (complex and autonomous tasks) experience a smaller wage increase than do males.

Hypothesis 3. The male wage premium following an increase in non-routine job tasks is greater for job changers.

Hypothesis 4. The female wage premium following an increase in non-routine job tasks is greater for job changers, but less so than that for male job changers.

5. Data and methods

5.1. Data

To put our hypotheses to an empirical test, we use unique longitudinal data from the adult cohort (starting cohort 6, SC6) of the National Educational Panel Study (NEPS) (NEPS Network, 2022). We use the scientific use file (SUF) 13.0.0 (doi: <https://doi.org/10.5157/NEPS:SC6:13.0.0>). The NEPS is carried out by the Leibniz Institute for Educational Trajectories (LifBi, Germany) in cooperation with a nationwide network (see Blossfeld & Roßbach, 2019). The SC6 data comprises a random sample of German residents born between 1944 and 1986. Thirteen waves of the panel are currently available. Data preparation and statistical analyses are carried out in Stata/MP 17.0 (Stata-Corp, 2021). The syntax files for data preparation and analyses (.do-files) are available under <https://doi.org/10.7802/2753>. As information on job tasks has been collected three times, in 2011/12 (wave 4), 2015/16 (wave 8), and 2019/20 (wave 12), we only make use of panel and spell information at these three measurement points. We derived all job-related variables from an identifier for the job episode to which the task relates, allowing us to identify the job characteristics associated with the respective job tasks.

5.2. Variables

Labor income. As our dependent variable, we use log-transformed gross hourly wages. We applied top coding for the top one percent of income earners by setting their income to the maximum income of the 99th percentile of income earners. We deleted individuals with monthly incomes below €450. Jobs paying less than €450 a month are most likely so-called "Minijobs," which are a form of low-wage employment prevalent in Germany and some other countries². We measure hourly wages and job tasks simultaneously. Legally, employees are supposed to be paid according to the tasks they perform. However, the remuneration for task changes could be lagged because new wages for the changed tasks need to be negotiated. Or the new job incumbents may not yet perform all the tasks in their new job profile, even though they are already being

² "Minijobs" are a type of position in which the employee earns no more than a certain income threshold on a regular basis. In Germany, this income threshold was set at €450 per month in 2021. Typically, a "Minijob" involves a low number of working hours and a correspondingly low salary. "Minijobs" are subject to specific regulations that exempt both employer and employee from certain social security contributions. This exemption is aimed at making "Minijobs" more appealing to both low-wage workers and employers.

paid for their new position. In both cases, a simultaneous measure may bias the association between task changes and wage changes. Given Germany's strict labor market regulations, where changes in task profiles are legally required to be reflected in corresponding wage adjustments, we argue that measuring these changes simultaneously offers the most accurate approach to assess the relationship between non-routine task changes and wage adjustments.

Job tasks. The NEPS data include the instrument developed by Matthes et al. (2014), which contains a job task module that collects various job task types describing the respondents' main employment spell. The construct comprises the following job tasks (the detailed item wordings can be looked up in Matthes et al., 2014: 288ff.; the detailed wordings for autonomous and complex tasks can be also found in Tables A1 and A2 in the Appendix):

- **Complex tasks** (Cronbach's Alpha: .83) were measured using the following six items: 1) Solving difficult problems; 2) Learning new things; 3) Getting acquainted with tasks; 4) Dealing with unanticipated situations; 5) Adapting to changing work assignments; 6) Performing new tasks.
- **Autonomous tasks** (Cronbach's Alpha: .67) are based on four items: 1) Scheduling work activities; 2) Choosing new task assignments; 3) Setting the pace of work; 4) Being involved in decision-making.
- **Analytical tasks** (Cronbach's Alpha 0.71) comprise 1) Reading 2) Writing, and 3) Mathematics.
- **Interactive tasks** (Cronbach's Alpha 0.75) are measured by 1) Customer contact, 2) Providing general information, 3) Counseling (e.g., financial, legal), 4) Assistance (Personal issues), 5) Teaching/training, 6) Dealing with candidates/applicants.
- **Manual tasks** (Cronbach's Alpha 0.84) encompass 1) Standing (for at least two hours), 2) Walking/Biking, 3) Lifting (at least 10 kg at a time), 4) Having to maintain an uncomfortable body posture, 5) Being exposed to heat/cold.

Our focus is on complex and autonomous, i.e., non-routine job tasks, as they are difficult to replace by computers or other technology. The other job tasks serve as control variables in our models. We calculated the overall scores for our five job task measures by taking the means of their items and standardizing them to range between values of 0 (no such task content) to 1 (very high amount of such task content). Importantly, the precision of self-reported job tasks may vary across skill levels, and social desirability may lead respondents to report more demanding job tasks than they actually perform. Research comparing self-reports of employees' skill use (as an indicator of subjective skill use) with the perception of their skill use as reported by their managers (as an indicator of more objective skill use) indicates a good match between these two measures (Green & James, 2003).

Gender. We differentiate between male and female persons. No other gender category is provided in the NEPS data.

Types of job change. We distinguish between individuals who change jobs between two measurement time points and those who do not, differentiating between job changes within occupational segments and job changes between occupational segments. Occupational segments consist of 14 categories and comprise professions as classified by the German classification of occupations (Bundesagentur für Arbeit, 2021) with similar task and skill profiles (see Matthes et al., 2015): (1) Agriculture, forestry, and horticulture, (2) Manufacturing, (3) Production engineering, (4) Construction and finishing, (5) Food and catering, (6) Medical and non-medical healthcare, (7) Social and cultural service sector, (8) Commerce, (9) Business management and organization, (10) Business-related service sector, (11) IT and scientific service sector, (12) Security, (13) Transportation and logistics, (14) Cleaning. About 30 % of the individuals in our sample experienced at least one job change within our observation window (up to nine years). Among the subsample of job changers, about 47 % experienced a change between occupational segments.

We define a job change between two measurement points as starting a new job episode, including a change of employer or the signing of a new employment contract. A change in salary, working hours, or other characteristics of an ongoing job is not understood as a job change if there is not also a change of employer or a new employment contract.

Further control variables. In our statistical models, we further control for several time-varying variables that we expect to affect our outcome and predictor variables, including age (metric and squared term), analytic, manual and interactive job tasks, and the presence of children below 6 years old in the household (dummy; reference no). In our imputation model, we further control for education, distinguishing between three degrees: 1) lower secondary or below (CASMIN categories 0–2); 2) middle or higher secondary (CASMIN categories 3–6); and 3) tertiary (CASMIN categories 7 and 8).

5.3. Analytical sample

Our original sample of the NEPS data consisted of 14,404 individuals. We restricted our analysis to individuals who 1) participated in at least two consecutive waves out of the three waves in which job tasks were surveyed (waves 4, 8, 12), thereby losing about 60 % of the respondents from the original sample; 2) were employed across at least two consecutive time points with available job task measures, thereby losing another 11 % of the respondents from the original sample. The remaining respondents were employed in waves 4 and 8, waves 8 and 12, or all three waves. Moreover, we only analyzed 3) individuals aged 25 to 55 years at the first measurement point (wave 4), thus losing another 4 % of respondents from the original sample.

Our final analytical sample consists of 3834 individuals corresponding to 11,502 person years. Table 1 contains the summary statistics for our analysis sample before running our multiple imputations. Our male and female samples differ most strongly in hourly gross income (~€20 for women and ~€26 for men). While job changes within an occupational segment happen slightly more often among women (~8 %) than among men (~6 %), job changes between occupational segments are more frequent for men (~6 %) than for women (~4 %). Men show slightly higher values in autonomous (.55) and complex (.58) job tasks as compared to women (.52 and .55 resp.). Table A1 in the Appendix contains the piecewise correlations between all variables used for our analyses.

5.4. Imputations

We draw on a two-level multiple imputation procedure with random intercepts to deal with the problem of missing values in the dependent and independent variables. This procedure allows us to consider the multilevel structure of our data (up to three observations per person) via a varying regression constant. Our first observation time point (wave 4 of the NEPS data) includes a refreshment sample (about 1/3 of all respondents in wave 4). For this refreshment sample, no data on job tasks were collected in wave 4. Since the job tasks of these individuals are missing at random, we imputed the job tasks for them. However, we also report the results based on non-imputed data in Table A8 (additive models) and Table A9 (interactive models). In addition to the variables used in our analysis models, in the imputation model, we included education as a time-constant auxiliary variable and imputed the data separately for the male and female samples. For every missing value, we calculated 50 imputations. The multiple imputations are carried out with BLIMP 3.2.1, a flexible, free software for multilevel multiple imputations (Enders et al., 2018). The syntax files for the imputations (.imp-files) are available under <https://doi.org/10.7802/2753>.

5.5. Analytical strategy

We proceeded in two steps in our examination of gender differences in the association between changes in wages and non-routine

Table 1
Summary statistics.

	Male (N = 2011)			Female (N = 1823)		
	Mean/%	SD	% Missings	Mean/%	SD	% Missings
<i>Focal variables</i>						
Hourly gross income in €	26.79	19.35	14.40	20.42	14.22	14.96
Autonomy [0,1]	0.55	0.20	18.56	0.52	0.20	19.93
Complexity [0,1]	0.58	0.17	18.56	0.55	0.18	19.93
<i>Job change, ref. no</i>	86.64		9.56	86.52		7.99
Within occupational segments	7.27			8.95		
Between occupational segments	6.27			4.53		
<i>Controls</i>						
Analytic [0,1]	0.61	0.21	18.47	0.54	0.19	19.60
Manual [0,1]	0.30	0.26	18.47	0.26	0.26	19.60
Interactive [0,1]	0.54	0.20	18.47	0.49	0.21	19.60
Age	47.78	8.60	7.66	48.20	8.23	8.94
Children < 6 yrs. in hhd	13.09		7.56	7.60		8.61
<i>Skill requirements, ref low</i>	44.06		19.91	59.94		21.17
Medium	18.48			14.08		
High	37.46			25.98		

Means across all measurement points. Values before imputation.

(autonomous and complex) job tasks. First, we estimated the linear FE regression of wages on job tasks, including the control variables specified above, for the total, female, and male samples. The FE model uses only the time-varying information on individual changes in wages and job tasks, thus allowing us to eliminate potential biases from time-constant confounders in the estimation of wage coefficients for job tasks (Wooldridge, 2010). These include factors that predict (self-)selection into specific (gender-segregated) job task profiles or occupations, including personal motives, personality, social influences, and employer biases. Second, we estimated FE models with interaction terms between job tasks and job changes within and between occupational segments (with no job change as the reference category) for the female and male samples to determine whether there were differences in the association between wages and job tasks for individuals who did or did not change jobs. Third, we exploratively analyzed the association between wages and the four facets of autonomous and six facets of complex job tasks in

conjunction with a job change in order to identify possible patterns of association and the relative explanatory contribution of the individual facets across gender.

Importantly, while the FE model overcomes the problem of biased estimates arising from observed and unobserved time-constant confounders, it neither solves the problem of time-varying unobserved variables nor the problem of simultaneity. FE estimates may therefore still be biased. Unobserved time-varying factors, such as motivation, organizational developments, or job performance, may affect hourly wages, job tasks, or job changes and, hence, our FE estimation results in different ways. We control for analytical, interactive, and manual tasks because the performance of non-routine tasks correlates with specific jobs or occupations and the full task bundles should reflect this. We further control for many time-varying variables that we expect to affect our outcome and predictor variables (see the section on “Control variables” under 5.2). However, these controls will not entirely reduce

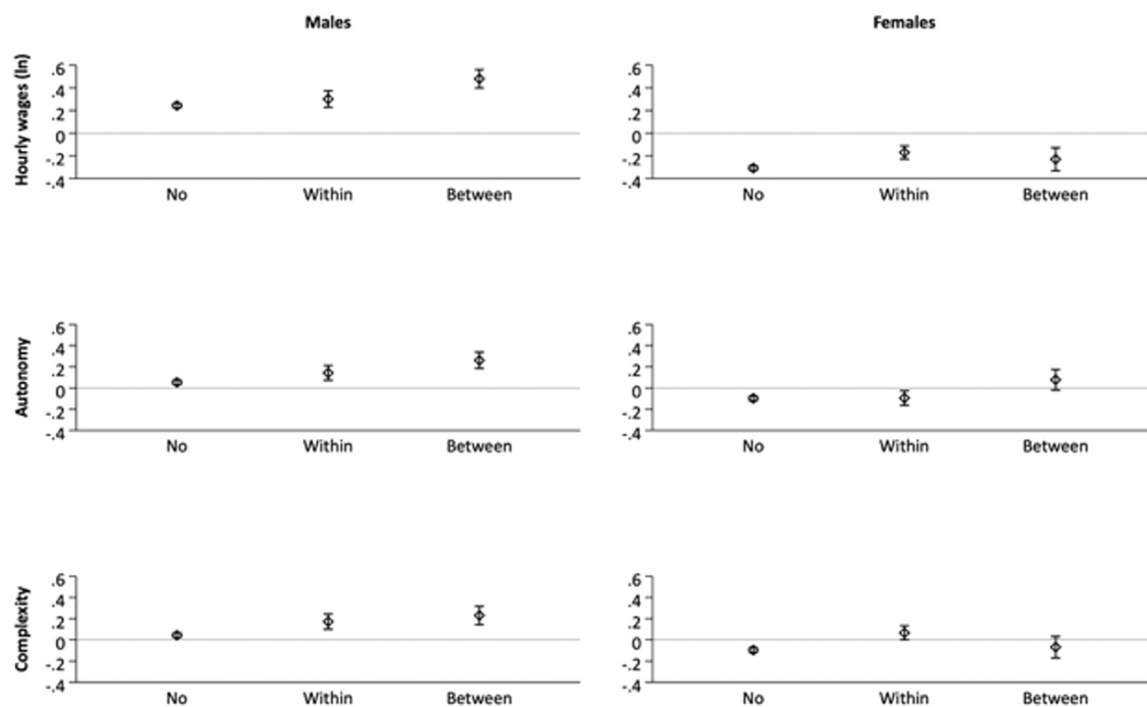


Fig. 1. Mean values for hourly wages, autonomous and complex job tasks by gender and job change within and between occupational segments. Notes. Estimates with 95 % confidence intervals. All variables were z-standardized.

potential biases arising from time-varying unobservables.

6. Descriptive results

Fig. 1 shows the mean values for log-transformed hourly wages and the two measures of non-routine job tasks (autonomy and complexity) by job change and gender. As the variables were z-standardized, the scales on the y-axes refer to changes in units of standard deviations. We can see that 1) independently of job changes, men show higher levels of income and higher levels of complex and autonomous job tasks than do women; 2) men with job changes show higher levels of income and more autonomous and complex job tasks, notably when they change jobs between occupational segments; and 3) women with job changes show increased levels of income and more complex tasks when they change jobs within an occupational segment, and more autonomous tasks when they change jobs between occupational segments.

To eliminate the potential presence of disparate task variations for each gender, or differing increases or decreases of task changes between the genders, we present in Figs. 2 and 3 the correlations between autonomous (Fig. 2) and complex tasks (Fig. 3) and wages by gender across all three measurement points. For both genders, there are large variations in the changes in wages and tasks. Moreover, for both genders and for both task types, there is a positive correlation between non-routine task increase and wages for individuals who change jobs, but smaller or no correlation for individuals who stay in their jobs. Among the individuals with a job change, the fitted regression lines are steeper for males, except for complexity in the case of a job change within an occupational segment where the fitted regression line is steeper for females.

7. Multivariate results

7.1. Do changes in non-routine job tasks pay off in hourly wages?

Fig. 4 shows the average predicted hourly wages at different change levels in non-routine job tasks for female and male workers, holding all other variables constant at their mean values. As the job task measures were z-standardized, the scale on the x-axis refers to changes in units of standard deviations. The full regression tables can be found in Table A2 in the Appendix.

Fig. 4 shows that, on average, changes in autonomous and complex job tasks are positively related to wages for both women and men. However, the correlations do not reach statistical significance in the female subsample (see Table A2 in the Appendix). An increase in autonomous or complex tasks by one standard deviation from the average of the respective tasks (value of 0) leads to an increase in hourly wages of around €0.50 for men. This corresponds to a wage increase of about two percent (see Table A2 in the Appendix). As expected, male workers who increase their share of non-routine job tasks experience a wage increase (Hypothesis 1). Also, we expected lower, or no wage increases for females who increase their share of non-routine tasks (Hypothesis 2), which is also supported by our findings.

7.2. Do types of job changes moderate the relationship between non-routine job tasks and hourly wages?

In the following, we examine the relationship between job changes, task changes, and wages for the subsamples of female and male workers. Fig. 5 (male sample) and 6 (female sample) show the joint association between task changes and job changes with wage differences. The full regression results can be found in Table A3 in the Appendix.

Fig. 5 shows that for men, job change does not moderate the association between autonomous job tasks and wages, but it does influence the association between complex job tasks and wages. The positive

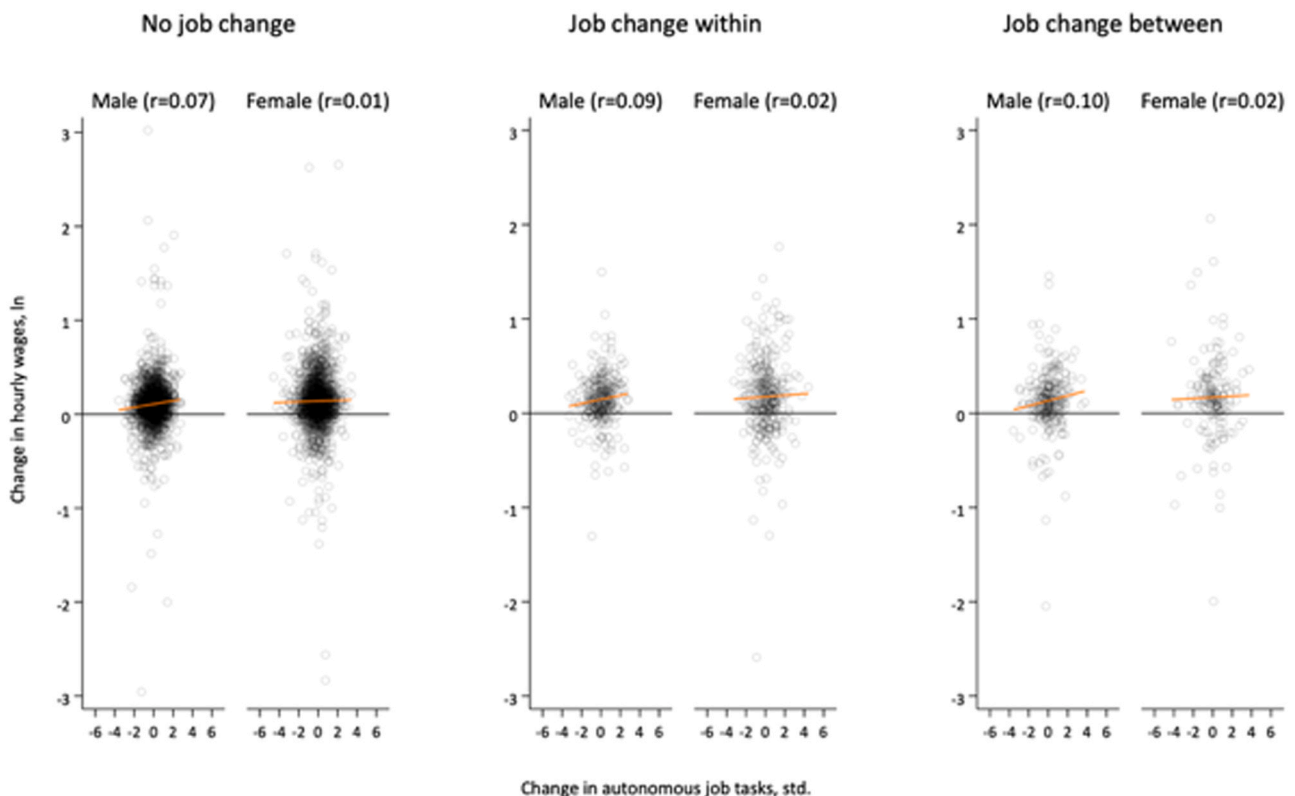


Fig. 2. Correlations between changes in autonomous job tasks (std.) and hourly wages by gender and job change.

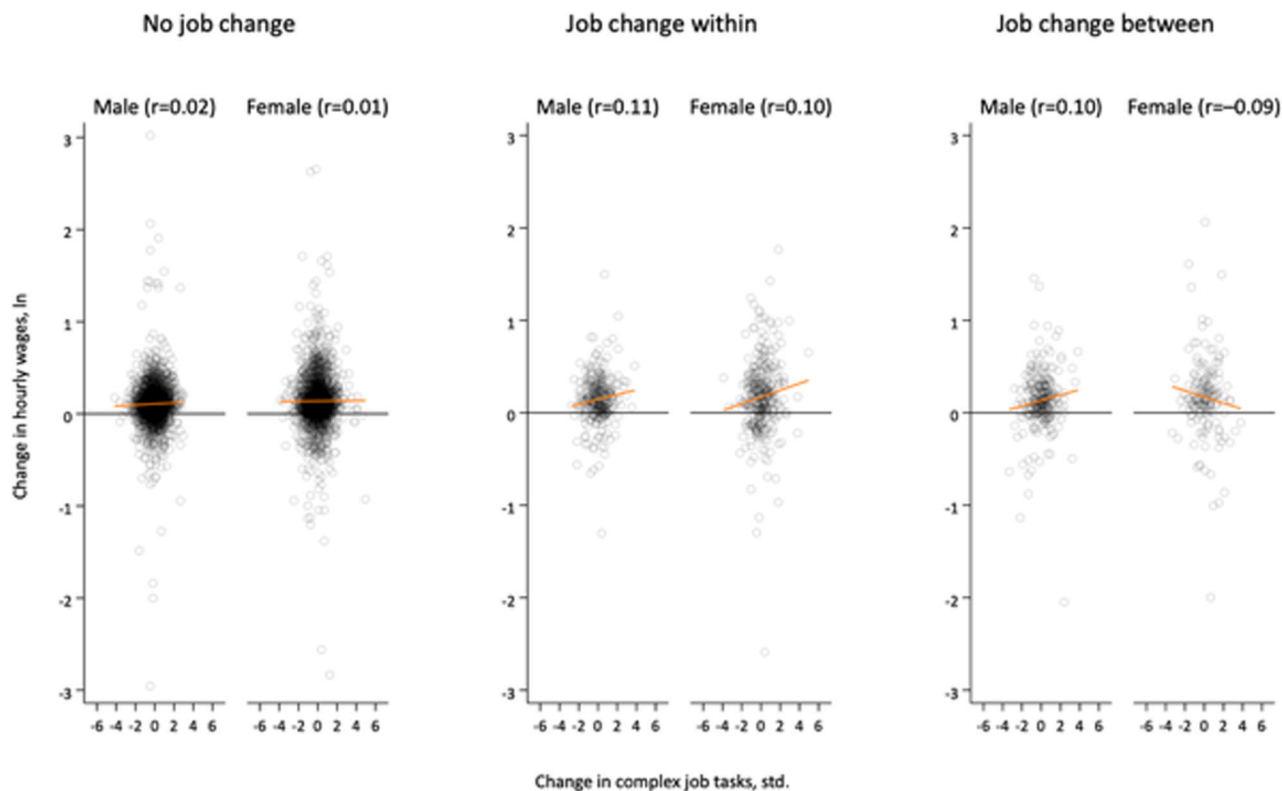


Fig. 3. Correlations between changes in complex job tasks (std.) and hourly wages by gender and job change.

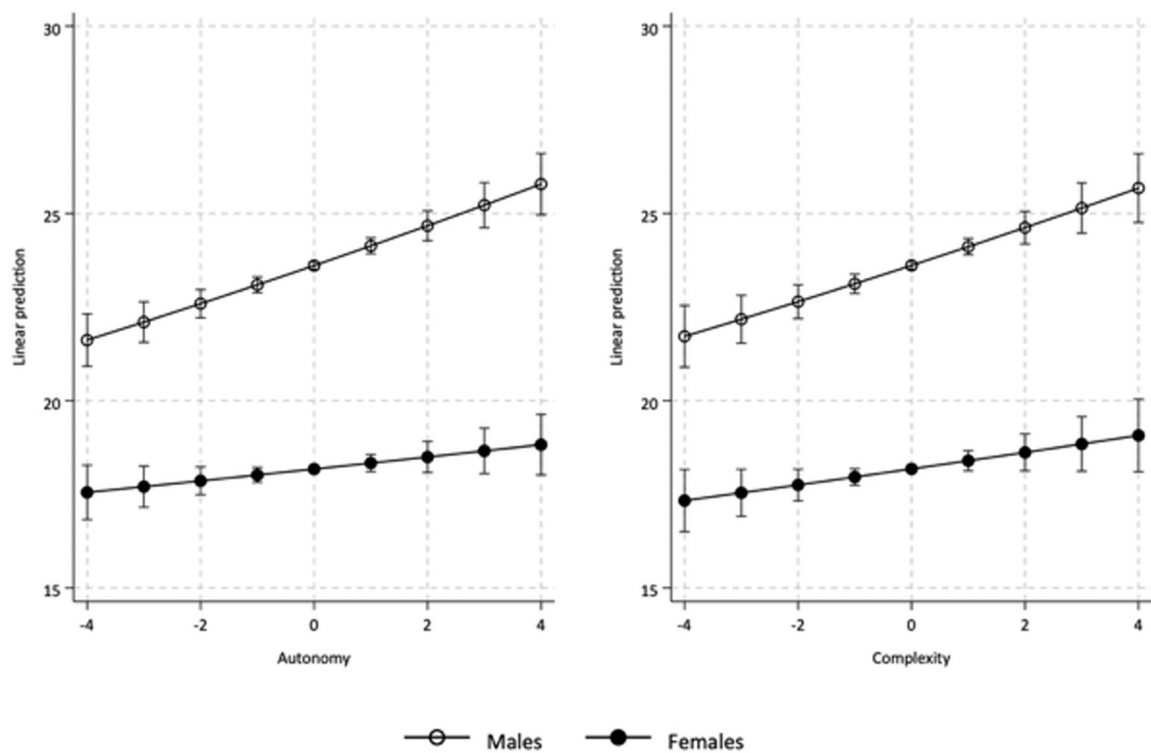


Fig. 4. Regression results for the impact of non-routine job tasks on hourly wages in Euros among female and male workers. Notes. Predictions with 84 % confidence intervals (MacGregor-Fors & Payton, 2013). Non-routine job tasks were z-standardized.

impact of an increase in complex tasks is larger among those who change occupational segments than for job stayers, as can be seen in the much steeper slopes of the regression line for the former. This finding is in line

with our Hypothesis 3. Though the confidence intervals of the two slopes partly overlap in our graphic illustration, a t-test revealed that the mean difference in wage returns to complex job tasks between those who

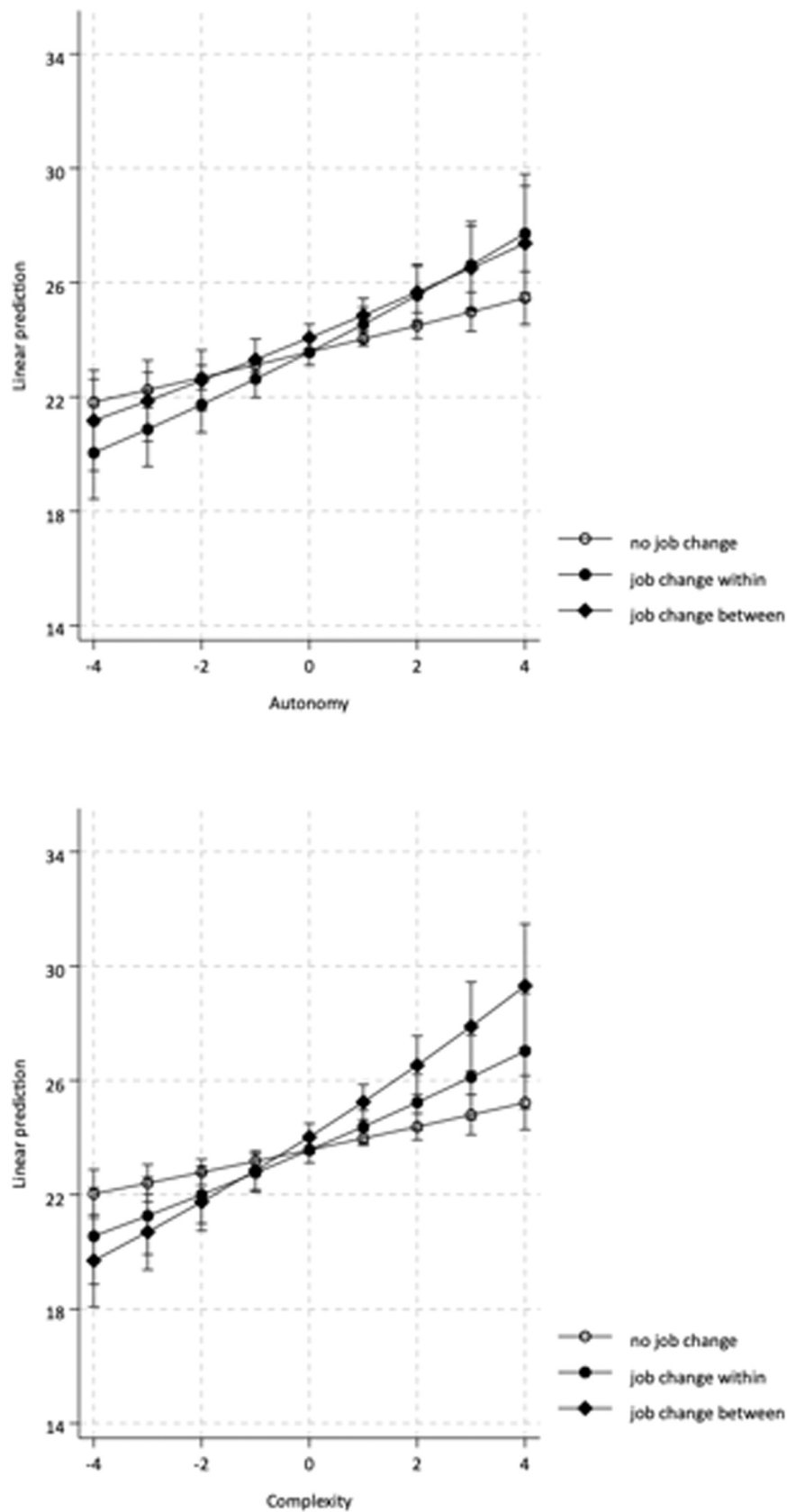


Fig. 5. Joint role of task change and job change for differences in hourly wages in Euros for the male sample. Notes. Predictions with 84 % confidence intervals (MacGregor-Fors & Payton, 2013). Non-routine job tasks were z-standardized.

change jobs between different occupational segments and job stayers is statistically significant on a $p < 0.05$ level. A one-standard deviation increase in complex job tasks from the sample mean is associated with an hourly wage increase of about €0.40 among male job stayers, and with an hourly wage increase of about €1.20 among male job changers between occupational segments.

Fig. 6 shows the results for females. We do not find systematic differences in the relationship between non-routine job tasks and wages between women who do and do not change jobs. This finding supports our Hypothesis 4, which is that women's wages are less affected by job changes than are men's. Figs. 5 and 6 also reveal the gender differences in wages across the distribution of non-routine tasks. Males show higher income levels than females independent of their level of increase in autonomous and complex job tasks.

7.3. Do specific task facets drive the results for autonomous and complex task changes?

In a third step, we exploratively analyze whether the connections between non-routine job tasks and wages are related to specific facets of autonomous and complex job tasks (i.e., the single items that compose our two task measures). The detailed item formulations are presented in Tables A4, and A5 in the Appendix and the piecewise correlations of the facets are reported in Table A6. Table 2 to Table 5 report the interaction models of the impact of changes in non-routine job tasks on wages by types of job changes for the male and female sample respectively. Because wages were log-transformed, the regression coefficients refer to percentage wage changes. The measures of job tasks were z-standardized, so that the regression coefficients indicate percentage wage changes associated with a one standard deviation increase in job tasks.

As concerns autonomy, men consistently derive benefits from more managerial tasks (Facet 4: Being involved in decision making) and to a lesser extent from more organizational tasks (Facet 1: Scheduling work activities). Those men who change jobs within occupational segments additionally experience wage increases if their new job involves organizational tasks (Facet 2: Choosing new task assignments; see Table 2). A one standard deviation increase in the facet "Setting the pace of work" is associated with no wage increase among male job stayers and with a three percent wage increase among male job changers within occupational segments. In contrast, females do not benefit from taking on individual facets of autonomous tasks, regardless of job changes (see Table 3).

Concerning complex job tasks, males consistently benefit monetarily from innovative tasks (Facet 1: Solving difficult problems). When changing jobs, they additionally benefit from required skill acquisition (Facet 2: Learning new things) and adaption (Facet 3: Getting acquainted with tasks; Facet 5: Adapting to changing work assignments; see Table 4). For females, we found no wage premium for the single facets of complex tasks, nor for the composite measure of complexity.

While for males, individual facets of non-routine tasks show stronger associations with wages than others, we do not detect systematic patterns that help us explain the associations we found for the overall task categories and wage returns. Thus, we are confident that the level of task dimensions (autonomous, complex) is a more appropriate level of analysis for our study than the single-item facets of tasks. Table 5.

8. Robustness checks

To substantiate our findings, we conducted a series of robustness analyses for the interaction models with job change (Tables A 7–10 in the Appendix). First, we performed models including the level of skills required as a control variable to test whether the associations found between wages, non-routine tasks, and job changes are due to the vertical dimension of the jobs, i.e., specific job positions (see Table A7). We measured the level of skills required, using the fifth digit of the German classification of occupations (KldB-10) and distinguishing between low

(level one [unskilled and semi-skilled jobs] and two [specialized jobs]), medium (level three [complex specialized jobs]), and high (level four [highly complex jobs]) (Bundesagentur für Arbeit, 2021). The coefficients for non-routine job tasks, as well as the interaction coefficient between complex job tasks and job changes between occupational segments, remained consistent within the male sample. This stability indicates that variations in non-routine job tasks influence wages independently of changes in the required skill level. Interestingly, changing to positions with high compared to low skill requirements leads to a wage increase of 9 % ($p < 0.001$) for males and 12 % ($p < 0.1$) for females.

Second, we conducted additional analyses on a sample exclusively comprising full-time female and male employees to investigate whether gender differences in wage gains resulting from changes in non-routine job tasks to the benefit of males were influenced by working hours, given that women are more likely to work part-time than are men (see Table A8 in the Appendix). While full-time employees might benefit from contractual provisions ensuring wage increases linked to task changes, such assurances may not extend to part-time workers. Contrary to our expectations of narrowing gender differences in wage gains linked to job task changes, our findings revealed no wage increases among full-time female workers. However, male employees experienced wage increases regardless of whether the change in non-routine tasks coincided with a job change within or between occupational segments. Thus, the lack of correlation between task changes and wages for women seems not to be due to (self-)selection into part-time work.

At the first measurement point of the job task measures (NEPS wave 4), a refreshment sample was drawn, in which the participants were not surveyed about their job tasks. Job tasks are thus missing by design for this group at the first measurement point. Additional missing values are due to item non-response or (temporary) panel attrition. Third, we applied our additive (see Table A9) and interactive models (see Table A10) to the non-imputed data. The results did not differ substantially from those previously presented. The point estimates for non-routine job tasks were slightly lower and exhibited lower statistical significance, particularly for the relationship between complex tasks and wages among males. By contrast, the models based on the female sample showed slightly increased point estimates for autonomous job tasks ($\beta = 0.015$; $p < 0.05$) among female job stayers.

9. Summary and discussion

Our study explored the relationship between gender-based wage increases and changes in non-routine job tasks in Germany. We made several contributions to the existing literature: (1) We evaluated individual wage returns to changes in individual non-routine job tasks; (2) we highlighted gender differences in these wage returns to non-routine task changes; and (3) we examined the role of non-routine task changes for gendered wage returns within the broader context of routine-biased technological change.

Our empirical results based on longitudinal data showed a positive association between intra-individual non-routine task changes and intra-individual changes in hourly wages for men, but not for women. If men increase their autonomous or complex tasks by one standard deviation, their hourly wage is two percent higher. The associations for women, by contrast, were not statistically significant. These findings are consistent with our theoretical expectations. We argued that men would experience a wage increase if they increased their share of non-routine tasks (Hypothesis 1), and we argued that women's wage increases would be smaller than that of men (Hypothesis 2). Indeed, we found these gendered associations to be to the advantage of men.

While wage premiums were found only among men, our results support the routine-biased technological change literature, which posits that non-routine tasks are increasingly rewarded in the labor market (Acemoglu & Restrepo, 2018; Autor et al., 2003; Böhm, 2020). Likewise, our findings are consistent with the findings from longitudinal studies

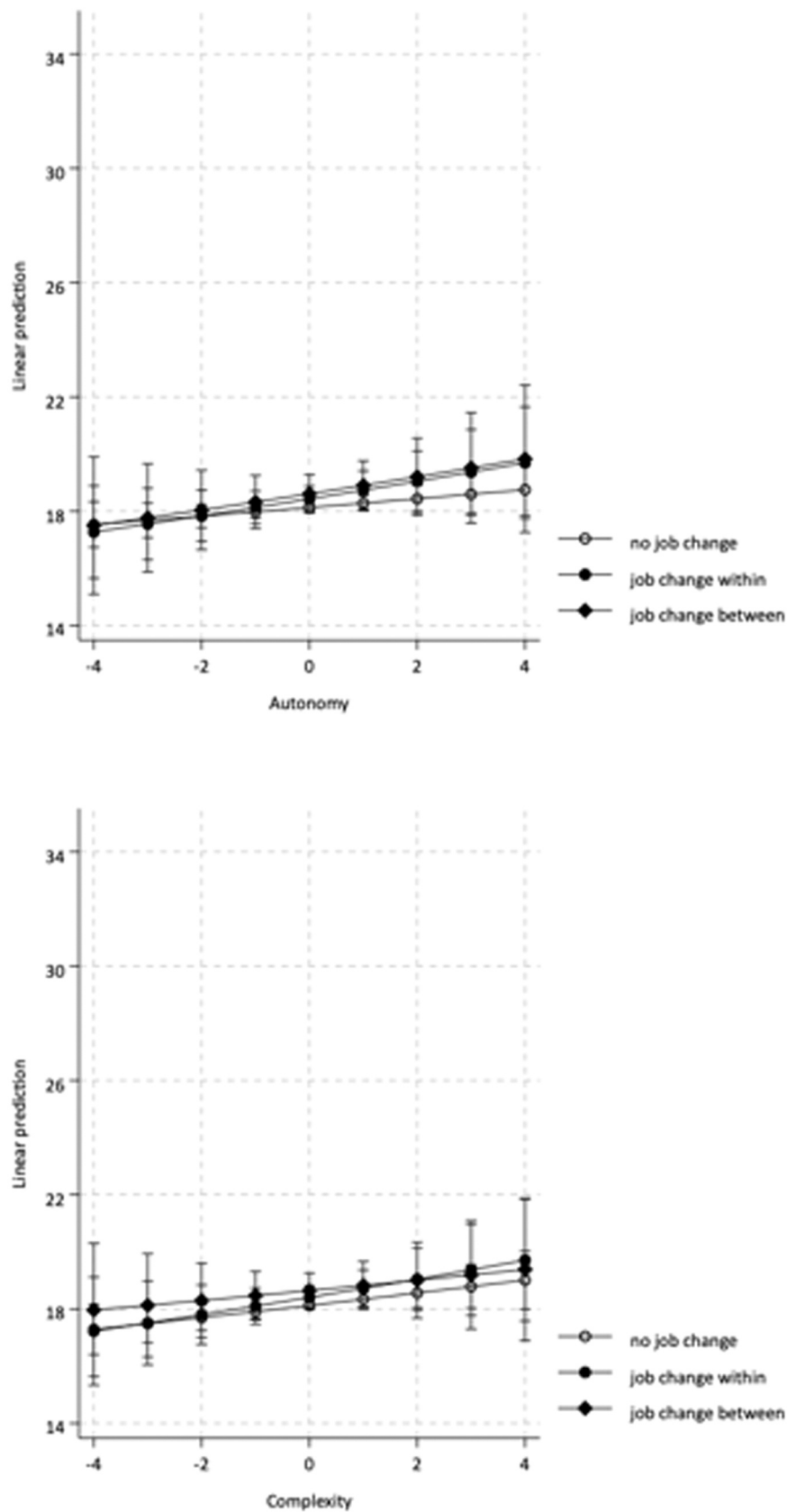


Fig. 6. Joint role of task change and job change for differences in hourly wages in Euros for the female sample. Notes. Predictions with 84 % confidence intervals (MacGregor-Fors & Payton, 2013). Non-routine job tasks were z-standardized.

Table 2

Associations between changes in facets of autonomy job tasks and hourly wages by job change, within estimates, wages logarithmized, males.

	Facet (1)		Facet (2)		Facet (3)		Facet (4)	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.
<i>Facets</i>								
(1) Scheduling work activities	0.018	[0.005]	0.009	[0.005]	0.010	[0.005]	0.010 *	[0.005]
(2) Choosing new task assignments	−0.000	[0.005]	−0.004	[0.006]	−0.000	[0.005]	−0.001	[0.005]
(3) Setting the pace of work	0.004	[0.005]	0.004	[0.005]	0.003	[0.005]	0.005	[0.005]
(4) Being involved in decision making	0.018* **	[0.005]	0.019* **	[0.005]	0.019* **	[0.005]	0.017 *	[0.006]
<i>Job change, ref. none</i>								
Within occupational segments	0.003	[0.014]	0.000	[0.014]	0.001	[0.014]	0.004	[0.014]
Between occupational segments	0.023	[0.015]	0.027	[0.014]	0.026	[0.015]	0.024	[0.014]
<i>Interaction terms</i>								
Facets (1)–(4) × °job change within occupational segments	0.006	[0.014]	0.031 *	[0.013]	0.022	[0.014]	0.003	[0.013]
Facets (1)–(4) × °job change between occupational segments	0.025	[0.015]	0.000	[0.014]	−0.003	[0.015]	0.014	[0.013]
<i>Controls</i>								
Complexity	0.022 * **	[0.006]	0.021 * *	[0.007]	0.022 * **	[0.006]	0.021 * **	[0.006]
Analytic	0.016 * **	[0.007]	0.016 *	[0.008]	0.016 *	[0.007]	0.015 *	[0.007]
Manual	−0.027 * *	[0.008]	−0.027 * *	[0.008]	−0.028 * *	[0.008]	−0.029 * **	[0.009]
Interactive	−0.005	[0.007]	−0.005	[0.007]	−0.005	[0.007]	−0.005	[0.008]
Children < 6, ref. none	0.032 *	[0.012]	0.031 *	[0.012]	0.031 *	[0.012]	0.033 * *	[0.012]
Age	0.082 * **	[0.005]	0.081 * **	[0.005]	0.081 * **	[0.005]	0.082 * **	[0.005]
Age ²	−0.001 * **	[0.000]	−0.001 * **	[0.000]	−0.001 * **	[0.000]	−0.001 * **	[0.000]
Constant	0.568 * **	[0.128]	0.577 * **	[0.133]	0.585 * **	[0.133]	0.563 * **	[0.132]
σ_u	0.426		0.427		0.426		0.426	
σ_e	0.185		0.185		0.185		0.185	
Largest FMI	0.322		0.356		0.352		0.331	
Average RVI	0.351		0.378		0.364		0.356	

Job tasks are standardized; all other variables are unstandardized. 50 imputations. N(persons) 2011, N(observations) 6033. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.**Table 3**

Associations between changes in facets of autonomy job tasks and hourly wages by job change, within estimates, wages logarithmized, females.

	Facet (1)		Facet (2)		Facet (3)		Facet (4)	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.
<i>Facets</i>								
(1) Scheduling work activities	0.001	[0.008]	0.001	[0.008]	0.001	[0.007]	0.001	[0.007]
(2) Choosing new task assignments	0.007	[0.007]	0.005	[0.008]	0.009	[0.007]	0.007	[0.007]
(3) Setting the pace of work	0.005	[0.007]	0.005	[0.007]	0.004	[0.008]	0.005	[0.007]
(4) Being involved in decision making	0.000	[0.008]	−0.000	[0.008]	−0.001	[0.007]	0.001	[0.008]
<i>Job change, ref. none</i>								
Within occupational segment	0.019	[0.018]	0.016	[0.018]	0.018	[0.018]	0.018	[0.017]
Between occupational segment	0.028	[0.024]	0.023	[0.023]	0.027	[0.024]	0.027	[0.024]
<i>Interaction terms</i>								
Facets (1)–(4) × °job change within occupational segments	0.010	[0.016]	0.011	[0.017]	−0.007	[0.016]	−0.011	[0.017]
Facets (1)–(4) × °job change between occupational segments	−0.001	[0.024]	0.015	[0.022]	0.002	[0.024]	0.001	[0.024]
<i>Controls</i>								
Complexity	0.012	[0.008]	0.012	[0.009]	0.011	[0.009]	0.012	[0.008]
Analytic	0.032 * *	[0.011]	0.031 * *	[0.010]	0.032 * *	[0.011]	0.031 * *	[0.011]
Manual	−0.022	[0.013]	−0.019	[0.012]	−0.019	[0.012]	−0.021	[0.013]
Interactive	−0.014	[0.010]	−0.015	[0.010]	−0.014	[0.009]	−0.015	[0.010]
Children < 6, ref. none	−0.099 * **	[0.021]	−0.099 * **	[0.022]	−0.099 * **	[0.022]	−0.103 * **	[0.023]
Age	0.073 * **	[0.008]	0.072 * **	[0.009]	0.072 * **	[0.009]	0.073 * **	[0.008]
Age ²	−0.000 * **	[0.000]	−0.000 * **	[0.000]	−0.000 * **	[0.000]	−0.000 * **	[0.000]
Constant	0.412 *	[0.208]	0.428 *	[0.211]	0.421 *	[0.212]	0.413 *	[0.209]
σ_u	0.441		0.442		0.442		0.442	
σ_e	0.248		0.248		0.248		0.248	
Largest FMI	0.392		0.418		0.387		0.411	
Average RVI	0.441		0.426		0.425		0.454	

Job tasks are standardized; all other variables are unstandardized. 50 imputations. N(persons) 1823, N(observations) 5469. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

for Sweden and the UK (Dastory, 2019; Ross, 2017). However, the associations we found for Germany are less pronounced. Most notably, our study indicates a gendered disparity, with women not benefiting from the increase in non-routine tasks. This contrasts with the findings of Rohrbach-Schmidt et al. (2023) based on cross-sectional data. It appears that cross-sectional and longitudinal data on tasks and wages reveal different degrees of gender inequality.

We argued that hourly wage increases related to non-routine task changes are higher for men and women who perform these tasks in a new job. We expected the premium for non-routine task changes in combination with job changes to be higher for men (Hypothesis 3) than for women (Hypothesis 4). Our empirical results partially support these

expectations based on previous research (Azzopardi et al., 2020; Haltiwanger et al., 2018; Reichelt & Abraham, 2017). For women, job changes did not appear to affect the relationship between task changes and wages; regardless of whether women changed jobs, increases in non-routine tasks did not translate into wage gains. Conversely, for men, our findings aligned with our hypothesis, though only for complex tasks and not for autonomous tasks. Men experienced wage gains from increases in both autonomous and complex tasks, with the greatest benefits coming from combining an increase in complex tasks with a job change across different occupational segments. In sum, job changes partially amplify the gendered association between increasing non-routine job tasks and hourly wages, benefiting men. Specifically,

Table 4
Associations between changes in facets of complex job tasks and hourly wages by job change, within estimates, wages logarithmized, males.

	Facet (1)		Facet (2)		Facet (3)		Facet (4)		Facet (5)		Facet (6)	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.
<i>Facets</i>												
(1) Solving difficult problems	0.010	[0.006]	0.013 *	[0.005]	0.014 *	[0.005]	0.013 *	[0.006]	0.014 *	[0.006]	0.014 *	[0.006]
(2) Learning new things	−0.000	[0.005]	−0.005	[0.005]	−0.002	[0.005]	−0.001	[0.005]	−0.001	[0.006]	−0.001	[0.006]
(3) Getting acquainted with tasks	0.006	[0.005]	0.005	[0.005]	0.003	[0.005]	0.005	[0.005]	0.004	[0.005]	0.006	[0.005]
(4) Dealing with unanticipated situations	0.003	[0.005]	0.002	[0.005]	0.002	[0.005]	−0.000	[0.005]	0.003	[0.005]	0.002	[0.005]
(5) Adapting to changing work assignments	0.005	[0.005]	0.004	[0.005]	0.004	[0.005]	0.004	[0.005]	0.002	[0.005]	0.004	[0.005]
(6) Performing new tasks	0.005	[0.005]	0.006	[0.005]	0.004	[0.005]	0.005	[0.005]	0.005	[0.005]	0.004	[0.005]
<i>Job change, ref. none</i>												
Within occupational segment	−0.002	[0.014]	0.002	[0.014]	0.002	[0.013]	0.002	[0.014]	0.002	[0.014]	0.003	[0.014]
Between occupational segment	0.019	[0.015]	0.024	[0.015]	0.015	[0.015]	0.027	[0.015]	0.022	[0.015]	0.019	[0.015]
<i>Interaction terms</i>												
Facets (1)–(6) × °job change within occupational segments	0.019	[0.015]	0.028 *	[0.013]	0.009	[0.013]	0.022	[0.014]	−0.005	[0.013]	−0.002	[0.012]
Facets (1)–(6) × °job change between occupational segments	0.016	[0.014]	0.036 *	[0.014]	0.041 **	[0.014]	0.026	[0.015]	0.031 *	[0.015]	0.019	[0.013]
<i>Controls</i>												
Autonomy	0.021 ***	[0.006]	0.021 ***	[0.006]	0.022 ***	[0.006]	0.021 ***	[0.006]	0.021 ***	[0.006]	0.023 ***	[0.006]
Analytic	0.016 *	[0.008]	0.016 *	[0.007]	0.015 *	[0.008]	0.015	[0.008]	0.016 *	[0.007]	0.016 *	[0.007]
Manual	−0.030 ***	[0.008]	−0.029 ***	[0.008]	−0.030 ***	[0.008]	−0.029 ***	[0.008]	−0.028 ***	[0.008]	−0.029 ***	[0.008]
Interactive	−0.006	[0.007]	−0.007	[0.007]	−0.008	[0.007]	−0.006	[0.007]	−0.007	[0.007]	−0.007	[0.007]
Children < 6, ref. none	0.032 *	[0.013]	0.033 *	[0.012]	0.033 *	[0.012]	0.031 *	[0.012]	0.031 *	[0.013]	0.032 *	[0.012]
Age	0.083 ***	[0.005]	0.082 ***	[0.005]	0.082 ***	[0.005]	0.082 ***	[0.005]	0.082 ***	[0.005]	0.082 ***	[0.005]
Age ²	−0.001 ***	[0.000]	−0.001 ***	[0.000]	−0.001 ***	[0.000]	−0.001 ***	[0.000]	−0.001 ***	[0.000]	−0.001 ***	[0.000]
Constant	0.545 ***	[0.130]	0.571 ***	[0.132]	0.562 ***	[0.135]	0.553 ***	[0.136]	0.553 ***	[0.132]	0.571 ***	[0.133]
σ_u	0.425		0.424		0.425		0.426		0.426		0.424	
σ_e	0.185		0.185		0.185		0.185		0.185		0.185	
Largest FMI	0.348		0.383		0.361		0.396		0.363		0.353	
Average RVI	0.390		0.407		0.382		0.410		0.186		0.358	

Job tasks are standardized; all other variables are unstandardized. 50 imputations. N(persons) 2011, N(observations) 6033. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$.

Table 5
Associations between changes in facets of complex job tasks and hourly wages by job change, within estimates, wages logarithmized, females.

	Facet (1)		Facet (2)		Facet (3)		Facet (4)		Facet (5)		Facet (6)	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.
<i>Facets</i>												
(1) Solving difficult problems	0.010	[0.008]	0.007	[0.008]	0.008	[0.008]	0.008	[0.008]	0.008	[0.007]	0.007	[0.008]
(2) Learning new things	0.008	[0.007]	0.005	[0.008]	0.008	[0.008]	0.008	[0.008]	0.008	[0.008]	0.007	[0.008]
(3) Getting acquainted with tasks	−0.005	[0.008]	−0.003	[0.008]	−0.006	[0.008]	−0.003	[0.007]	−0.004	[0.007]	−0.004	[0.007]
(4) Dealing with unanticipated situations	0.001	[0.007]	0.001	[0.008]	0.002	[0.008]	−0.003	[0.008]	0.001	[0.007]	0.002	[0.008]
(5) Adapting to changing work assignments	−0.001	[0.007]	−0.000	[0.007]	0.000	[0.007]	0.001	[0.007]	0.002	[0.007]	0.001	[0.007]
(6) Performing new tasks	0.006	[0.007]	0.006	[0.007]	0.006	[0.007]	0.005	[0.007]	0.006	[0.007]	0.003	[0.008]
<i>Job change, ref. none</i>												
Within occupational segment	0.014	[0.018]	0.015	[0.019]	0.016	[0.018]	0.016	[0.018]	0.018	[0.018]	0.015	[0.018]
Between occupational segment	0.028	[0.025]	0.029	[0.023]	0.030	[0.024]	0.029	[0.024]	0.026	[0.024]	0.031	[0.025]
<i>Interaction terms</i>												
Facets (1)–(6) × °job change within occupational segments	−0.019	[0.016]	−0.000	[0.017]	0.027	[0.017]	0.023	[0.016]	−0.017	[0.017]	0.017	[0.017]
Facets (1)–(6) × °job change between occupational segments	0.005	[0.023]	0.011	[0.022]	−0.029	[0.023]	0.023	[0.025]	0.000	[0.026]	−0.011	[0.023]
<i>Controls</i>												
Autonomy	0.010	[0.008]	0.010	[0.008]	0.010	[0.008]	0.008	[0.008]	0.008	[0.008]	0.009	[0.008]
Analytic	0.030 * *	[0.011]	0.031 * *	[0.011]	0.032 * *	[0.011]	0.033 * *	[0.011]	0.030 * *	[0.011]	0.030 * *	[0.011]
Manual	−0.022	[0.013]	−0.018	[0.013]	−0.019	[0.014]	−0.019	[0.013]	−0.020	[0.013]	−0.019	[0.013]
Interactive	−0.013	[0.010]	−0.013	[0.010]	−0.014	[0.010]	−0.014	[0.010]	−0.013	[0.010]	−0.015	[0.010]
Children < 6, ref. none	−0.100 * **	[0.022]	−0.103 * **	[0.021]	−0.098 * **	[0.022]	−0.099 * **	[0.022]	−0.100 * **	[0.022]	−0.098 * **	[0.022]
Age	0.073 * **	[0.009]	0.072 * **	[0.008]	0.072 * **	[0.008]	0.072 * **	[0.008]	0.073 * **	[0.009]	0.071 * **	[0.008]
Age ²	−0.000 * **	[0.000]	−0.000 * **	[0.000]	−0.000 * **	[0.000]	−0.000 * **	[0.000]	−0.000 * **	[0.000]	−0.000 * **	[0.000]
Constant	0.395	[0.213]	0.421 *	[0.207]	0.420 *	[0.201]	0.438 *	[0.205]	0.391	[0.219]	0.441 *	[0.205]
σ_u	0.442		0.442		0.441		0.441		0.444		0.442	
σ_e	0.248		0.248		0.248		0.248		0.248		0.248	
Largest FMI	0.378		0.405		0.443		0.420		0.414		0.413	
Average RVI	0.427		0.455		0.465		0.464		0.455		0.445	

Job tasks are standardized; all other variables are unstandardized. 50 imputations. N(persons) 1823, N(observations) 5469. * $p < 0.05$, * * $p < 0.01$, * * * $p < 0.00$.

the wage advantage for men who increase their complex tasks by one standard deviation and change their jobs across occupational segments is three times greater compared to men who stay in the same job.

Through our additional analyses focusing on the single facets of job tasks, we examined whether the observed results for autonomous and complex job tasks were driven by particular components within these task dimensions. For men, the positive association between increasing complex job tasks and hourly wages can be attributed to the combination of several single complex task facets. Concerning autonomous tasks, however, we found one notable item in our analysis. Especially men who increasingly take part in important strategic decisions within the company tend to have higher hourly wages. This suggests that the managerial aspects of autonomy, rather than independently scheduling one's tasks and work pace, play a key role in the positive relationship between increasing autonomous job tasks and hourly wages for men. In line with that, previous research reports a persistent gender pay gap in managerial positions, largely due to differences in initial salaries that becomes even wider the higher the positions (Geiler & Renneboog, 2015; Kulich et al., 2011; Sterling & Fernandez, 2018). A reason for this could be that work contracts for men often have stronger upward remuneration potential compared to women who are offered contracts that are less performance-sensitive and more suited to risk-averse managers (Kulich et al., 2011). In contrast to men, as with the composite measures of non-routine job tasks, the facet analyses also show no evidence of wage premiums for women.

While the positive association between increasing non-routine tasks and hourly wages is relatively weak, it is still noteworthy that we found no positive association for women. We suggest that gender differences in wage returns to non-routine job tasks may be related to: 1) discrimination against women in hiring, 2) differences in non-cognitive skills, including a disadvantage in wage negotiation, and 3) the self-selection of women and men into different tasks, jobs, and career paths. Our data do not allow us to identify the specific mechanisms behind these gender differences, but all three may contribute to the observed disparity in wage returns: women may not be selected for these tasks due to discriminatory practices by supervisors, may not negotiate for these tasks or for higher wages, and may not choose these tasks for various reasons. Our finding that the gendered associations between changes in non-routine job tasks and wages do not substantially diminish when comparing full-time working men and women suggests that women's self-selection into part-time work is not responsible for this disparity.

We argued that Germany may serve as a conservative test case for the association of increasing non-routine job tasks and hourly wages. Given the rigid structure of the German labor market, the freedom of employers to set wages is limited. Empirically, this is supported by the finding that a job change reinforces the positive association between non-routine job tasks and wages for men (only for complexity). But changes in non-routine tasks in conjunction with job changes increase male wages by not more than five percent. In other countries, job changes and changes in non-routine tasks may pay off more. Thus, our results on the returns to non-routine task changes may indeed serve as a lower-bound estimate for other countries. It is more difficult, however, to extrapolate the findings of the pronounced gender differences to other countries. Compared to other OECD countries, Germany has high labor market participation rates for women, high rates of part-time employment for women and an above-average gender pay gap. The above-average gender pay gap may hint at mechanisms that disadvantage women in Germany more than in other countries. But we need to leave this conclusion to further comparative research.

10. Limitations and future research

One limitation of our study pertains to the operationalization of job tasks and its potential impact on the generalizability of our findings. The original classification of job tasks was developed by Autor et al. (2003) for the US labor market. Using German data, we applied an

operationalization of job tasks that is based on the work of Autor et al. (2003), albeit strongly adjusted to the specifics of the German labor market. This operationalization developed by Matthes et al. (2014) cannot be directly translated into the original operationalization of Autor et al. (2003). As we did not formulate hypotheses about the five specific types of job tasks, however, but instead focused on the (two) job task dimensions that are least prone to automatization according to Matthes et al. (2014), namely autonomy and complexity, we contend that our results are still comparable across country contexts and different job task operationalizations. Studies seeking to replicate our findings with the job task operationalization of Autor et al. (2003), should focus on the least automatable job tasks according to his definition, namely non-routine interactive and non-routine analytic job tasks. For a recent discussion on the shortcomings of existing job task measures and a suggestion of new indices for measuring complex (and routine) job tasks, see Haslberger (2022).

We used fixed effects models for our empirical analyses. These models account for time-invariant characteristics of individuals, such as their gender, education, and work experience. This helps to reduce bias in the results, as these characteristics can also affect wages. However, fixed effects models do not control for time-varying characteristics, thus our findings might still be biased (Collischon, 2021). One source of bias may be occupational characteristics that lead to gender differences in the selection of certain occupations that provide different levels of opportunity for performing non-routine tasks as well as different levels of reward for this performance. For example, there is a possibility that returns to non-routine tasks are weaker in female-dominated occupations than in male-dominated occupations. We attempted to control for such selection effects by considering the entire task profiles, encompassing cognitive and manual tasks. However, future research could systematically examine differences along the horizontal gender segregation into male- and female-dominated occupations.

Our study focuses on gender differences, but the relationship between job tasks and wage growth can be further complicated when considering other dimensions of inequality, such as race, ethnicity, and socioeconomic status. Future research should explore how these factors intersect with job tasks to influence wage outcomes, contributing to a more comprehensive understanding of inequality in the workplace.

Our results showed that changes in non-routine tasks – as predicted by the routine-biased technological change literature – are indeed associated with higher wages for men. Due to the key role of non-routine tasks for future labor markets, our findings highlight the necessity to study the mechanisms of differential returns as a potential source for persistent and even increasing gendered pay differences.

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CRediT authorship contribution statement

Nora Müller: Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Alexandra Wicht:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Reinhard Pollak:** Writing – review & editing.

Declaration of Competing Interest

We have no known conflicts of interest to disclose.

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Appendix

Table A1

Correlation matrix.

	Male	Age	Age ²	Children < 6	Job change within	Job change between	Complexity	Autonomy	Manual	Interactive	Analytic
Age	–0.0247										
Age ²	–0.0218	0.9944									
Children < 6	0.0894	–0.3658	–0.3632								
Job change within	–0.0342	–0.0342	–0.0316	0.0697							
Job change between	0.0383	–0.0103	–0.0092	0.0260	–0.0706						
Complexity	0.0733	–0.1157	–0.1177	0.0695	0.0368	0.0291					
Autonomy	0.0806	–0.0636	–0.0645	0.0434	0.0061	0.0486	0.3112				
Manual	0.0684	0.0136	–0.0136	–0.0233	–0.0146	–0.0528	–0.1011	–0.1712			
Interactive	0.1363	0.0218	0.0255	–0.0120	–0.0342	0.0461	–0.3899	–0.25282	–0.0192		
Analytic	0.1769	–0.0766	–0.0777	0.0649	0.0055	0.0204	0.5172	0.3592	–0.2876	–0.3151	
Log (hourly wages)	0.2768	0.1547	0.1517	0.0230	0.0152	0.0486	0.2949	0.2113	–0.2899	–0.1496	0.4446

Means across all measurement points. Values before imputation.

Table A2

Item wordings for autonomous tasks.

No.	Item	Wording (English translation)
1	Scheduling work activities	How often does it happen that you may schedule your work activities all by yourself?
2	Choosing new task assignments	How often is it possible for you to choose new task assignments by yourself?
3	Setting the pace of work	How often does it happen that you may choose your work pace all by yourself?
4	Being involved in decision making	How often are you personally involved in important strategic decisions of your company, like e.g., decisions on the kinds of products or services produced, the number of employees, or company finances?

Notes: Wording taken from Matthes et al. (2014).

Table A3

Item wordings for complex tasks.

No.	Item	Wording (English translation)
1	Solving difficult problems	The following question will be on solving difficult problems. A difficult problem is one that might not be solved easily right away. As part of your job, how often do you have to solve such difficult problems?
2	Learning new things	How often do you have to learn new things at work?
3	Getting acquainted with tasks	How often does it happen that you are assigned tasks at work you do first have to get acquainted with?
4	Dealing with unanticipated situations	How often does it happen that you have to react on situations at work, which could not be anticipated?
5	Adapting to changing work assignments	How often do the work-assignments at your job change?
6	Performing new tasks	How often do you have to perform tasks at work that you did not do before?

Notes: Wording taken from Matthes et al. (2014).

Table A4

Correlation matrix for facets of autonomy and complexity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Facets Autonomy</i>									
(1) Scheduling work activities									
(2) Choosing new task assignments	0.3938								
(3) Setting the pace of work	0.5034	0.2940							
(4) Being involved in decision making	0.2271	0.3255	0.1385						
<i>Facets Complexity</i>									

(continued on next page)

Table A4 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(5) Solving difficult problems	0.1809	0.2328	0.0829	0.2824					
(6) Learning new things	0.1364	0.2616	0.0349	0.1869	0.4412				
(7) Getting acquainted with tasks	0.1633	0.2247	0.0701	0.1789	0.4428	0.5197			
(8) Dealing with unanticipated situations	0.0478	0.2299	−0.0104	0.1732	0.3795	0.3672	0.3157		
(9) Adapting to changing work assignments	0.0945	0.2378	0.0142	0.1941	0.3162	0.3557	0.3669	0.3886	
(10) Performing new tasks	0.1326	0.2669	0.0511	0.2004	0.3851	0.4443	0.5392	0.3607	0.4579

Means across all measurement points. Values before imputation.

Table A5

Task and job changes regressed on hourly wages, within estimates, wages logarithmized.

	Overall		β	Female		β	Male	
	β	S.E.		β	S.E.		β	S.E.
Autonomy (std.)	0.015 **	[0.005]	0.009		[0.007]	0.022 ***		[0.006]
Complexity (std.)	0.017 **	[0.005]	0.012		[0.009]	0.021 **		[0.007]
Job change, ref. none								
Within occupational segments	0.007	[0.011]	0.015		[0.017]	0.002		[0.014]
Between occupational segments	0.024	[0.014]	0.029		[0.023]	0.024		[0.015]
<i>Controls</i>								
Analytic (std.)	0.024 ***	[0.006]	0.033 **		[0.011]	0.015 *		[0.007]
Manual (std.)	−0.025 **	[0.008]	−0.021		[0.013]	−0.029 ***		[0.009]
Interactive (std.)	−0.012	[0.006]	−0.015		[0.010]	−0.007		[0.007]
Age	0.078 ***	[0.005]	0.072 ***		[0.008]	0.082 ***		[0.005]
Age ²	−0.000 ***	[0.000]	−0.000 ***		[0.000]	−0.001 ***		[0.000]
Children < 6, ref. none	−0.020	[0.011]	−0.100 ***		[0.022]	0.031 **		[0.012]
Constant	0.471 ***	[0.120]	0.426 *		[0.209]	0.561 ***		[0.131]
σ_u	0.455		0.441			0.427		
σ_e	0.218		0.248			0.185		
Largest FMI	0.376		0.372			0.335		
Average RVI	0.414		0.403			0.369		
N(persons)	3834		1823			2011		
N(observations)	11,502		5469			6033		

Notes: Job tasks are standardized; all other variables are unstandardized. 50 imputations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Interpretation of relevant regression coefficients: because wages were logarithmized, the regression coefficients refer to wage changes in percent.

Table A6

Associations between changes in job tasks and hourly wages by job change, within estimates, wages logarithmized.

	Females				Males			
	Autonomy β	S.E.	Complexity β	S.E.	Autonomy β	S.E.	Complexity β	S.E.
Autonomy (std.)	0.008	[0.008]	0.009	[0.008]	0.019 **	[0.006]	0.022 ***	[0.00]
Complexity (std.)	0.011	[0.009]	0.012	[0.009]	0.021 ***	[0.006]	0.017 *	[0.01]
Job change, ref. none								
Within occupational segment	0.016	[0.019]	0.016	[0.018]	−0.000	[0.014]	−0.000	[0.014]
Between occupational segment	0.026	[0.027]	0.028	[0.025]	0.021	[0.015]	0.019	[0.015]
<i>Interaction terms</i>								
Autonomy ^o × °job change within	0.008	[0.017]			0.021	[0.013]		
Autonomy ^o × °job change between	0.007	[0.023]			0.013	[0.014]		
Complexity ^o × °job change within			0.005	[0.018]			0.017	[0.013]
Complexity ^o × °job change between			−0.002	[0.022]			0.033 *	[0.014]
<i>Controls</i>								
Analytic (std.)	0.030 **	[0.011]	0.031 **	[0.011]	0.015 *	[0.007]	0.015 *	[0.008]
Manual (std.)	−0.021	[0.013]	−0.019	[0.013]	−0.028 ***	[0.009]	−0.029 ***	[0.009]
Interactive (std.)	−0.015	[0.010]	−0.013	[0.010]	−0.007	[0.007]	−0.006	[0.008]
Children < 6, ref. none	−0.102 ***	[0.022]	−0.097 ***	[0.021]	0.032 **	[0.012]	0.032 **	[0.012]
Age	0.072 ***	[0.008]	0.073 ***	[0.009]	0.083 ***	[0.005]	0.082 ***	[0.006]
Age ²	−0.000 ***	[0.000]	−0.000 ***	[0.000]	−0.001 ***	[0.000]	−0.001 ***	[0.000]
Constant	0.427 *	[0.210]	0.409	[0.210]	0.545 ***	[0.129]	0.571 ***	[0.136]
σ_u	0.443		0.442		0.427		0.426	
σ_e	0.248		0.248		0.185		0.185	
Largest FMI	0.420		0.384		0.373		0.352	
Average RVI	0.475		0.456		0.376		0.410	
N(persons)	1823				2011			
N(observations)	5469				6033			

Job tasks are standardized; all other variables are unstandardized. 50 imputations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$.

Table A7

Associations between changes in job tasks and wages by job change, within estimates, wages logarithmized, controlling for level of skill requirements.

	Females				Males			
	Autonomy		Complexity		Autonomy	Complexity		
	β	S.E.	β	S.E.	β	β	S.E.	S.E.
Autonomy (std.)	0.007	[0.008]	0.008	[0.008]	0.017 **	[0.006]	0.020 ***	[0.006]
Complexity (std.)	0.010	[0.009]	0.010	[0.009]	0.021 **	[0.006]	0.015 *	[0.007]
Job change, ref. none								
Within occupational segment	0.012	[0.018]	0.012	[0.017]	−0.001	[0.014]	−0.000	[0.014]
Between occupational segment	0.026	[0.024]	0.023	[0.024]	0.017	[0.015]	0.014	[0.014]
Interaction terms								
Autonomy ^o × °job change within	0.003	[0.017]			0.019	[0.013]		
Autonomy ^o × °job change between	0.006	[0.026]			0.013	[0.014]		
Complexity ^o × °job change between			0.004	[0.017]			0.014	[0.014]
Complexity ^o × °job change between			−0.003	[0.023]			0.034 **	[0.013]
Controls								
Analytic (std.)	0.025 *	[0.011]	0.028 *	[0.011]	0.014 *	[0.007]	0.012	[0.008]
Manual (std.)	−0.019	[0.013]	−0.018	[0.014]	−0.025 **	[0.009]	−0.016 **	[0.008]
Interactive (std.)	−0.011	[0.010]	−0.011	[0.010]	−0.005	[0.008]	−0.006	[0.008]
Children < 6, ref. none	−0.099 ***	[0.022]	−0.101 ***	[0.022]	0.02 *	[0.01]	0.02 *	[0.01]
Age	0.072 **	[0.008]	0.071 ***	[0.009]	0.09 ***	[0.00]	0.08 ***	[0.00]
Age ²	−0.000 ***	[0.000]	−0.000 ***	[0.000]	−0.00 ***	[0.00]	−0.00 ***	[0.00]
Level of skill requirements, ref. low								
Medium	0.079 *	[0.032]	0.081 **	[0.031]	0.044	[0.023]	0.045	[0.023]
High	0.116 **	[0.042]	0.125 **	[0.039]	0.092 ***	[0.027]	0.092 ***	[0.027]
Constant	0.397	[0.210]	0.423 *	[0.210]	0.557 ***	[0.134]	0.535 ***	[0.136]
σ_u	0.423		0.420		0.410		0.410	
σ_e	0.248		0.248		0.186		0.185	
Largest FMI	0.415		0.420		0.347		0.371	
Average RVI	0.452		0.430		0.378		0.407	
N(persons)	1823				2011			
N(observations)	5469				6033			

Job tasks are standardized; all other variables are unstandardized. 50 imputations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$.**Table A8**

Associations between changes in job tasks and wages by job change, within estimates, wages logarithmized, only full-time workers.

	Females				Males			
	Autonomy		Complexity		Autonomy	Complexity		
	β	S.E.	β	S.E.	β	β	S.E.	S.E.
Autonomy (std.)	−0.002	[0.010]	−0.006	[0.009]	0.014 *	[0.006]	0.017 **	[0.006]
Complexity (std.)	−0.012	[0.010]	−0.016	[0.011]	0.016 **	[0.006]	0.013 *	[0.006]
Job change, ref. none								
Within occupational segment	0.014	[0.024]	0.015	[0.023]	0.002	[0.013]	0.002	[0.013]
Between occupational segment	0.025	[0.030]	0.019	[0.031]	0.020	[0.014]	0.017	[0.014]
Interaction terms								
Autonomy ^o × °job change within	−0.019	[0.022]			0.023	[0.013]		
Autonomy ^o × °job change between	−0.011	[0.029]			0.011	[0.013]		
Complexity ^o × °job change within			0.033	[0.023]			0.011	[0.012]
Complexity ^o × °job change between			0.042	[0.032]			0.022	[0.013]
Controls								
Analytic (std.)	0.016	[0.016]	0.016	[0.016]	0.009	[0.007]	0.009	[0.007]
Manual (std.)	−0.024	[0.017]	−0.025	[0.017]	−0.021 *	[0.008]	−0.022 **	[0.008]
Interactive (std.)	−0.005	[0.012]	−0.007	[0.012]	0.005	[0.007]	0.005	[0.007]
Children < 6, ref. none	−0.022	[0.045]	−0.019	[0.046]	0.022	[0.012]	0.022	[0.012]
Age	0.078 ***	[0.010]	0.076 ***	[0.010]	0.080 ***	[0.005]	0.080 ***	[0.005]
Age ²	−0.000 ***	[0.000]	−0.000 ***	[0.000]	−0.001 ***	[0.000]	−0.001 ***	[0.000]
Constant	0.430	[0.253]	0.468	[0.249]	0.610 ***	[0.132]	0.600 ***	[0.130]
σ_u	0.440		0.438		0.441		0.440	
σ_e	0.192		0.192		0.171		0.172	
Largest FMI	0.306		0.305		0.208		0.238	
Average RVI	0.198		0.199		0.167		0.174	
N(persons)	755				1909			
N(observations)	1932				5145			

Job tasks are standardized; all other variables are unstandardized. 50 imputations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$.

Table A9

Task and job changes regressed on hourly wages, within estimates, wages logarithmized, unimputed data.

	Overall		Female		Male	
	β	S.E.	β	S.E.	β	S.E.
Autonomy (std.)	0.017 * **	[0.005]	0.014	[0.007]	0.022 * **	[0.006]
Complexity (std.)	0.009	[0.005]	0.002	[0.008]	0.016 *	[0.006]
Job change, ref. none						
Within occupational segments	0.010	[0.011]	0.026	[0.017]	−0.004	[0.014]
Between occupational segments	0.014	[0.013]	0.029	[0.023]	0.007	[0.015]
<i>Controls</i>						
Analytic (std.)	0.005	[0.006]	0.005	[0.010]	0.003	[0.007]
Manual (std.)	−0.006	[0.007]	−0.002	[0.012]	−0.008	[0.009]
Interactive (std.)	−0.007	[0.006]	−0.010	[0.009]	−0.002	[0.007]
Age	0.100 * **	[0.005]	0.106 * **	[0.009]	0.095 * **	[0.006]
Age ²	−0.001 * **	[0.000]	−0.001 * **	[0.000]	−0.001 * **	[0.000]
Children < 6, ref. none	−0.032 * *	[0.012]	−0.113 * **	[0.023]	0.013	[0.013]
Constant	−0.117	[0.127]	−0.496 *	[0.220]	0.220	[0.145]
σ_u	0.497		0.497		0.462	
σ_e	0.207		0.229		0.182	
N(persons)	3737		1782		1955	
N(observations)	8868		4213		4655	

Notes: Job tasks are standardized; all other variables are unstandardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.**Table A10**

Associations between changes in job tasks and hourly wages by job change, within estimates, wages logarithmized, unimputed data.

	Females			Males				
	Autonomy	S.E.	Complexity	S.E.	Autonomy	S.E.	Complexity	S.E.
	β		β		β		β	
Autonomy (std.)	0.015 *	[0.007]	0.013	[0.007]	0.019 * *	[0.006]	0.021 * **	[0.007]
Complexity (std.)	0.002	[0.008]	0.002	[0.008]	0.016 *	[0.006]	0.012	[0.006]
Job change, ref. none								
Within occupational segment	0.025	[0.017]	0.026	[0.017]	−0.006	[0.014]	−0.005	[0.014]
Between occupational segment	0.029	[0.023]	0.029	[0.023]	0.005	[0.015]	−0.000	[0.015]
<i>Interaction terms</i>								
Autonomy ^o × "job change within	−0.007	[0.016]			0.016	[0.014]		
Autonomy ^o × "job change between	−0.004	[0.023]			0.010	[0.014]		
Complexity ^o × "job change within			0.013	[0.017]			0.007	[0.013]
Complexity ^o × "job change between			−0.013	[0.022]			0.034 *	[0.013]
<i>Controls</i>								
Analytic (std.)	0.005	[0.010]	0.005	[0.010]	0.003	[0.007]	0.003	[0.007]
Manual (std.)	−0.002	[0.012]	−0.002	[0.012]	−0.008	[0.009]	−0.009	[0.009]
Interactive (std.)	−0.010	[0.009]	−0.010	[0.009]	−0.002	[0.007]	−0.002	[0.007]
Children < 6, ref. none	−0.113 * **	[0.023]	−0.112 * **	[0.023]	0.013	[0.013]	0.012	[0.013]
Age	0.106 * **	[0.009]	0.106 * **	[0.009]	0.095 * **	[0.006]	0.094 * **	[0.006]
Age ²	−0.001 * **	[0.000]	−0.001 * **	[0.000]	−0.001 * **	[0.000]	−0.001 * **	[0.000]
Constant	−0.501 *	[0.221]	−0.488 *	[0.221]	0.222	[0.145]	0.235	[0.145]
σ_u	0.497		0.496		0.462		0.461	
σ_e	0.229		0.229		0.182		0.181	
N(persons)	1782		1782		1955		1955	
N(observations)	4213		4213		4655		4655	

Job tasks are standardized; all other variables are unstandardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$.

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