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Autonomy and wage divergence: Evidence from European survey data

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Abstract

This paper contributes to the understanding of wage inequality in Western Europe. We assess the relationship between worker autonomy, defined as the degree of control workers have over their work process, and job wage growth in Western Europe from 2003 to 2018. We present econometric analyses using high-quality microdata from the EU Survey of Income and Living Conditions. Our key finding is that wages in high-autonomy jobs have grown significantly faster than in low-autonomy jobs. In other words, the autonomy premium has increased. Because workers in high-autonomy jobs are at the top of the wage distribution, this trend contributes to wage inequality. In addition, we assess the role of technological change, institutions, and demographics for the autonomy premium using additional worker survey data. Our analysis reveals that (i) the autonomy premium increases faster in industries and countries with faster technological change; (ii) strong collective bargaining institutions reduce the autonomy premium but could not halt increases in wage inequality in recent years; (iii) the autonomy premium rises for men and women similarly. However, the increase in the autonomy premium intensifies gender inequality because women are more likely to work in low-autonomy jobs.

Keywords: worker autonomy; technological change; survey data; collective bargaining

JEL Classification E24; J31; J50

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1 Introduction

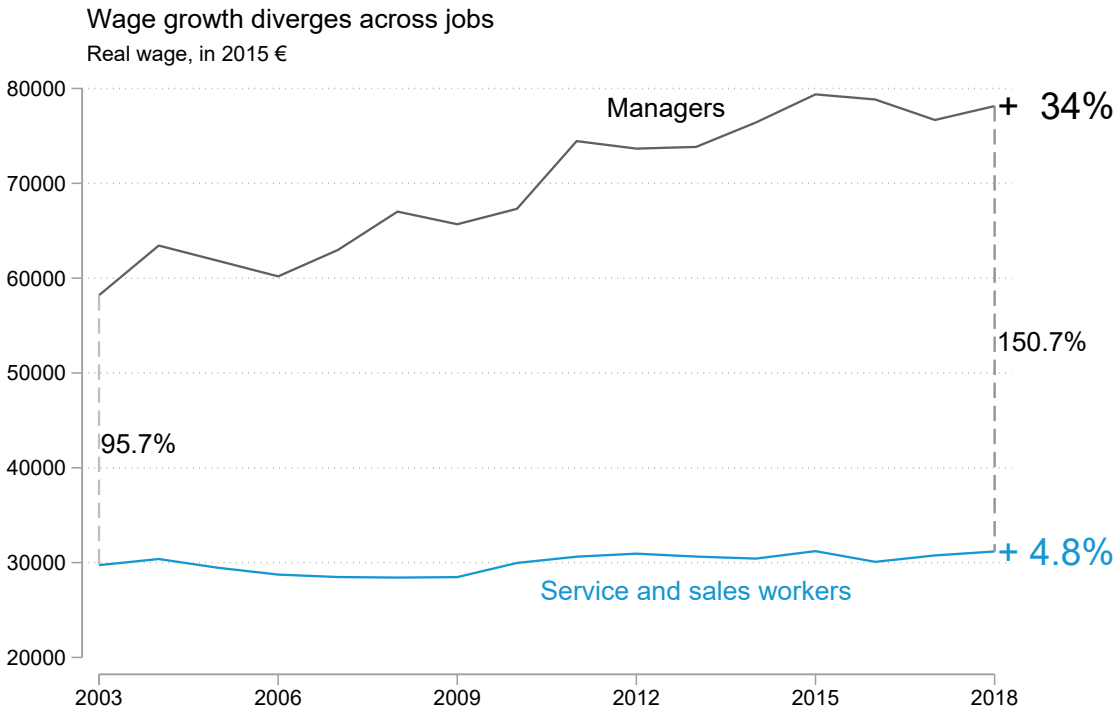
In the years preceding the pandemic, wages in Western Europe have diverged across jobs, contributing to rising income inequality. While *managers* enjoyed real wage growth of 24% between 2005 and 2017, wages of *services and sales workers* grew by merely 4.4% in real terms (Figure 1). This trend is particularly worrying in the context of a looming cost-of-living crisis.

This paper assesses the relationship between worker autonomy, defined as the degree of control workers have over their work process, and job wage growth in Western Europe from 2003 to 2018. Previous theoretical and empirical evidence suggests that workers with higher autonomy have higher wage levels because they are harder to control and monitor and have more disruptive potential if they withdraw their labour (Bayer and Kuhn, 2019; Bloesch et al., 2022; Kalleberg, 2003; Wright, 1997). However, how the relationship between autonomy and wages develops over time is unclear.

We address two key questions in this paper. First, what is the relationship between worker autonomy and wage growth in western Europe? Second, how do technology, institutions and demographics relate to wage growth differences?

In answering these questions, we provide four contributions to the literature. First, we present the first cross-country analysis of the relationship between worker autonomy and job wage growth, contributing to the recent literature on the increasing importance of

Figure 1: Wage growth diverges across jobs



Source: EU SILC, own calculations

worker autonomy for labour market outcomes (Blundell et al., 2022; Deming, 2021). Our second contribution is investigating how institutions relate to changes in the autonomy premium. While collective bargaining institutions are critical determinants of the wage distribution (Farber et al., 2021), they have received less attention in recent empirical research on the autonomy premium. Third, we contribute to understanding the relationship between technological change and job wage growth. Recent studies have argued that technological change complements workers in high-autonomy jobs and thereby contributes to increases in wage inequality. (Deming, 2021). Finally, our demographic subgroup analysis provides a better understanding of the winners and losers from changes in the autonomy premium.

Using high-quality individual-level wage data from the European Union Survey of Income and Living Conditions (EU SILC) for a sample of 15 Western European countries from 2003-2018 [1], we econometrically test the relationship between autonomy and job wage growth. Our main unit of analysis is a job, defined as an occupation-industry-country group. We operationalise worker autonomy with an index capturing the degree of control workers have over their work process, depending on their occupation. This autonomy index is based on prior work by Firpo et al. (2011), using data on job tasks by O*NET provided by the Bureau of Labour Statistics. The index combines information on

[1]The countries are Austria, Belgium, Denmark, Finland, France, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The sample is determined by data availability as discussed in section 3.

autonomy-related job tasks, such as engagement in decision-making, problem-solving or critical thinking. Based on the composition of tasks that are typically performed within an occupation, each occupation is assigned a value of the autonomy index.

Our key finding is a statistically and economically significant relationship between worker autonomy and higher job wage growth. A high autonomy job (one standard deviation above the mean in worker autonomy) is associated with 0.27 percentage points higher annual real wage growth. If both jobs start with the same wage level, the wage gap across these jobs would be 4.2% after 15 years. However, initial wage levels between high- and low-autonomy occupations differ substantially. For example, in 2003, the average wage of managers was 95.7% higher than those of service and sales workers. These groups are roughly three standard deviations apart on the autonomy index. Our main finding suggests an increase in the wage gap between managers and service and sales workers to 120.8% by 2018. All else equal, differences in autonomy predict 46% of the observed wage divergence between these groups.

We highlight the robustness of our main finding across different measures of worker autonomy in several ways. First, we generate alternative worker autonomy indices based on O*NET, in which we change the composition of occupational characteristics. These alternative indices do not alter our result. Second, we reconstruct a subjective measure of worker discretion by Menon et al. (2020) based on the European Work Conditions Survey (EWCS). This measure allows us to include country-specific differences in job designs. Our regression analysis with the EWCS-based measure yields an even more substantial relationship between autonomy and wage growth than our baseline result, suggesting that our baseline result captures is a lower-bound estimate. Finally, we use a measure of supervisory tasks of individual workers provided by EU SILC, which captures differences in the degree of autonomy of workers within the same job. We show that the wages of supervisory workers have grown faster than non-supervisory workers even within the same job, providing further evidence that workers with higher autonomy were able to achieve higher wage increases.

Previous research has highlighted two alternative determinants of wage growth: the ease to routinise (automate) or offshore specific job tasks (see e.g., Autor et al. (2006) and Firpo et al. (2011)). In contrast, we do not find evidence that the ease to routinise or offshore a job explains job wage growth patterns. Splitting our sample into sub-periods reveals that the workers in jobs with routine tasks show slower wage growth up until 2010 but not after. Changes in the return to education or increasing returns to cognitive analytical jobs (i.e. STEM jobs) are also unrelated to job wage growth patterns in our sample. Instead, worker autonomy exhibits a robust association with job wage growth.

After establishing our main finding, the increase in the autonomy premium, we show that technological and institutional factors shape the relationship between autonomy and wage growth. One crucial result is that the autonomy premium increases faster in industries and countries with faster technological change, measured by computer adoption or ICT invest-

ment. In other words, technological change is *autonomy-biased*. In addition, we show that the autonomy wage premium is lower in countries with relatively high union density, high coordination of wage-setting, and where governments regularly consult unions and employer organisations in policy-making and legislation. We infer that collective bargaining institutions can mediate inequalities resulting from technological change.

Finally, our demographic subgroup analysis reveals winners and losers from changes in the autonomy premium and can guide policies that support low-autonomy workers. We do not find differences in the increased autonomy premium across genders. However, the overall increase in the autonomy premium contributes to the gender wage gap because women are more likely to work in low-autonomy jobs. The autonomy premium is higher among older and more experienced workers than among younger workers. Over our sample period, the autonomy premium has increased across all age and experience groups. This increase is most pronounced among workers older than 40. We also show that the autonomy premium increases in areas with high and low population density but not in regions with intermediate density.

Section 2 discusses the previous literature on worker autonomy and wage growth. Section 3 presents our data and shows descriptive statistics. In section 4, we introduce our empirical model. Section 5 exhibits the findings of our analysis. Section 6 concludes.

2 Literature review

Worker autonomy describes the degree of control and influence that workers have over their work process and has been defined and analysed along different dimensions, such as ownership structures of companies (Burdín and Dean, 2009), employment types (Kalleberg, 2003), workplace discretion (Menon et al., 2020), work organisation and occupation design (Lopes and Calapez, 2021), or workplace hierarchies (Bloom et al., 2012). In this paper, we focus on the occupational task dimension of autonomy. Autonomy, in this view, is an inherent feature of the tasks in an occupation and reflects decision-making, problem-solving, critical thinking and supervising other workers.

Worker autonomy has long been highlighted as a crucial wage determinant in the sociology of work, the efficiency wage model and the Marxist notion of labour discipline (Bowles, 1985; Marx et al., 1981; Shapiro and Stiglitz, 1984; Wright, 1997). Because of incomplete contracts, employers must discipline workers by paying higher wages or more intense monitoring. However, workers with higher autonomy are hard to monitor because they perform complex and open-ended tasks requiring decision-making, human judgement and creative thinking. Moreover, these tasks are critical for the production process, and disruption from or withdrawal of these workers is costly for firms. Consequently, high-autonomy workers have higher power and can demand higher wages.

Recent empirical research confirms the relationship between higher autonomy and higher wage levels. Bloesch et al. (2022) find that workers in jobs with critical roles in the produc-

tion process have higher hold-up power and, thus, higher wages in Norway. For Germany, Bayer and Kuhn (2019) show that workers in positions with higher autonomy have higher wages. For the UK, Blundell et al. (2022) show higher wages for workers with stronger influence over work decisions. In contrast to these papers, our primary focus is on how the relationship between autonomy and wages changes over time.

An influential strand in the labour economics literature concerns changing returns to job tasks. Technological change is the most established explanation of why autonomy-related tasks are related to faster wage growth. The increasing use of computers and information and communication technology (ICT) replaces routine tasks (Autor et al., 2003). The remaining tasks are open-ended and require workers to be good at decision-making, problem-solving, critical thinking and adapting to sudden changes in circumstances. This structural shift in the labour market complements occupations with higher worker autonomy and increases demand for tasks that require higher autonomy. Consequently, relative wages for workers with this set of tasks rise.

Deming (2021) shows empirically that technological change increases demand for tasks related to decision-making and raises life-cycle wage growth for workers performing these tasks in the US. The return to decision-making tasks has grown over time, particularly for workers with higher measured ability. These findings suggest a version of skill-biased technological change applied to different levels of autonomy. Notably, the causal chain implies that technology leads to a shift in labour demand for other occupations, which subsequently results in wage growth divergence. Recently, Blundell et al. (2022) argue that ICT innovation changes workplace organisation and reallocation, which requires workers to operate in smaller, more flexible group settings. They show that decision-making in workplaces in the UK has been transferred from top managers to a range of jobs primarily held by university graduates, who subsequently benefitted from higher wage growth. Both Blundell et al. (2022) and Deming (2021) use data for a single country (the UK and the US).

Institutions have long been emphasised as determinants of the wage distribution but have received less attention in recent work on the relationship between autonomy and wages. Collective bargaining institutions allow workers to form alliances across occupations, negotiate wage increases jointly, and compress wage differences. For example, Freeman (1982) shows that wage dispersion within the group of unionised workers is smaller than in non-unionised workers. Similarly, Jaumotte and Osorio (2015) find that powerful labour unions restrain top management remuneration and reduce wage dispersion. In addition, high collective bargaining coverage guarantees that wage gains are shared across jobs (Visser, 2006). In line with this literature, we expect smaller wage growth differences under strong collective bargaining institutions.

Jobs differ in their demographic composition, such as the share of women or the average age in an occupation. Demographic subgroups, in turn, differ concerning their bargaining power or exposure to new technologies. Thus, we expect that the relation between

autonomy and wage growth differs for workers depending on their gender, age, experience, or location. For example, the lower bargaining power of women suggests that the autonomy wage premium rises faster among women. Another example is that workers in larger cities tend to be exposed to faster technological change and related shifts in labour demand (Baum-Snow and Pavan, 2013; Moretti, 2013). Consequently, we expect a stronger relationship between autonomy and wage growth in higher-density areas. Previous empirical research also shows that wage growth differs across the life cycle for workers with varying degrees of autonomy and that high-autonomy workers have more gradual but extended periods of wage growth (Deming, 2021).

Before the recent interest in worker autonomy, the ease to offshore or routinise a job has been suggested as a relevant indicator of wage growth differences. Autor et al. (2003) introduced the routine-biased technological change (RBTC) hypothesis. They showed in a simple production function framework how information and computer technologies (ICT) substitute for middle-skill (routine) occupations but to complement high-skilled (abstract) and low-skilled (manual) occupations (see also Autor et al. (2006) and Goos et al. (2014)). Blinder (2009) and Blinder and Krueger (2013) focus on another task dimension: offshorability. Tasks are offshorable if they can be performed remotely without loss of quality. The causal argument is that declines in transportation and communication costs, tariffs or falling relative wages abroad drive changes in the demand for domestic tasks and occupations. This framework is also used to analyse changes in the job structure and to explain the reduction in the share of middle-skilled jobs - so-called job polarisation. Another critical finding is RBTC can generate the polarised pattern of wage growth observed between the 1980s and the 2000s (Autor, 2013; Autor et al., 2008; Firpo et al., 2011; Goos et al., 2011). However, it is unclear if these factors can explain wage growth patterns for more recent years.

Based on the literature presented in this section, we answer several questions. First, we test if higher worker autonomy is related to higher wage growth in Western Europe. Second, we assess if the autonomy premium grows faster in industries (and countries) with faster technological change. In line with the autonomy-biased technological change hypothesis, we expect a faster increase in the autonomy premium within industries (and countries) with faster adoption of new technologies. Third, we investigate how institutions relate to changes in the autonomy premium because collective bargaining institutions mediate wage inequality. We use differences in labour market settings to assess this relationship. Fourth, we gauge how the rising autonomy premium affects different demographic subgroups, highlight potential heterogeneity, and discuss the winners and losers of recent changes in the wage structure.

3 Data and descriptive statistics

Our primary variable of interest is the gross annual real wage of employees. To obtain individual-level wages, we use harmonised survey data from the scientific use files of

the European Union Survey of Living Conditions (EU SILC). We adjust nominal wages with consumer price inflation data from EUROSTAT. Our data spans from 2003-2018 and includes workers in 15 Western European countries: Austria, Belgium, Denmark, Finland, France, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. We drop Greece because of insufficient sample size.

We follow standard data-cleaning procedures to ensure consistency in our sample. Due to data limitations, we only include workers in regular full-time employment for all 12 months in the reference year. We exclude part-time workers because we do not have precise information on how many hours they have worked over the reference period, and thus we cannot calculate their wage rate consistently. Our analysis excludes self-employed workers to ensure consistency across countries and to exclude employers. Finally, we want to focus on private-sector wage formation and exclude workers in public-sector industries or occupations.

EU SILC provides two-digit International Standard Occupational Classification (ISCO) codes and one-digit industry codes based on the Classification of Economic Activities in the European Community (NACE). The NACE industry classification changes during our sample period from NACE Rev.1 to NACE Rev.2. To account for this, we match industries to six consistent groups: 'Manufacturing and Mining', 'Construction', 'Retail, transport and accommodation', 'Business services', 'Finance' and 'Other private sector services'.

We generate our worker autonomy index with data on job tasks from the Activities and Work Context datasets of the Occupational Information Network (O*NET) database provided by the Bureau of Labor Statistics[2].

Our index varies at the occupation-level and includes the following elements:

- 4.A.2.b.1 Making Decisions and Solving Problems
- 4.A.2.b.2 Thinking Creatively
- 4.A.2.b.4 Developing Objectives and Strategies
- 4.C.1.c.2 Responsibility for Outcomes and Results
- 4.C.3.a.2.b Frequency of Decision Making

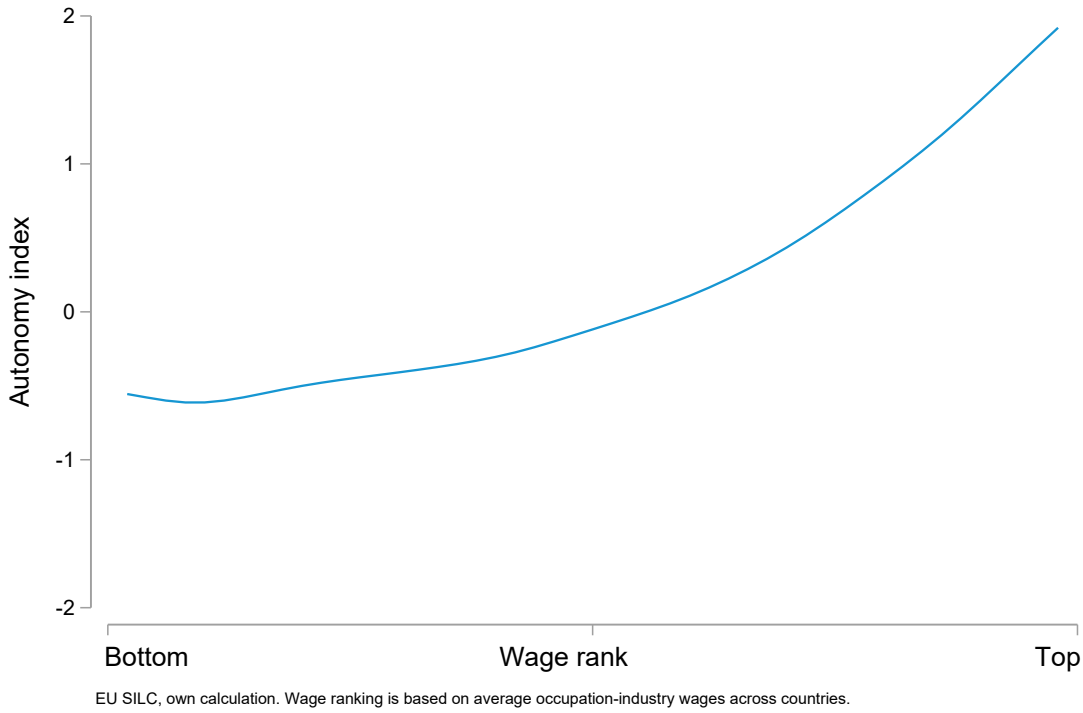
Each occupation is valued according to the five task characteristics outlined above. We argue that each of these characteristics measures relevant dimensions of worker autonomy. For example, if an occupation requires creative thinking or problem solving, workers in this occupation have more control and influence on how work is organised. We additively combine the values of our elements for each occupation and then standardise the index with zero mean and unit standard deviation. A higher value means more worker autonomy.

[2]We use version 20.1. of the O*NET database.

The five characteristics of our index have been used in previous research on occupation-level labour market outcomes. Autor et al. (2003) implicitly use some of these elements in their index of non-routine cognitive tasks, such as problem-solving and communicational tasks. Our index is also related to previous measures capturing decision-making in the work process. Jensen and Kletzer (2010) use decision-making measures to capture an occupation's potential offshorability. Similarly, Firpo et al. (2011) use the elements of our autonomy index as a subcomponent of a broader measure for offshorability without explicitly interpreting their measure as worker autonomy. We argue that our worker autonomy measure is a good proxy for worker autonomy because decision-making and other elements are highly relevant for control and influence over the work process, a critical sign of the ease of monitoring.

High-wage jobs generally have higher autonomy; low-wage jobs have low autonomy. Figure 2 shows worker autonomy along the wage distribution, averaged across European countries. The horizontal axis ranks the average wage of occupation-industry pairs in 2005, the first year when data for all countries is available, while the vertical axis shows the worker autonomy index. The blue dotted line represents the Lowess smooth curve of the relationship between autonomy and wage ranks.

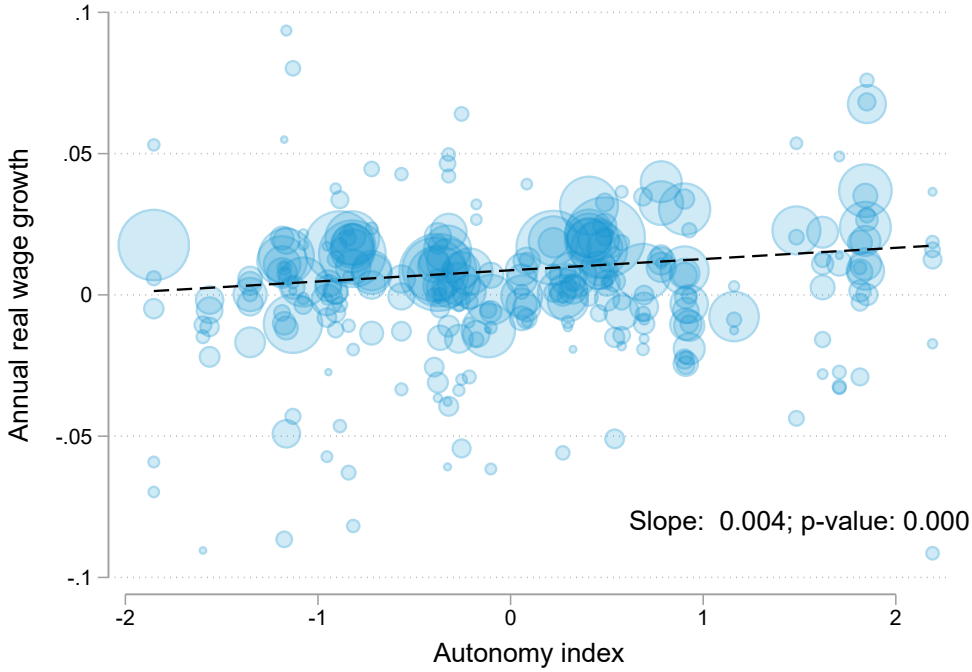
Figure 2: Autonomy index vs wage rank, lowess smooth



The pattern in Figure 2 suggests that inequality increases if wages in high-autonomy jobs grow faster than in low-autonomy jobs. Moreover, Figure 3 plots the correlation between our autonomy measure and job-country groups' annual average wage growth. The correlation is positive and statistically significant at the 1% level, suggesting a link between

autonomy and wage growth.

Figure 3: Annual wage growth vs autonomy index, 2003 - 2018



The linear fit is weighted by employment shares. Circle sizes represent employment shares.

One critical assumption of using our index computed on US data is that the task content of jobs is exogenous to the country-specific institutional context (Belloc et al., 2022). Alternatively, we create a measure of autonomy that reflects country-specific job design based on European Work Conditions Survey (EWCS) data. In contrast to our baseline worker autonomy index, the EWCS-based measure allows us to generate different occupational autonomy values for each country. The EWCS provides workers' self-reported task content. To capture autonomy through workers' control over tasks, methods and speed at work, we replicate a measure of work discretion by Menon et al. (2020). We show details of the EWCS-based measure in Appendix A1. The O*NET- and EWCS-based measures are similar and strongly correlated. Nonetheless, the O*NET based worker autonomy index is the preferred measure for our empirical exercises. The two key reasons for this are that the EWCS based data is more prone to endogeneity issues and measurement error. Endogeneity issues arise because self-reported levels of worker discretion might be affected by cent wage or wage growth changes, thus inducing bias in our regressions in section 4. In addition, the EWCS dataset has a relatively small sample size, leading to imprecise measurement at the job level, which might induce attenuation bias in our regression. However, we will show that our main results are robust to the choice of autonomy measures.

Based on previous work, we generate index measures for the ease of routinising or offshoring an occupation from the O*NET database. We take the offshorability measure from Acemoglu and Autor (2011) and the routinisability measure from Firpo et al. (2011). We

provide details on the replication of these measures and descriptive statistics in Appendix A1.

Autonomy differs from routinisability or offshorability in critical ways. Many low-wage service sector jobs with low autonomy are neither routinisable nor offshorable because these jobs often include tacit manual motions or customer interaction and need to be carried out at specific sites. While worker autonomy generally increases along the wage distribution, offshorability and routinisability exhibit different patterns when plotted against the wage distribution, as shown in Appendix A1. For example, clerical, administrative support, production and operative jobs are highly routinisable. These jobs are often in the middle of the wage distribution, yielding the well-document inverted U-shape pattern of routinisability along the wage distribution (Acemoglu and Autor, 2011). Offshorability is generally proxied with face-to-face interaction and whether a task can be done remotely. Highly offshorable jobs often relate to ICT, which induces remote work. Such jobs span from (low-skilled) call centre workers to (middle- or high-skilled) computer programmers. At the same time, operative jobs are also highly offshorable. Therefore, we can find offshorable jobs in all parts of the wage distribution.

Finally, we use a set of demographic variables at the individual level from EU SILC to account for wage determinants rooted in the Mincerian literature (Mincer, 1958,7), including age, education levels (measured in five ISCED levels), sex, experience, the degree of urbanisation of a workers' residence and migrant [3] status. We show details summary statistics for these variables in Appendix A1.

4 Empirical model and methodology

To answer our main question, we estimate wage growth regressions based on Acemoglu and Autor (2011) and Altonji et al. (2014) and in line with the Mincerian (Mincer, 1958,7) wage model. Thus, we model wage growth as a function of worker autonomy and other job-level variables:

$$w_{ijkct} = b_0 e^{(\beta_1 A_j + \beta_2 X_j)t + \mathbf{B}\boldsymbol{M}_{ijkct}} \quad (1)$$

where w is the real wage of worker i in a job cell, defined by occupation j, industry k, country c, in a given year t. The worker autonomy index A_j differs across occupations. A vector of other task-based measures $\boldsymbol{X_j}$ includes *routinisability* and *offshorability*, indicating how routinisable or offshorable an occupation is. $\boldsymbol{M_{ijkct}}$ is a vector of control variables based on the Mincerian wage equation (Mincer, 1974, 1958) and includes sex, education, age (or experience[4]), age-squared, and country of birth. We log-transform equation 1 to

[3] We do not have data on country of birth or ethnic groups.

[4] In our baseline estimation, we prefer to use age, because experience data is missing for ~5% of our observations. For these observations, we impute potential experience as *Age minus years of education needed to reach the ISCED level of the individual minus 6*.

yield our baseline estimation equation:

$$ln(w_{ijkct}) = \beta_1(A_j \times t) + \boldsymbol{\beta_2(X_j \times t)} + \mathrm{B}\boldsymbol{M_{ijkct}} + \lambda_{jkc} + \theta_{kct} + \varepsilon_{ijkct} \quad (2)$$

Our primary variable of interest is the autonomy index A_j, which is time-invariant and interacts with a linear time trend t. The coefficient β_1 captures the relationship between a higher autonomy measure A_j and annual wage growth. This estimation equation is in line with standard practice in the task-based indicator literature (Acemoglu and Autor, 2011). Other task-based measures $\boldsymbol{X_j}$ also interact with a linear time trend t. The Mincerian variables $\boldsymbol{M_{ijkct}}$ do not interact with a time trend; their coefficient captures the relationship between changes in these variables on the level of log wages.

We estimate equation 2 by OLS, using job (occupation-industry-country) fixed effects λ_{jkc} because we are primarily concerned with wage growth differences across jobs with different levels of autonomy. Our fixed effects strategy accounts for unobserved worker heterogeneity across job cells, such as differences in ability or motivation, as λ_{jkc} conditions out all preexisting wage level differences. If, for example, more able workers sort into high autonomy occupations, job fixed effects capture that.

We include industry-country-year fixed effects θ_{kct} to condition out all time-variant country and industry-specific wage growth trends. Finally, we cluster standard errors at the job level. All wage regressions are weighted using the survey weights provided by EU-SILC, rescaled to weigh each country equally. [5]

Our primary coefficient of interest β_1 captures the relationship between one standard deviation higher worker autonomy and the percentage point deviation of job wage growth from the industry-country wage growth trend. If β_1 equals 0.01, a high-autonomy job is associated with wage growth one percentage point above the average wage growth in an industry-country cell. The same interpretation holds for the coefficients of other task-based measures $\boldsymbol{X_j}$ that interact with time trend t. One standard deviation is, for example, the difference between (more senior) business professionals and (more junior) business associate professionals or between a clerical worker and a cleaner. Managers and service and sales workers, two broad job groups, are three standard deviations apart.

The effects of variables included in Mijkct follow a log-linear interpretation; an increase in, e.g., age by one year relates to wages being B_1% higher. The Mincerian variables $\boldsymbol{M_{ijkct}}$ account for observed individual-level heterogeneity and changes in workers' job composition over time. For example, if a job profile changes because higher educated workers sort into this job, this might subsequently change the average wage in this job. Controlling for the level of education (as part of $\boldsymbol{M_{ijkct}}$) accounts for this effect. Including $\boldsymbol{M_{ijkct}}$ further accounts for potential sampling outliers, e.g., if many young workers are surveyed in a job in a specific year. Finally, we caution that the nonrandom sorting of

[5] Using weights according to different population sizes of our countries does not alter our results. These regression tables are available upon request.

workers over time might make it harder to interpret our findings without controls for unobserved worker skills. Our fixed effects strategy already eliminates unobserved heterogeneity across occupation-industry cells arising from differences in ability or motivation. If, for example, more able workers systematically sort into high autonomy jobs, this will be captured by the job fixed effect. A critical assumption is that the sorting pattern is stable over time, which we believe is plausible because of our relatively short period.[6]

5 Results

5.1 Autonomy and wage growth

Table 1 shows our baseline estimation results based on equation 2 above. We find a strong and statistically significant (at the 0.1%-level) association between worker autonomy and higher wage growth in Western Europe. The economic interpretation of this finding is that a high-autonomy job (one standard deviation above the mean in worker autonomy) is associated with 0.27 percentage points higher annual real wage growth. If wages in the mean autonomy job grew by 1%, wages in a job one standard deviation higher on the autonomy scale grew by 1.27%. If both jobs initially start at the same wage level, the wage level gap would be 4.2% higher after 15 years. This difference increases if we consider that wage levels differ substantially between high- and low-autonomy jobs. In 2003, the average wage of managers was 95.7% above service and sales workers (see Figure 1). These groups are roughly three standard deviations from each other on our autonomy scale. Our baseline estimate for autonomy suggests a wage gap between these two jobs of 120.8% in 2018, all else equal. Thus, our estimate can account for around 46% of the observed increase in the wage gap between these job groups from 2003 to 2018.

While this example illustrates only two job groups, it highlights an important aspect of the difference between the autonomy index and routinisability or offshorability measures. *Managers* and *service and sales workers* are three standard deviations apart in the autonomy index, but both groups have similar values for offshorability and routinisability. Our results in table 1 show that offshorability and routinisability are not related to job wage growth differences in our sample. Thus, the relationship between autonomy and wage growth is in line with the fact that many low-income jobs, which are less easily routinised or offshored (e.g., *service and sales workers*, have experienced low wage growth.

Turning to the control variables based on the Mincer equation, wage levels increase with education and age, although at a declining rate. The gender wage gap in our sample of full-time employees is 19%. While this does not account for various factors, e.g. if the worker has managerial responsibilities or the observation that more women than men are

[6]Card et al. (2013) suggest one simple exercise to analyse sorting patterns with observables. We adopt their estimation strategy and regress the average education level in a job on the education level of the individual each year. Our results for this test are available upon request. We find that the coefficients for sorting on observables are not significantly different between early and late years in our sample, but they exhibit a slight inverted u-shape pattern in between. Thus, we do not find evidence that sorting on observables did change over years. This finding supports our estimation strategy and the interpretation of our main results.

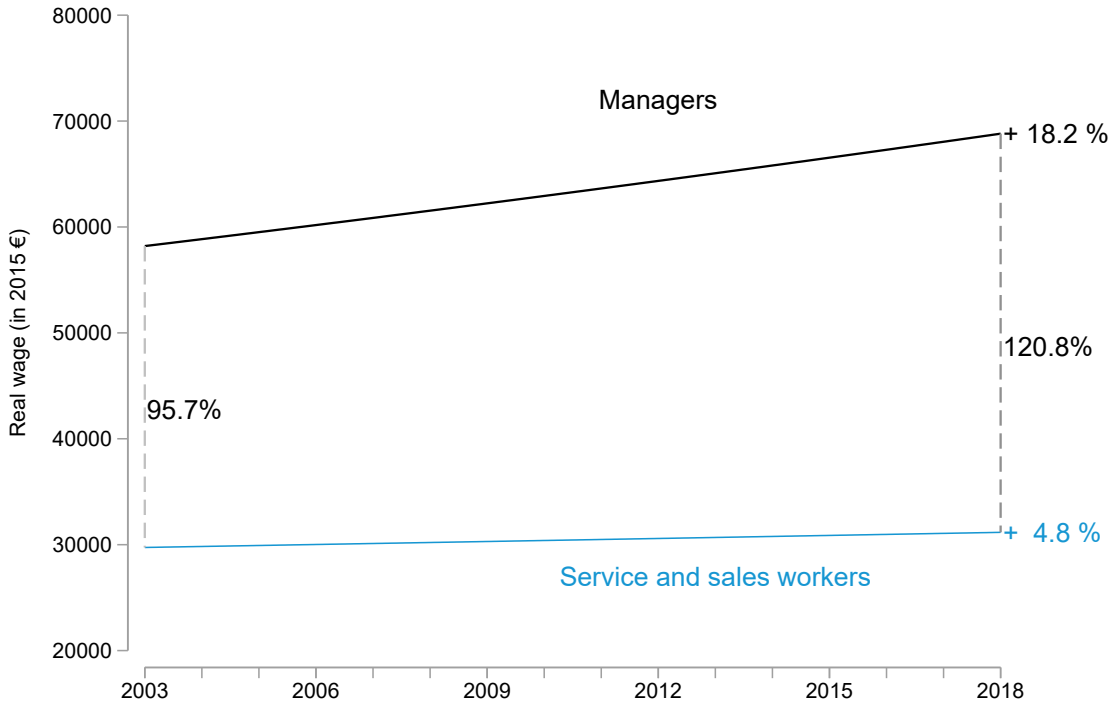
Table 1: Main finding

	(1) Baseline
Autonomy	0.0027^{***}
	(0.0006)
Routinisation	0.0004
	(0.0006)
Offshoring	0.0003
	(0.0004)
Women	-0.1919^{***}
	(0.0035)
Lower sec. educ.	0.0720^{***}
	(0.0071)
Upper sec. educ.	0.1704^{***}
	(0.0076)
Post-sec. non tert. educ.	0.2358^{***}
	(0.0103)
Tertiary education	0.3287^{***}
	(0.0086)
Age	0.0566^{***}
	(0.0011)
Age2	-0.0005^{***}
	(0.0000)
EU foreign	-0.0370^{***}
	(0.0065)
Other foreign	-0.0836^{***}
	(0.0057)
Observations	808122
r2	0.5450

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4: Autonomy can account for a substantial increase in the wage gap between Managers and Service and sales workers



in part-time employment and are therefore excluded from our sample, the magnitude of this gap is substantial. EU foreign-born workers and other foreign workers have statistically significantly lower wages than native workers.

5.2 Robustness of our main finding

Table 2 highlights that worker autonomy is the main wage growth determinant over our sample period. Column 1 shows that the coefficient for autonomy is still significant after excluding routinisability and offshorability. In column 2, we test whether increasing returns to higher education predict job wage growth patterns, in line with the canonical model of Katz and Murphy (1992). We do that by adding an interaction term between a dummy for higher education and a linear time trend to our specification. However, we find that the return to higher education declines after accounting for autonomy. Column 3 includes a variable for cognitive analytical jobs, which proxies for STEM jobs. The inclusion of this measure does not alter our finding for autonomy, and the STEM job measure is negatively related to wage growth, conditional on autonomy. Finally, our demographic variables are robust to several specifications, with expected signs across all robustness checks, thus supporting our model specification.

Next, we show that our main finding is robust to different job-level autonomy measures. First, we support our analysis with a country-specific measure based on self-reported worker data on autonomy from EWCS. In contrast to our baseline worker autonomy index,

Table 2: Robustness 1

	(1) excl. Rou and Off	(2) Return to education	(3) Cognitive anal.
Autonomy	0.0025***	0.0029***	0.0042***
	(0.0005)	(0.0007)	(0.0010)
Routinisation		0.0003	
		(0.0006)	
Offshoring		0.0004	
		(0.0004)	
College return		−0.0006*	
		(0.0003)	
Cognitive analytical (AA)			−0.0019**
			(0.0009)
Women	−0.1919***	−0.1918***	−0.1919***
	(0.0035)	(0.0035)	(0.0035)
Lower sec. educ.	0.0720***	0.0764***	0.0719***
	(0.0071)	(0.0074)	(0.0071)
Upper sec. educ.	0.1704***	0.1796***	0.1703***
	(0.0076)	(0.0091)	(0.0076)
Post-sec. non tert. educ.	0.2358***	0.2495***	0.2357***
	(0.0103)	(0.0129)	(0.0103)
Tertiary education	0.3287***	0.3482***	0.3286***
	(0.0086)	(0.0137)	(0.0086)
Age	0.0566***	0.0566***	0.0566***
	(0.0011)	(0.0011)	(0.0011)
Age2	−0.0005***	−0.0005***	−0.0005***
	(0.0000)	(0.0000)	(0.0000)
EU foreign	−0.0370***	−0.0369***	−0.0370***
	(0.0065)	(0.0065)	(0.0065)
Other foreign	−0.0836***	−0.0836***	−0.0836***
	(0.0057)	(0.0057)	(0.0057)
Observations	808122	808122	808122
r2	0.5450	0.5450	0.5450

Standard errors in parentheses

Column 1 excludes Routinisation and Offshoring from our baseline specification.

The measure for Cognitive analytical is from Acemoglu and Autor (2011).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

computed on US data, this EWCS-based measure for worker discretion allows us to generate different occupational autonomy values for each country. Thus, this measure accounts for the fact that job designs might be country-specific, e.g. because institutions ensure job designs with higher autonomy.

Column 1 in Table 3 shows regressions with the worker discretion measure from Menon et al. (2020), capturing perceived job discretion. We show details of the EWCS-based measure in Appendix A1. In the regression shown in column 1, the coefficient for the EWCS-based measure is positive, statistically significant and even higher than our baseline estimate. One standard deviation higher worker discretion relates to 0.4 percentage-point higher annual wage growth. Thus, the size of this coefficient suggests that our baseline estimate in column 1 in Table 1 might capture a lower-bound estimate for the effect of autonomy on wage growth.

Column 2 and 3 shows the robustness of our results for alternative O*NET-based autonomy measures. We show details of these measures in Appendix A1. In column 2, we replace our autonomy measure with a decision-making index by Deming (2021). This measure is significant, and the coefficient is similar to our baseline result. Column 3 shows the coefficient for the extended autonomy index, consisting of nine characteristics. These findings address concerns that small changes in our main index affect our main result.

Finally, we add further insight into wage growth between workers with and without supervisory roles within the same occupation. Workers with supervisory roles have higher autonomy than those without supervisory roles. We use information about supervisory roles from EU SILC, asking workers, 'Does your job include supervising others?'[7]. In column 4 in Table 3, we include this supervisory task variable as a dummy to capture the wage level difference between workers with and without supervisory tasks (i.e., the supervisory task premium). Moreover, we interact the supervisory task variable with a linear time trend to capture wage growth differences (i.e., the increase in the supervisory task premium). We find that the adjusted wage difference between workers with and without supervisory tasks is 14% and increases by 0.25pp each year. We argue that supervisory roles are a valuable proxy for worker autonomy, capturing different job levels within an job. Thus, this finding provides further evidence of the increasing wage return to worker autonomy.

Another set of robustness tests is summarised in Figure 5, which reports the coefficients for autonomy from alternative model specifications. All regression tables from Figure 5 are shown in more detail in Appendix A2. To address concerns that changes in the occupational classification could impact our results, we split our sample into two sub-periods according to the changes in ISCO classification (2003-2010 and 2010-2018). Our coefficient is similar over both periods, as shown in rows 2 and 3. Another observation from this sub-period analysis is that routinisation has a negative and statistically significant effect

[7]In Appendix A1 we show that almost a third of all workers in our sample have supervisory duties and that workers with supervisory tasks are concentrated at the top of the wage distribution.

Table 3: Robustness 2: Alternative measures

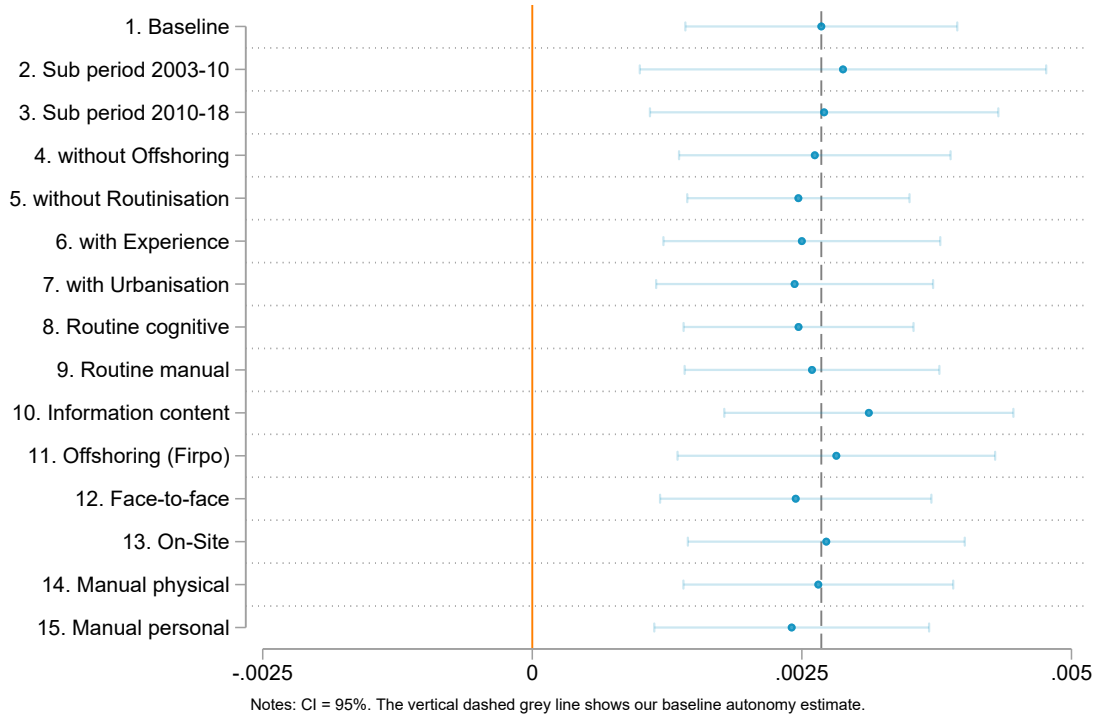
	(1) Autonomy (EWCS)	(2) Decision (Deming)	(3) Autonomy alternative	(4) Supervisory tasks
Autonomy (EWCS)	0.0047***			
	(0.0010)			
Decision-making (Deming)		0.0027***		
		(0.0006)		
Autonomy altern. index			0.0032***	
			(0.0008)	
Supervisory tasks				0.0025***
				(0.0006)
Routinisation	0.0001	0.0004	0.0010	-0.0004
	(0.0006)	(0.0006)	(0.0007)	(0.0005)
Offshoring	-0.0010**	0.0003	-0.0003	0.0003
	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Women	-0.1919***	-0.1919***	-0.1919***	-0.1801***
	(0.0035)	(0.0035)	(0.0035)	(0.0033)
Lower sec. educ.	0.0720***	0.0720***	0.0720***	0.0690***
	(0.0071)	(0.0071)	(0.0071)	(0.0069)
Upper sec. educ.	0.1704***	0.1704***	0.1705***	0.1603***
	(0.0076)	(0.0076)	(0.0076)	(0.0074)
Post-sec. non tert. educ.	0.2359***	0.2358***	0.2359***	0.2193***
	(0.0103)	(0.0103)	(0.0103)	(0.0097)
Tertiary education	0.3287***	0.3287***	0.3288***	0.3118***
	(0.0086)	(0.0086)	(0.0086)	(0.0084)
Age	0.0566***	0.0566***	0.0566***	0.0529***
	(0.0011)	(0.0011)	(0.0011)	(0.0010)
Age2	-0.0005***	-0.0005***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
EU foreign	-0.0370***	-0.0370***	-0.0370***	-0.0307***
	(0.0065)	(0.0065)	(0.0065)	(0.0062)
Other foreign	-0.0836***	-0.0836***	-0.0836***	-0.0727***
	(0.0057)	(0.0057)	(0.0057)	(0.0054)
Supervisory task premium				0.1367***
				(0.0055)
Observations	808122	808122	808122	764415
r2	0.5450	0.5450	0.5450	0.5931

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

on wage growth in the period until 2010 (see Table A2.2 in Appendix A2). While routinisability is related to lower wage growth between 2003-2010, its coefficient is positive and significant for 2010-2018, suggesting that, controlling for autonomy, average wages in routinisable jobs have risen.

Figure 5 highlights that our coefficient for worker autonomy remains unaffected by a variety of robustness checks. In row 4 we exclude the measure for routinisability and in row 5 the measure for offshorability. We substitute age with a measure for experience in row 6. Row 7 includes a measure for the degree of urbanisation of a workers' residence to address concerns that our result is driven by urbanisation. Rows 8 to 10 include alternative measures for routinisability or automatability. Rows 11 to 13 include alternative measures for offshoring. Rows 14 and 15 include task-based measures for non-routine manual jobs.

Figure 5: Further robustness checks



Lastly, we conduct jackknife analyses to account for concerns that a single country or industry has an outsized influence on our results. Figure A2.1 in Appendix A2 plots the autonomy coefficient after excluding single countries one by one. Figure A2.2 addresses the same concern for each industry. Our results for autonomy remain unaffected, strongly supporting our main finding that worker autonomy can explain wage growth differences in Western Europe between 2003-2018.

Further robustness checks are available on request. For example, trimming the top and bottom 0.1%, 1%, or 5% of wage earners in each country-year group does not change our finding. These regressions suggest that it is not only top managers or CEOs capturing the

increase in wages but also that the increasing return to autonomy is pervasive across the income distribution. Managers, as defined as ISCO's one-digit occupation group, include roughly 5-15% of wage earners across countries. Lastly, we include synthetic job panels, which support our results. However, we strongly prefer the approach presented here as it uses individual-level variation, whereas synthetic panels collapse each job cell, thereby reducing variation in our data and reducing the precision of our results. Nonetheless, our results from the synthetic panel regressions confirm our main findings.

6 Technological change, institutions, and demographic characteristics

Section 5 showed our main finding, an increase in the autonomy premium. Now we shed light on how technology, institutions and demographic characteristics relate to this finding.

6.1 Autonomy and technological change

We measure technological change as changes in ICT investment and computer use using data from EU KLEMS and EWCS. First, we compare changes in the autonomy premium in countries with fast and slow technology adoption. We create a binary variable TC for countries with above- and below-median change in the share of ICT investments measured as the change of ICT investments divided by gross fixed capital formation (GFCF) and re-estimate our baseline regression with the interaction term TC as shown in equation 3.

$$ln(w_{ijkc}) = \gamma_1 A_j + \gamma_2 (A_j \times TC) + \text{controls} + \theta_{kc} + \varepsilon_{ijkc} \quad (3)$$

The coefficient γ_1 estimates the increase in the autonomy premium in countries with below-median increases in the share of ICT investments of GFCF, $\gamma_1 + \gamma_2$ is the estimate for countries with above-median increases. The result for this regression in column 1 of table 4 shows that the autonomy premium rises faster in countries with more substantial increases in ICT investments. The estimation in column 2 interacts autonomy with the continuous change in the ICT investment share. The result confirms that faster changes in ICT investments are related to faster increases in the autonomy premium. A 1% faster increase in the share of ICT investments in GFCF is related to a 1.1% increase in the autonomy premium.

We visualise the relationship between ICT adoption and the autonomy premium in figure 6. To yield this figure, we first estimate equation 2 for each country separately to get country-specific changes in the autonomy premium. In the second step, we estimate the relationship between changes in the autonomy premium and increased ICT investments, as shown in equation 4 below. We find a strong correlation between faster ICT investment and an increased autonomy premium across countries.[8]

[8] EU KLEMS does not provide data for Norway, Switzerland and Belgium.

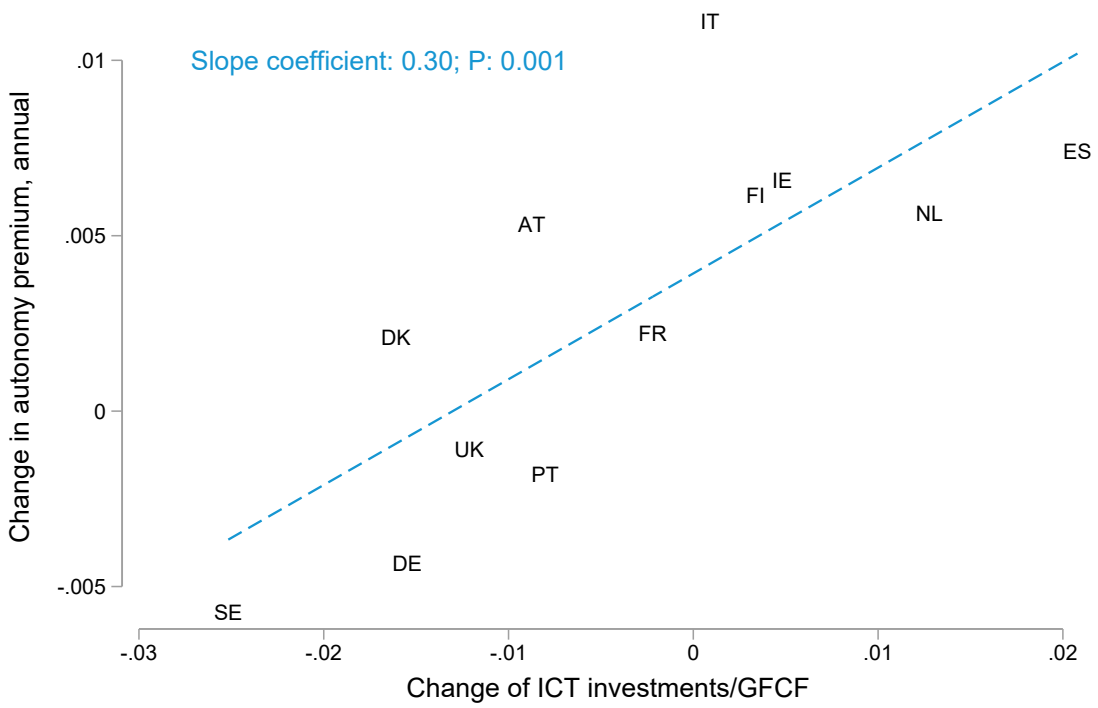
Table 4: ICT adoption

	(1) Fast ICT adoption, dummy	(2) Change in ICT share of GFCF, continuous
Autonomy	0.0009 (0.0008)	0.0028*** (0.0006)
Autonomy × ICT: Fast adoption	0.0030** (0.0012)	
Autonomy × Change in ICT share of GFCF		0.0011** (0.0005)
Observations	695038	695038

Regressions as in equation xx. Controls include gender, age, education, migrant status.
All regressions include occupation-industry-country and industry-country-year fixed effects.
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

$$\Delta\text{autonomy premium}_c = \gamma_1 \Delta\text{ICT}_c + \varepsilon_c \quad (4)$$

Figure 6: Increases in ICT investments are strongly related to the increasing autonomy premium



These results align with arguments that technological change is biased towards high-autonomy jobs. Next, we focus on technological change at the industry level. The technological change argument suggests that the autonomy premium increases more in industries with faster technology adoption. We estimate equation 2 for each industry-country group ic separately to yield group-specific changes in the autonomy premium. We draw on data from EWCS and generate the change in computer use within each country-industry pair from 2005 to 2015.[9] Then, we regress the industry-country-specific changes in the

[9]The EWCS is conducted every five years. The variable for computer use is based on the questions 'How

autonomy premium on the change in computer use in each group in line with equation 5.

$$\Delta\text{autonomy premium}_{ic} = \beta_1 \Delta\text{computer use}_{ic} + \kappa_c + \varepsilon_{ic} \quad (5)$$

Table 5 presents the result from estimating equation 5 by OLS with robust standard errors across industries. Country-specific fixed effects κ_c adjust for country-specific trends. The autonomy premium increases significantly faster in industries with faster adoption of computer use from 2005 to 2015.[10] While we caution that the estimations in this section cannot isolate technology's causal effect on the autonomy premium the results support a tight relationship between these two factors.

Table 5: Computer use and the autonomy wage premium

	(1) Δ Autonomy wage premium
Δ Computer use	0.0265**
	(0.0131)
Observations	90
r2	0.2911
Country FE	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2 Autonomy and collective bargaining institutions

We test the relationship between collective bargaining power and the autonomy wage premium using differences in labour market settings across European countries. In countries with strong collective bargaining across jobs, workers across jobs can bargain for wages jointly, leading to lower inequality. To test this argument, we split countries by collective bargaining features and analyse levels and trends in the autonomy premium. We capture collective bargaining power through several measures, such as union density, the level of wage coordination, the involvement of employees in policy-making, collective bargaining coverage and employment protection legislation (EPL). We use data from the OECD-AIAS-ICTWSS database and the OECD EPL indicator.

often does your main paid job involve each of the following? Working with computers: PCs, network, mainframe' in 2005 and slightly changed in 2015 to 'Please tell me, does your main paid job involve ...? working with computers, laptops, smartphones etc.?' to include laptops and smartphones.
EWCS codes respond to the computer use questions with seven categories ranging from *never* to *all the time*. Following Menon et al. (2020), we create a binary measure for a worker using computers at least some of the time (1) or never (0). Finally, we calculate the proportion of computer users by industry and use the change of this proportion from 2005 to 2015 in estimating equation 4.

[10] We use ICT measures on the country level and computer use at the industry level for the following reasons. ICT at the country level allows focusing on the adoption of ICT infrastructure in a country. For example, a business service company invests in new keystroke monitoring techniques, this service, in turn, is then consumed by a retail firm, but does not appear as ICT capital formation by the retail firm. In contrast, computer use is a more direct measure of changes in work processes at the industry level.

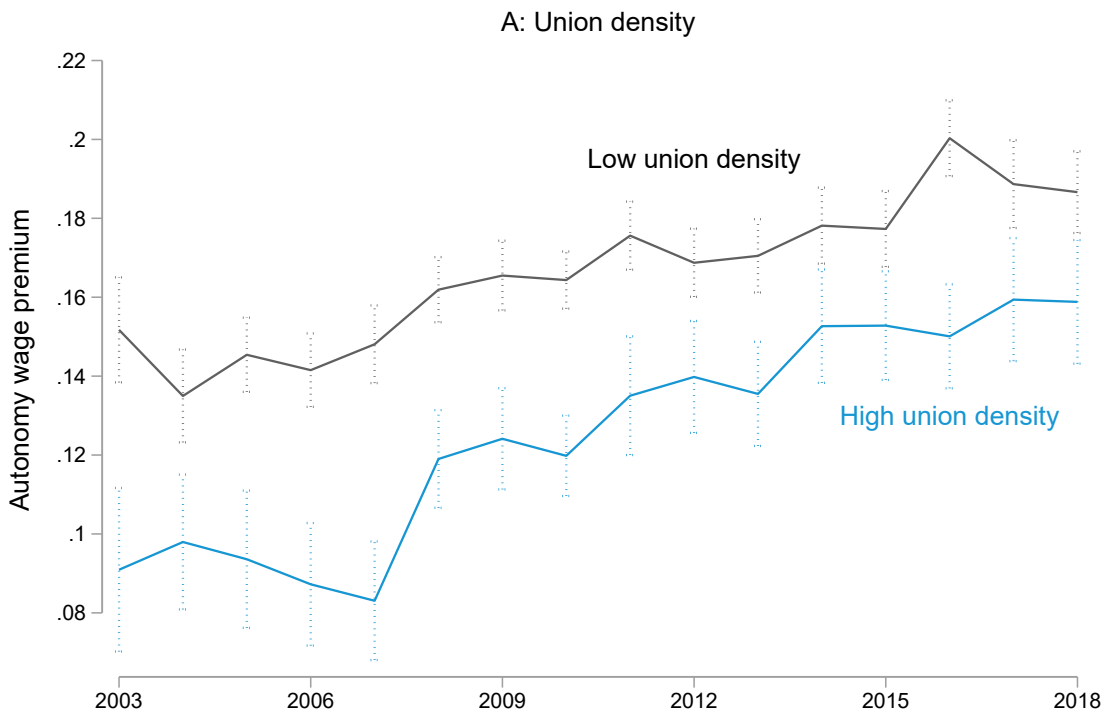
First, we shed light on the differences in wage levels across high- and low-collective bargaining countries and estimate individual-level wage (level) regressions in each year, as shown in equation 6,

$$ln(w_{ijkc}) = \lambda_1 A_j + \lambda_2 \text{CB} + \lambda_3 (A_j \times \text{CB}) + \text{controls} + \theta_{kc} + \varepsilon_{ijkc} \quad (6)$$

where $ln(w_{ijkc})$ is the log of annual wages for individual i in occupation j in industry k, country c. A_j is the autonomy index. We add a dummy variable for high or low country-level collective bargaining CB, defined as countries with union density above (CB = 1) and below the median (CB = 0, and an interaction term between the autonomy index and the dummy).

We estimate equation 6 by OLS for each year t. We do not interact our index measure index with a time trend because we estimate the equation for each year separately. We cluster standard errors at the job (occupation-industry-country) level. We include the same control variables discussed in equation 2 above: task measures for routinisability and offshorability and the Mincerian variables. The industry-country fixed effect θ_{kc} conditions out wage growth differences across industries and countries. Thus, estimating equation 6 yields coefficients for the wage level difference between two occupations one standard deviation apart in autonomy - the autonomy premium. The coefficient λ_1 captures the autonomy premium in low-union density countries and the sum of coefficients $\lambda_1 + \lambda_3$ the autonomy premium in countries with high union density. We plot these coefficients in Figure 7.

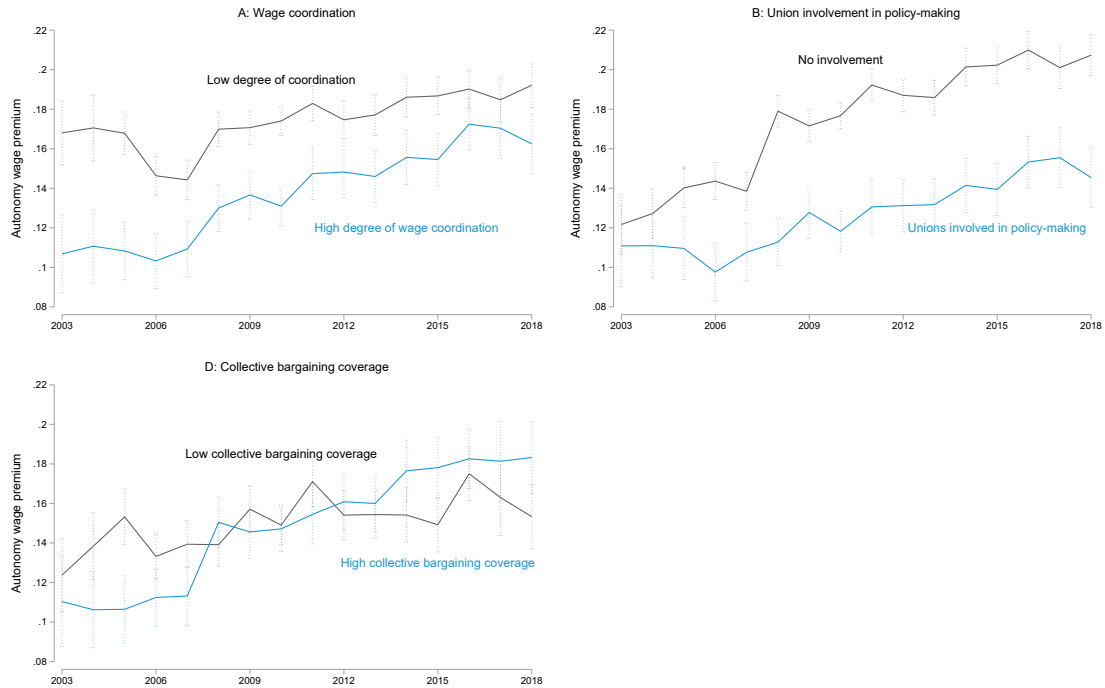
Figure 7: Countries with low union density have a higher autonomy premium



The autonomy premium is larger in low-union countries, indicating that countries with higher union density have lower wage level differences between high- and low-autonomy occupations. This pattern suggests that union density is related to a lower autonomy premium by improving the relative bargaining power of low-autonomy workers. This finding might indicate that labour unions while related to lower autonomy premia, were less able to keep wage divergence in check over the last two decades.

In some European countries, other institutions are more appropriate measures of collective bargaining. These include the degree of wage-setting coordination (defined as an index measure that increases with more centralised wage negotiations and binding norms regarding wage negotiations), the routine involvement of employees in social and labour policy legislation, private sector collective wage agreement coverage (defined as the share of workers covered by wage bargaining agreements) or employment protection legislation (EPL). Thus, we estimate equation 6 by splitting countries along these variables. Figures 8A-D reproduce the results reported in Figure 7 after replacing union density with alternative bargaining measures.[11]

Figure 8: The autonomy premium and collective bargaining



Source: EU SILC, own calculations

Results for the coordination of wage-setting (Figure 8A) and the involvement of unions in economic policy (Figure 8B) confirm our findings for union density. Both variables suggest a higher autonomy premium in weak collective bargaining countries. Countries with high collective bargaining coverage show a more rapid increase in the autonomy premium

[11]Details on the institutional measurement variables and the country grouping are also shown in Appendix A3.

(Figure 8C), in line with our findings for union density. In contrast, countries with higher involvement of unions in policy-making show a slower growth of the autonomy premium (8B). The difference in the autonomy premium between countries with and without the involvement of unions in policy-making has increased noticeably during the Great Financial Crisis, indicating that the involvement of worker and employer organisations is crucial in crisis periods.

Figure 8C contrasts the autonomy premium across countries with high and low coverage of collective wage agreements. While the autonomy premium in high collective wage agreement countries was lower until the Great Financial Crisis, it surpassed the premium in low collective wage agreement countries after the crisis. However, the difference across both country groups is generally not statistically significant. One potential explanation for why collective wage agreements have a negligible impact on job-level wage inequality is that these agreements are often occupation-specific and, thus, do not span across occupations. In such settings, workers with high and low autonomy do not bargain jointly for wage increases. Figure 8D show that countries with high and low EPL have similar levels and trends in the autonomy premium.

Next, we shed more light on the slopes in figures 7 and 8, which suggest collective bargaining power is unrelated to increases in the autonomy premium. Thus, we estimate a set of wage growth regression with interaction terms for high and low bargaining countries, as in equation 3 in section 6.1.

In Table 6 we estimate regressions with an interaction term for low collective bargaining levels at the beginning of our sample period. In line with our findings in figures 8A-C and 7, none of our bargaining variables suggests that the autonomy premium rises faster in high-collective bargaining countries. In contrast, column 3 shows that the autonomy premium grows significantly faster in countries with high collective wage bargaining coverage. In Table 7 we split countries into above- and below-median changes in collective bargaining. For example, the interaction term in column 1 signals that countries with faster declines in union density do not see significantly different trends in the autonomy premium. Results in columns 2 to 4 follow the same interpretation. In table 8, we interact autonomy with the continuous change in collective bargaining variables. Again, we do not find any significant interaction terms for union density, bargaining coverage or EPL. Only column 2 suggests that an increase in the degree of wage coordination is related to a statistically significant slower increase in the autonomy premium. To sum up, we do not find robust patterns between collective bargaining and increases in the autonomy premium in our sample.

The bottom line from this section is that we do not find a robust pattern between collective bargaining and increases in the autonomy premium in our sample. Collective bargaining does not appear to mitigate the relationship between autonomy and wage growth because the autonomy premium increases in countries with high and low collective bargaining over our period. However, wage inequality is lower in countries with stronger collective

Table 6: Collective bargaining, levels, dummy

	(1) Union density	(2) Wage coordination	(3) Bargaining coverage	(4) Routine involvement	(5) Employment protection
Autonomy	0.0021***	0.0014**	0.0012	0.0029***	0.0030***
	(0.0007)	(0.0007)	(0.0009)	(0.0007)	(0.0007)
Autonomy × High union density	0.0009				
	(0.0011)				
Autonomy × High coordination		0.0016			
		(0.0010)			
Autonomy × High coverage			0.0021*		
			(0.0011)		
Autonomy × Routine involvement				-0.0008	
				(0.0010)	
Autonomy × High employment protection					-0.0011
					(0.0011)
Observations	808122	808122	808122	808122	808122

Regressions as in equation xx. Controls include gender, age, education, migrant status.
All regressions include occupation-industry-country and industry-country-year fixed effects.
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Collective bargaining, changes, dummy

	(1) Decline union density	(2) Decline coordination	(3) Decline coverage	(4) Decline EPL
Autonomy	0.0032***	0.0020***	0.0027***	0.0024***
	(0.0007)	(0.0006)	(0.0007)	(0.0008)
Autonomy × Decline union density	-0.0015			
	(0.0011)			
Autonomy × Decline coordination		0.0019		
		(0.0014)		
Autonomy × Decline coverage			-0.0006	
			(0.0011)	
Autonomy × Decline EPL				0.0001
				(0.0010)
Observations	808122	808122	808122	808122

Regressions as in equation xx. Controls include gender, age, education, migrant status.
All regressions include occupation-industry-country and industry-country-year fixed effects.
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Collective bargaining, changes, continuous

	(1) Change union density	(2) Change coordination	(3) Change coverage	(4) Change EPL
Autonomy	0.0031***	0.0025***	0.0030***	0.0025***
	(0.0009)	(0.0005)	(0.0006)	(0.0005)
Autonomy × Change union density	0.0001			
	(0.0001)			
Autonomy × Change coordination		-0.0008**		
		(0.0003)		
Autonomy × Change coverage			0.0001	
			(0.0002)	
Autonomy × Change EPL				0.0057
				(0.0150)
Observations	808122	786972	657278	808122

Regressions as in equation xx. Controls include gender, age, education, migrant status.
All regressions include occupation-industry-country and industry-country-year fixed effects.
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

bargaining institutions. While we cannot identify a causal effect of collective bargaining on individual wage levels due to unobserved individual-level heterogeneity in ability or motivation, our results suggest that collective wage bargaining institutions generally relate to smaller wage inequality. One possible interpretation of these findings is that collective bargaining compresses the wage distribution but has become less effective in supporting low-autonomy workers in recent years.

6.3 Autonomy and demographic factors: age, experience, urbanisation, and gender

Next, we discuss potential heterogeneity in the autonomy premium to see if specific demographic subgroups drive our results and to shed light on the winners and losers of changes in the autonomy premium, possibly allowing more targeted policy support. In particular, we discuss differences across gender, age and population density.

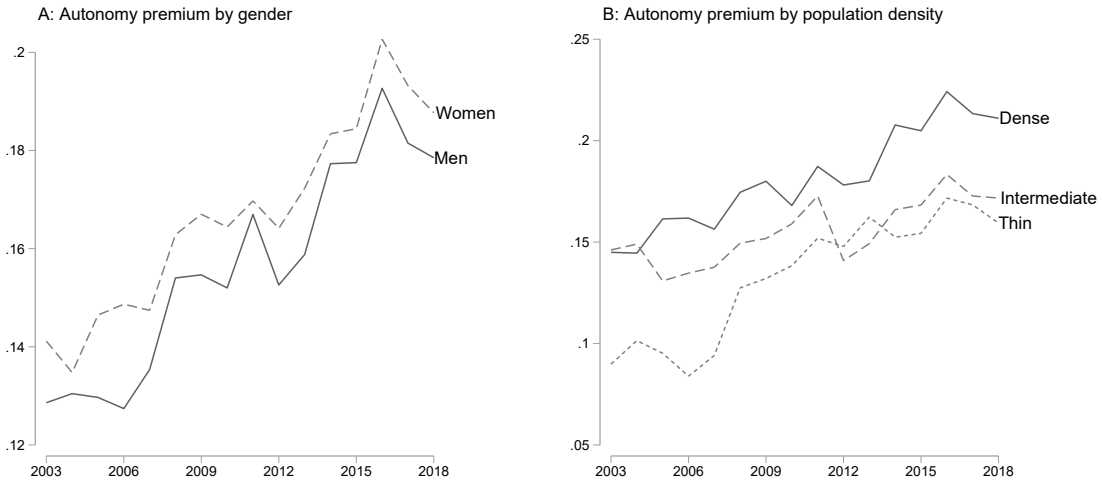
Women have lower bargaining power and are less often unionised. This suggests that the autonomy premium might increase more for women. Figure 9 shows changes in the autonomy wage premium for men and women separately. The autonomy premium follows a similar trend in both groups, and there is no statistical difference between the level or the growth rate of the autonomy premium in our sample of full-time employed workers.[12] As women are more often in non-regular employment relationships, our sample of full-time employed workers might underestimate the increase in wage inequality among women. Even though we do not find differences in the autonomy wage premium across gender, our findings have implications for the gender wage gap. In our sample of full-employment workers, the share of women in low-autonomy occupations is higher than men.[13] Because women often work low-autonomy jobs, the increase in the autonomy premium disadvantages women and increase the gender wage gap.

Figure 9B shows the autonomy premium across different levels of population density based on geographic data from EU SILC. We find that the autonomy premium is higher in densely populated regions and increases in densely and thinly populated regions, but not in regions with intermediate density. As dense regions might have seen faster technological change and corresponding shifts in labour demand (Baum-Snow and Pavan, 2013; Moretti, 2013), our result for dense areas aligns with our findings on the relationship between technological change and the autonomy premium. The increase in wage inequality within thinly populated areas is less established but might reflect increasing disparities between prosperous and less prosperous rural areas.

We find that workers with higher autonomy experience longer and more gradual periods of wage growth in Western Europe, in line with earlier work by Deming (2021) on the US. The solid line in Figure 10A. The solid line exhibits the autonomy premium along the

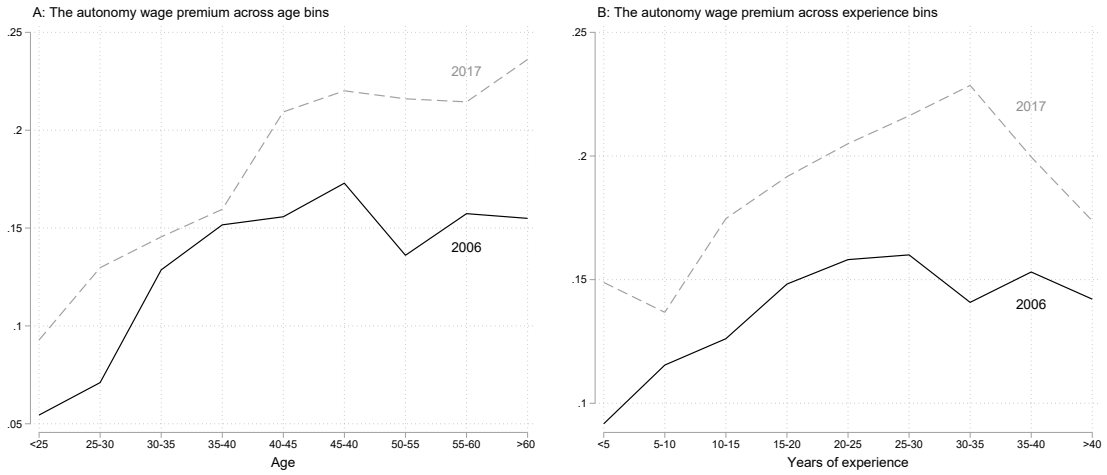
[12]The underlying regression tables for all figures in section 6 are available upon request.
[13]Data shown in Appendix A3.

Figure 9: The autonomy premium over time for gender and population density



age distribution averaged in 2006 [14]. The dashed line exhibits the autonomy premium in 2017. We generate 5-year age bins and interact them with our autonomy measure, following the estimation strategy in equation 4. Three facts emerge. First, the autonomy premium is higher for older workers than younger workers. Second, the autonomy premium has increased across all age bins. Third, the autonomy premium increase is most pronounced among workers older than 40. One potential interpretation for this set of results is that many high-autonomy workers are not in regular employment for substantial periods across their life cycle. They might be in education throughout their 20s, retire early if they accumulate sufficient wealth, or leave regular employment to start a company.

Figure 10: The autonomy premium along age and experience



Our findings for changes in the autonomy premium across experience bins confirm the

[14] We chose 2006 as the starting point for this exercise because it requires highly detailed data, which we think is not available in all countries prior to that.

overall findings from age, shown in Figure 10B. The autonomy premium is higher for more experienced workers and has increased across all experience bins. In 2017, the autonomy premium slightly decreases in the highest experience bins (workers with over 35 years of experience). We prefer the age measure because of its broader coverage. For missing experience observations, we impute potential experience as age minus years of education level minus 6, proxying potential experience.

7 Conclusion

Our results provide a new perspective on the role of job characteristics and wage inequality. We find a significant relationship between worker autonomy and job wage growth in Western Europe. Wages in a high-autonomy job have grown on average 0.27 percentage points faster each year from 2003 to 2018 than wages in a job with mean autonomy. This process has increased wage inequality as high-autonomy jobs are generally at the top of the wage distribution. Our main finding is robust to several alternative measures of autonomy and to the inclusion of other job characteristics and a rich set of control variables. Specifically, we show that previously favoured task characteristics, such as the ease to routinise or offshore a job, cannot explain wage growth differences in our sample. Moreover, no single country or industry drives the autonomy premium. Instead, the increase in the autonomy premium is a persistent feature across Western European economies.

In line with earlier work, we show a tight relationship between technology adoption and changes in the wage distribution. We highlight that the increase in the autonomy premium is tightly linked to technological change, measured by computerisation and ICT, the general-purpose technologies of recent decades.

Using different institutional settings across European countries, we find that the autonomy premium is lower in countries with relatively high union density, high coordination of wage-setting and where governments regularly consult unions and employer organisations in policy-making. We infer that collective bargaining can mediate inequalities resulting from technological change and allows productivity gains to be shared more equally. However, we find that the autonomy premium is increasing across countries with strong and weak collective bargaining countries, suggesting that labour unions could not halt the recent increase in the autonomy premium.

We also shed light on the interaction between demographic factors and the autonomy premium. The autonomy wage premium is higher and increases faster among more experienced workers and workers in urban areas. In addition, the autonomy premium increases across both genders in a similar magnitude. However, the increase in the autonomy wage premium contributes to the gender wage gap because women more often work in low-autonomy jobs.

Our work has important policy implications. Recent technological change is not neutral across the income distribution. It strengthens the wage bargaining power of relatively

high-wage workers while reducing the bargaining power of low-wage workers. If concerned about wage inequality, policymakers should focus on workers in low-autonomy jobs, particularly in industries with fast technological adoption and weak collective bargaining institutions. Strengthening collective bargaining institutions that enhance worker power across occupations, such as unions, wage coordination and the involvement of employee organisations in economic policy, enhance worker wage bargaining power across jobs and can reduce wage inequality.

Finally, our work has implications for future research. While we only focus on regularly employed workers due to data limitations, future research could explore how changes in the employment structure affect changes in inequality. Over recent years, self-employment has increased, particularly at the bottom of the distribution. Because of this trend, our analysis may understate wage growth patterns across worker groups. Against the background of the rich and multidimensional research on autonomy (Burdín and Dean, 2009; Kalleberg, 2003; Lopes and Calapez, 2021; Menon et al., 2020), our concept of autonomy follows a narrow definition based on tasks typically performed in an occupation. Future research could assess how different dimensions of autonomy interact and if, for example, the autonomy premium develops similarly among workers in cooperatives and regular firms.

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A Appendix

A.1 Appendix A1

A.1.1 Routinisability and offshorability

The ease to offshore or routinise a task has been highlighted as a key job-level indicator of wage growth (Autor et al., 2003) introduced the routine-biased technological change (RBTC) hypothesis and showed in a simple production function framework how information and computer technologies (ICT) substitute for middle-skill (routine) occupations but complement high-skilled (abstract) and low-skilled (manual) occupations (see also Autor et al. (2006) and Goos and Manning (2007). Blinder (2009) and Blinder and Krueger (2013) focus on another task dimension: offshorability. Tasks are offshorable if they can be performed remotely without loss of quality. The causal argument is that declines in transportation and communication costs, tariffs or falling relative wages abroad drive changes in the demand for domestic tasks and occupations. This framework has been used to analyse changes in the occupational structure and the reduction in the share of middle-skilled occupations - so-called job polarisation. Another key finding is that routinisation and offshoring can generate the polarised pattern of wage growth that was observed between the 1980s and the 2000s (Autor et al., 2008; Firpo et al., 2011; Goos et al., 2011) but it is unclear if these factors can explain wage growth patterns for more recent years.

We take the measure for how offshorable an occupation is from Acemoglu and Autor (2011) and the measure for how routinisable an occupation is from Firpo et al. (2011). We call these measures offshoring and routinisation.

The offshoring measure includes the following set of occupation characteristics.

- 4.C.1.a.2.l Face to face discussions (reverse)
- 4.A.4.a.5 Assisting and Caring for Others (reverse)
- 4.A.4.a.8 Performing for or Working Directly with the Public (reverse)
- 4.A.1.b.2 Inspecting Equipment, Structures, or Material (reverse)
- 4.A.3.a.2 Handling and Moving Objects (reverse)
- 4.A.3.b.4 0.5* Repairing and Maintaining Mechanical Equipment (reverse)
- 4.A.3.b.5 0.5*Repairing and Maintaining Electronic Equipment (reverse)

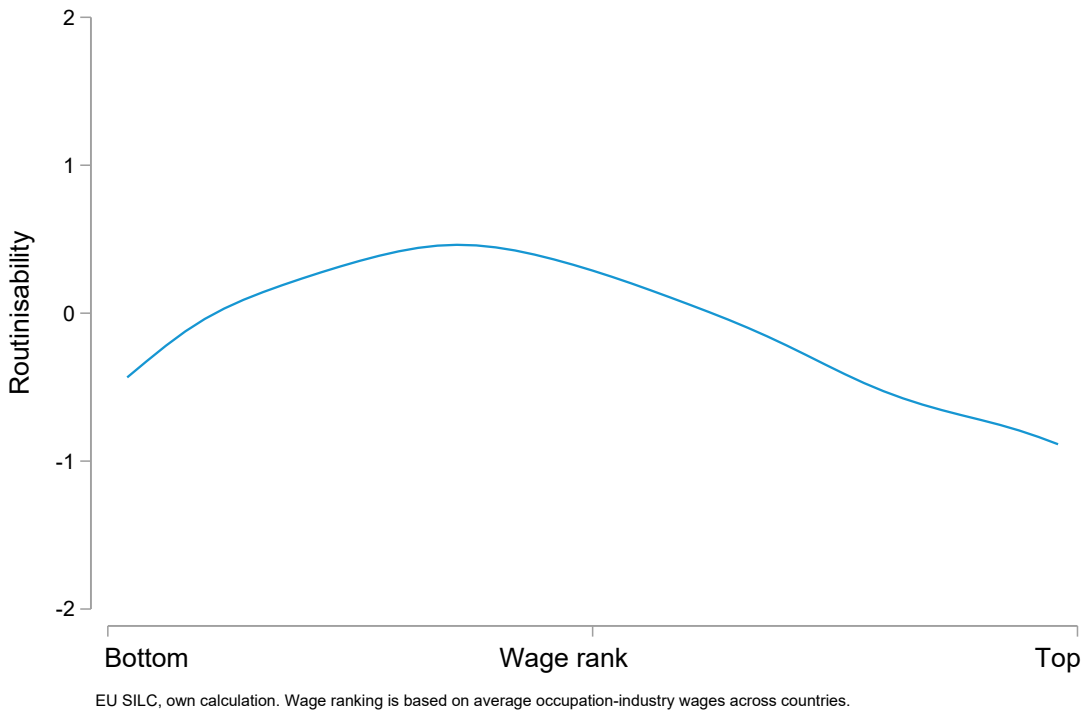
The routinisation measure includes the following set of occupation characteristics.

- 4.C.3.d.3 Pace determined by speed of equipment
- 4.A.3.a.3 Controlling machines and processes
- 4.C.2.d.1.i Spend time making repetitive motions
- 4.C.3.b.7 Importance of repeating the same tasks

- 4.C.3.b.4 Importance of being exact or accurate
- 4.C.3.b.8 Structured v. Unstructured work (reverse)

Figures A1.1 and A1.2 show our measures for routinisation and offshoring along the wage distribution.

Figure A1.1: Routinisation index vs wage rank, lowess smooth

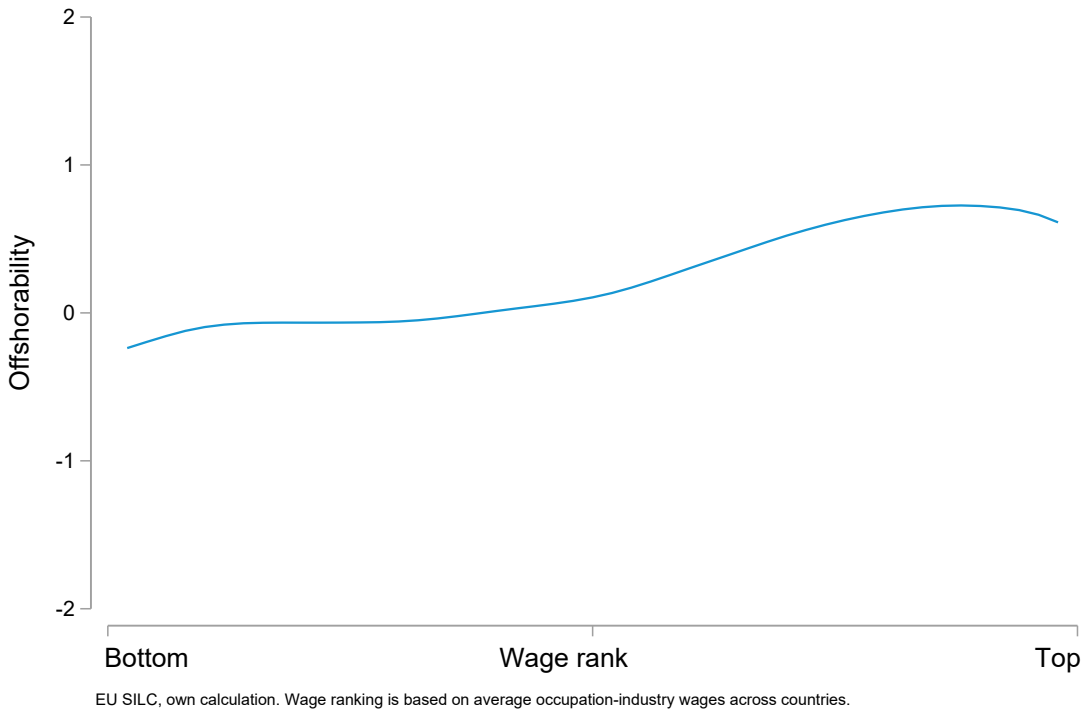


In figures A1.3 and A1.4 we show the relationships between routinisability (offshorability) and wage growth. The figures do not suggest a strong relationship between these factors and wage growth.

In robustness checks, we include alternative measures for routinisation (or non-routinisation) and offshoring. These include the following task-based measures.

- Routine manual (Acemoglu and Autor 2011, hereafter AA)
- Routine cognitive (AA)
- Routine combined: manual and cognitive
- Cognitive analytical (AA)
- Manual physical (AA)
- Manual personal (AA)
- Offshorable (an alternative measure based on Firpo, Fortin and Lemieux 2011, hereafter FFL)

Figure A1.2: Offshoring index vs wage rank, lowess smooth



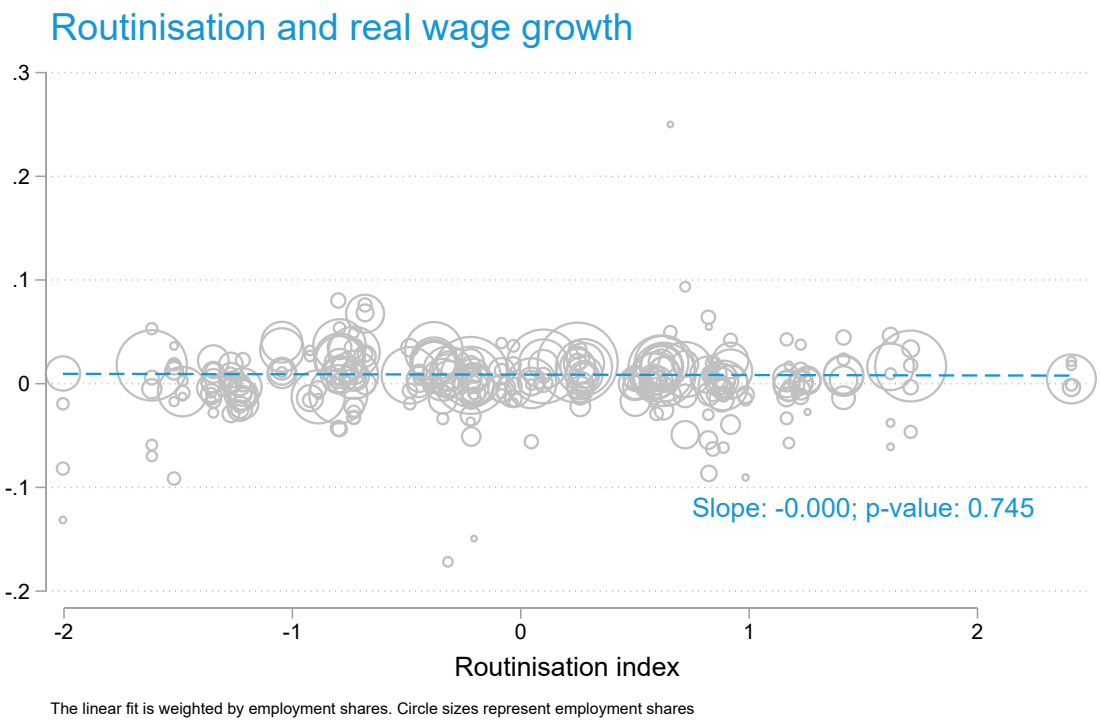
- Face-to-face (FFL)
- On-site (FFL)
- Information content (FFL)

Table A1.1: Correlation table: Index measures

	Correlation with Autonomy index
Routinisation	−0.56
Offshoring	0.00
Routine cognitive	−0.27
Routine manual	−0.46
Routinisation combined	−0.47
Manual physical	−0.31
Manual personal	0.61
Information content	0.70
Non-offshorable	−0.56
Face to face	0.53
On-site job	−0.19

We generate all indices by an additive procedure of all elements. All indices are standardised with zero mean and unit standard deviation.

Figure A1.3: Annual wage growth vs routinisation index, 2003 - 2018



Notes:

A.1.2 Alternative measures for worker autonomy

Alternative O*NET index measures

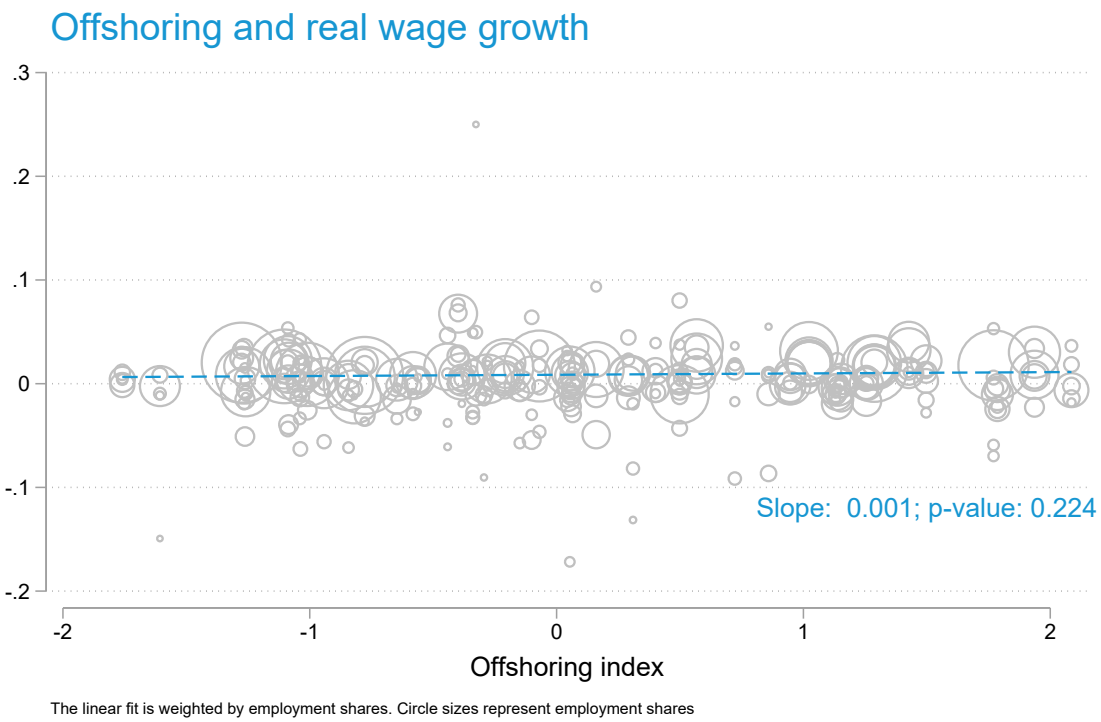
The decision-making index from Deming (2021) includes the following elements:

- 4.A.2.b.1 Making Decisions and Solving Problems
- 4.A.2.b.4 Developing Objectives and Strategies
- 4.A.2.b.6 (Organizing), Planning and Prioritizing Work

The extended autonomy index includes the following nine elements:

- 4.A.2.b.1 Making Decisions and Solving Problems
- 4.A.2.b.2 Thinking Creatively
- 4.A.2.b.4 Developing Objectives and Strategies
- 4.C.3.a.2.b Frequency of Decision Making
- 4.A.2.b.6 Organizing, Planning and Prioritizing Work
- 2.A.2.a Critical Thinking
- 2.A.2.d Monitoring
- 4.C.3.d.3 Pace determined by Speed of Equipment (reversed)

Figure A1.4: Annual wage growth vs offshoring index, 2003 - 2018



Notes:

- 4.C.3.a.4 Freedom to make decisions

Table A1.2 shows correlations between our O*NET-based index measures for autonomy.

Table A1.2: Autonomy index measures - cross-correlations

Variables	Autonomy	Decision-making (Deming)	Autonomy (own)
Autonomy	1.000		
Decision-making (Deming)	0.964	1.000	
Autonomy (own)	0.920	0.966	1.000

Autonomy as worker discretion We replicate a measure for worker discretion from Menon et al. (2020) based on the European Work Conditions Survey (EWCS). One perk of this measure is that the EWCS allows accounting for potential differences in job autonomy measures across countries. This worker discretion measure consists of three binary indicators generated from workers' answers to the following questions: 'Are you able to choose or change?;'

1. Your order of tasks
2. Your methods of work
3. Your speed or rate of work

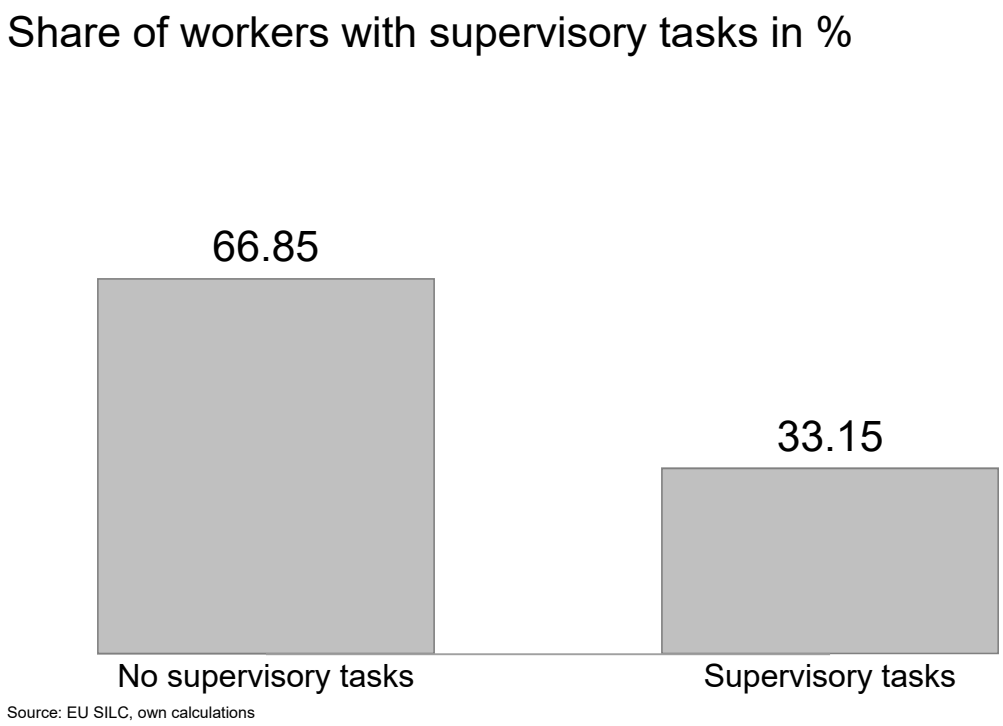
Following Menon et al. (2020), we run a principal component analysis with a polychoric

correlation matrix to construct this index. The first component can explain 84 per cent of the overall variance, the same share as Menon et al. We use this first component as our Worker Discretion Index. We standardise the index at zero mean and unit standard deviation. The EWCS is conducted every five years from 2005, 2010 and 2015, and we generate a pooled measure for each job cell. The main disadvantages of this measure are that they only capture a narrow aspect of worker autonomy and that we rely on workers' subjective perception of autonomy, which might be endogenous to their wage growth. Table A1.2 shows correlations between different job-level measures of autonomy.

Autonomy as supervision

Figure A1.5 shows that almost a third of all workers in our sample have supervisory duties. Workers with supervisory tasks are concentrated at the top of the wage distribution (see Figure A1.6).

Figure A1.5: Share of workers with supervisory tasks



Demographic variables

Figure A1.6: Share of workers with supervisory tasks, by income decile

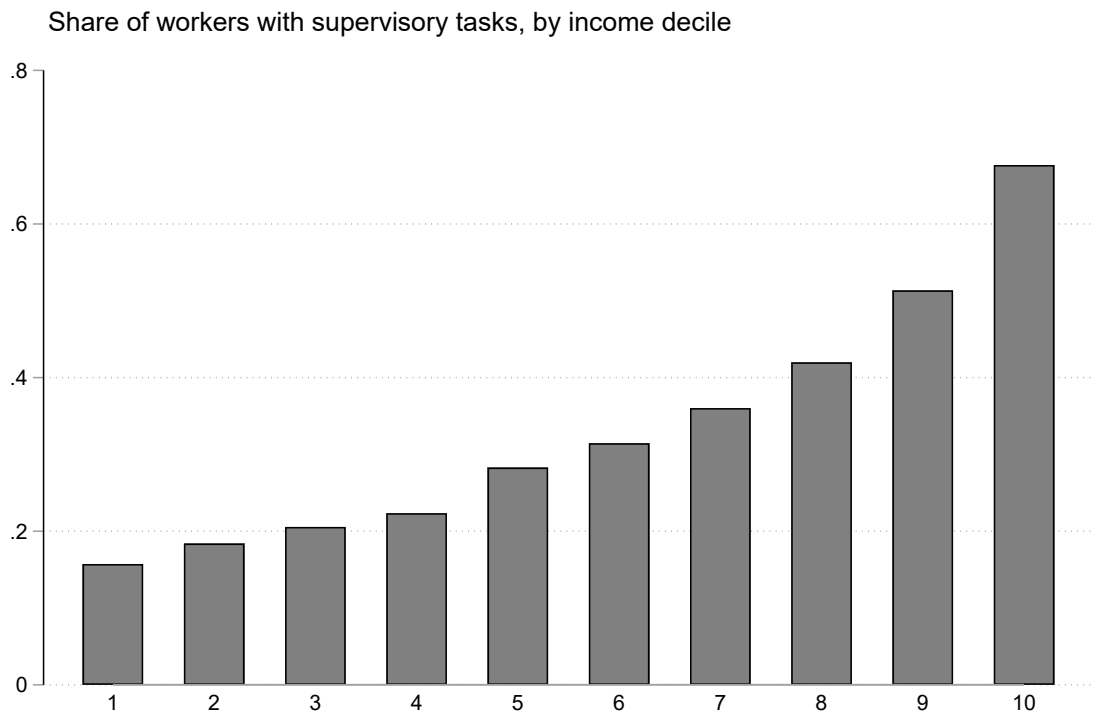


Table A1.3: Demographic variables

	$Value$
Average age	40.84
Average years of experience	20.23
Average education level (ISCED)	3.43
Share of women	0.36
Share of foreign born	0.13
Share of urban residents	0.48
Share with higher education	0.36
Observations	821974

A.2 Appendix A2

Appendix A2 shows the regression tables from robustness checks presented in Figure 5 in section 5.2.

In Columns 1 and 2 of Table A2.1 we split our sample into sub-periods according to the changing ISCO classification, ISCO88 for 2003-2010 and ISCO08 from 2010-2018. These results reflect rows 2 and 3 in Figure 5 in the main body of this paper. Our coefficient for autonomy is stable over both periods, highlighting the relevance of this measure. A noteworthy finding is that the effect of routinisability reverses across our two time periods. While routinisability reduces wage growth between 2003-2010, the coefficient is positive and significant for 2010-2018, suggesting that, controlling for autonomy, average wages in routinisable occupations have risen. This casts further doubt on the relevance of RBTC in explaining wage divergence. A plausible explanation for the positive effect of routinisable is that the least-productive workers in an occupation get automated or offshored first. Only the more productive workers remain, which results in an increase in the average wage in these jobs.

In columns 3 and 4 we exclude routinisation and offshoring, respectively in the model. Our autonomy coefficient and its standard error is not affected by these changes. These specifications mirror rows 4 and 5 in Figure 5.

Table A2.2 reflects rows 6 to 9 in Figure 5. First, we show robustness checks for changes in the Mincerian variables. Column 1 includes potential experience instead of age. The second column includes a variable that captures the change in the college wage premium. We include this variable to address concerns that our autonomy measure captures a change in the return to higher education. Our effect for autonomy is robust for this inclusion. In fact, the college wage premium declines when controlling for autonomy. Column 2 includes an indicator variable for the residential status of workers with respect to population density(urban, mixed, and rural). Our results for autonomy are robust to all these specifications. Columns 3 and 4 include measures for routine cognitive and routine manual tasks from Acemoglu and Autor (2011).

In Table A2.3 we show specifications including other task-based measures from Firpo et al. (2011). Column 1 includes a measure for information content, and columns 2 to 4 include alternative offshoring measures. The non-offshorable measure included in column 2 includes a decision-making component, accounting for the fact that workers in managerial or supervisory functions are less likely to be offshored, even though their occupation tasks are easily offshorable in other dimensions because these occupations do not require face-to-face or on-site presence. The inclusion of this index does not change our results for autonomy. These regressions reflect rows 13-15 in Figure 5. Column 3 includes a measure for face-to-face tasks, and column 4 includes a measure for tasks that need to be carried out on-site. Firpo et al. (2011) provide further details on these measures.

Table A2.4 shows regressions that include other task-based measures for non-routine man-

Table A2.1: Robustness checks: Rows 2-5 in Figure 5

	(1) 2003-2010	(2) 2010-2018	(3) no Offshoring	(4) no Routinisation
Autonomy	0.0029***	0.0027***	0.0026***	0.0025***
	(0.0010)	(0.0008)	(0.0006)	(0.0005)
Routinisation	−0.0025**	0.0015**	0.0003	
	(0.0011)	(0.0008)	(0.0006)	
Offshoring	−0.0002	0.0003		0.0002
	(0.0008)	(0.0005)		(0.0004)
Lower sec. educ.	0.0670***	0.0722***	0.0720***	0.0720***
	(0.0090)	(0.0114)	(0.0071)	(0.0071)
Upper sec. educ.	0.1624***	0.1721***	0.1704***	0.1704***
	(0.0102)	(0.0117)	(0.0076)	(0.0076)
Post-sec. non tert. educ.	0.2378***	0.2237***	0.2358***	0.2358***
	(0.0136)	(0.0158)	(0.0103)	(0.0103)
Tertiary education	0.3258***	0.3268***	0.3287***	0.3287***
	(0.0120)	(0.0128)	(0.0086)	(0.0086)
Age	0.0576***	0.0571***	0.0566***	0.0566***
	(0.0017)	(0.0013)	(0.0011)	(0.0011)
Age2	−0.0006***	−0.0005***	−0.0005***	−0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Women	−0.2001***	−0.1852***	−0.1919***	−0.1919***
	(0.0053)	(0.0047)	(0.0035)	(0.0035)
EU foreign	−0.0340***	−0.0381***	−0.0370***	−0.0370***
	(0.0098)	(0.0084)	(0.0065)	(0.0065)
Other foreign	−0.0847***	−0.0835***	−0.0836***	−0.0836***
	(0.0084)	(0.0077)	(0.0057)	(0.0057)
Observations	352861	455261	808122	808122
r2	0.4524	0.6109	0.5450	0.5450

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.2: Robustness checks: Rows 6-9 in Figure 5

	(1) w Experience	(2) w Urbanisation	(3) Routine cognitive	(4) Routine manual
Autonomy	0.0025***	0.0024***	0.0025***	0.0026***
	(0.0007)	(0.0007)	(0.0005)	(0.0006)
Routinisation	0.0006	0.0002		
	(0.0006)	(0.0007)		
Offshoring	0.0002	0.0003	0.0002	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0006)
Lower sec. educ.	0.0588***	0.0746***	0.0720***	0.0720***
	(0.0087)	(0.0073)	(0.0071)	(0.0071)
Upper sec. educ.	0.1773***	0.1760***	0.1704***	0.1704***
	(0.0089)	(0.0078)	(0.0076)	(0.0076)
Post-sec. non tert. educ.	0.2802***	0.2416***	0.2358***	0.2358***
	(0.0114)	(0.0106)	(0.0103)	(0.0103)
Tertiary education	0.3963***	0.3268***	0.3287***	0.3287***
	(0.0100)	(0.0088)	(0.0086)	(0.0086)
Experience (potential)	0.0259***			
	(0.0005)			
Experience squared	−0.0004***			
	(0.0000)			
Women	−0.1931***	−0.1942***	−0.1919***	−0.1919***
	(0.0035)	(0.0036)	(0.0035)	(0.0035)
EU foreign	−0.0277***	−0.0444***	−0.0370***	−0.0370***
	(0.0067)	(0.0065)	(0.0065)	(0.0065)
Other foreign	−0.0682***	−0.1004***	−0.0836***	−0.0836***
	(0.0058)	(0.0058)	(0.0057)	(0.0057)
Age		0.0563***	0.0566***	0.0566***
		(0.0011)	(0.0011)	(0.0011)
Age2		−0.0005***	−0.0005***	−0.0005***
		(0.0000)	(0.0000)	(0.0000)
Intermediate area		−0.0394***		
		(0.0025)		
Thinly populated area		−0.0800***		
		(0.0031)		
Routine cognitive (AA)			0.0000	
			(0.0005)	
Routine manual (AA)				0.0003
				(0.0007)
Observations	794364	776547	808122	808122
r2	0.5425	0.5474	0.5450	0.5450

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.3: Robustness checks: Rows 10-13 in Figure 5

	(1) Info. content	(2) Offshoring (FFL)	(3) Face-to-face	(4) On-site
Autonomy	0.0031***	0.0028***	0.0024***	0.0027***
	(0.0007)	(0.0008)	(0.0006)	(0.0007)
Information content (FFL)	−0.0010			
	(0.0007)			
Offshoring	0.0006			
	(0.0005)			
Lower sec. educ.	0.0719***	0.0720***	0.0720***	0.0720***
	(0.0071)	(0.0071)	(0.0071)	(0.0071)
Upper sec. educ.	0.1704***	0.1704***	0.1704***	0.1704***
	(0.0076)	(0.0076)	(0.0076)	(0.0076)
Post-sec. non tert. educ.	0.2357***	0.2358***	0.2358***	0.2359***
	(0.0103)	(0.0103)	(0.0103)	(0.0103)
Tertiary education	0.3287***	0.3287***	0.3287***	0.3287***
	(0.0086)	(0.0086)	(0.0086)	(0.0086)
Age	0.0566***	0.0566***	0.0566***	0.0566***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Age2	−0.0005***	−0.0005***	−0.0005***	−0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Women	−0.1919***	−0.1919***	−0.1919***	−0.1919***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
EU foreign	−0.0370***	−0.0370***	−0.0370***	−0.0370***
	(0.0065)	(0.0065)	(0.0065)	(0.0065)
Other foreign	−0.0836***	−0.0836***	−0.0836***	−0.0836***
	(0.0057)	(0.0057)	(0.0057)	(0.0057)
Routinisation		0.0004	0.0005	0.0006
		(0.0006)	(0.0007)	(0.0007)
Non-offshorable (via FFL)		0.0002		
		(0.0005)		
Face-to-face (FFL)			0.0007	
			(0.0007)	
On-Site Job (FFL)				−0.0005
				(0.0005)
Observations	808122	808122	808122	808122
r2	0.5450	0.5450	0.5450	0.5450

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ual jobs from Acemoglu and Autor (2011). Again, the statistical significance of the autonomy coefficient or the Mincer variables is unchanged. These results reflect rows 14-15 in Figure 5.

Figure A2.1: Robustness check: countries

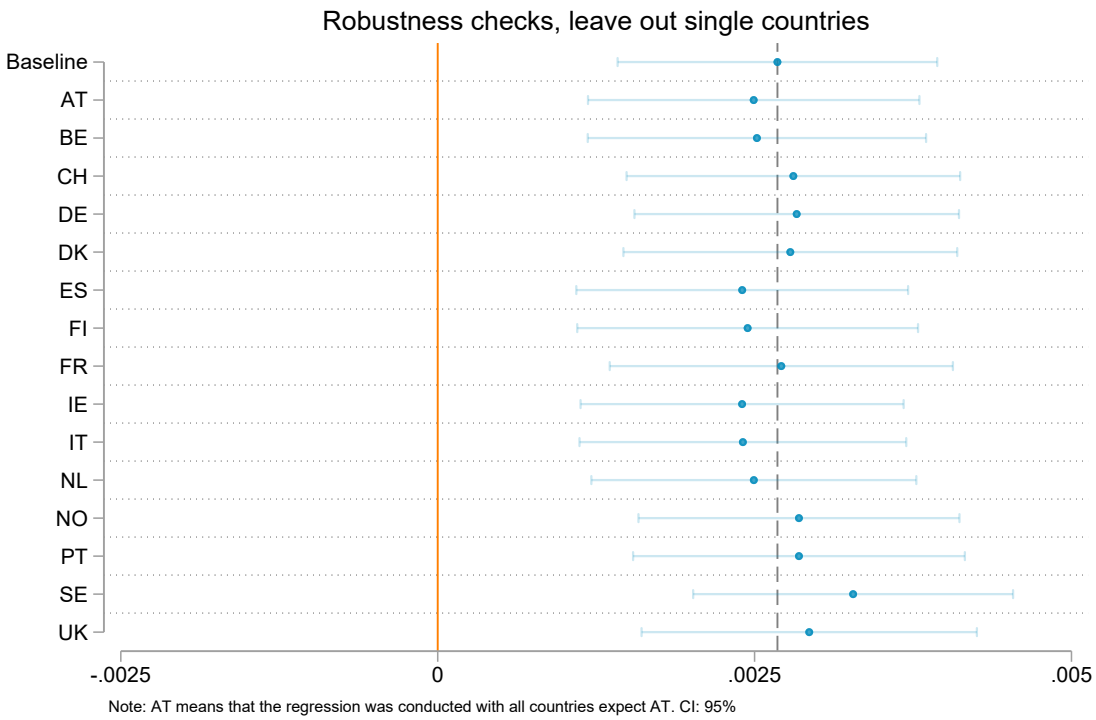


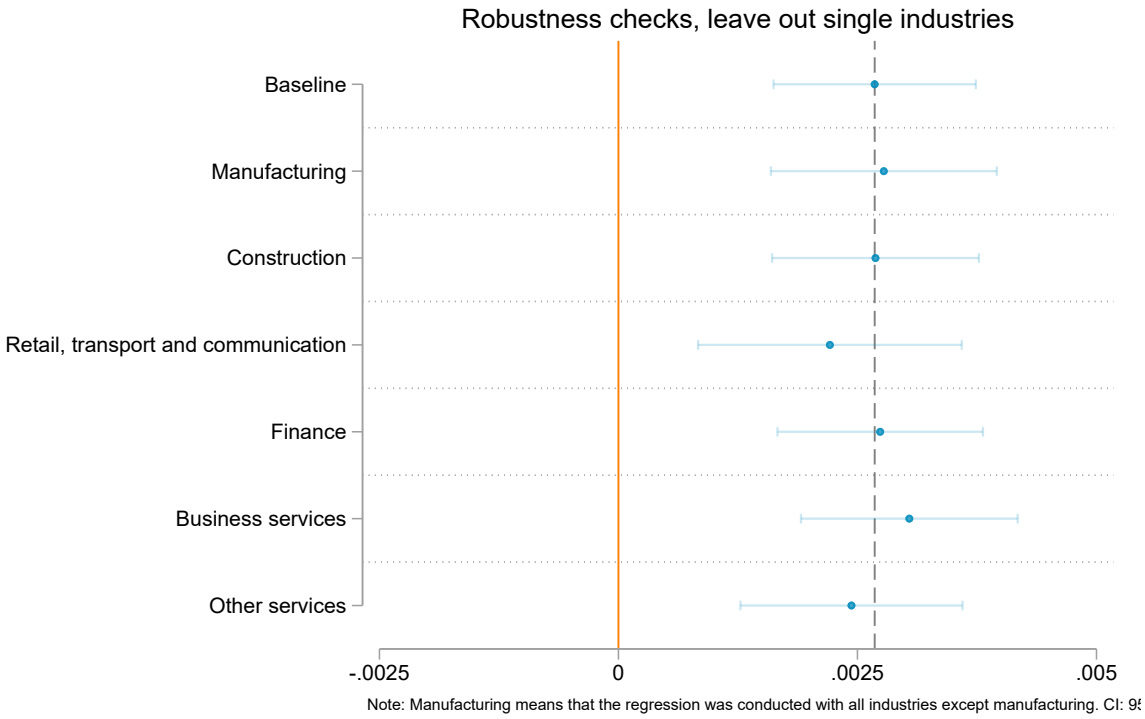
Table A2.4: Robustness checks: Rows 14-15 in Figure 5

	(1) Manual physical	(2) Manual personal
Autonomy	0.0027***	0.0024***
	(0.0006)	(0.0006)
Routinisation	0.0006	0.0010
	(0.0007)	(0.0007)
Offshoring	−0.0001	0.0002
	(0.0008)	(0.0004)
Manual physical (AA)	−0.0005	
	(0.0010)	
Lower sec. educ.	0.0720***	0.0720***
	(0.0071)	(0.0071)
Upper sec. educ.	0.1704***	0.1704***
	(0.0076)	(0.0076)
Post-sec. non tert. educ.	0.2359***	0.2359***
	(0.0103)	(0.0103)
Tertiary education	0.3287***	0.3287***
	(0.0086)	(0.0086)
Age	0.0566***	0.0566***
	(0.0011)	(0.0011)
Age2	−0.0005***	−0.0005***
	(0.0000)	(0.0000)
Women	−0.1919***	−0.1919***
	(0.0035)	(0.0035)
EU foreign	−0.0370***	−0.0370***
	(0.0065)	(0.0065)
Other foreign	−0.0836***	−0.0836***
	(0.0057)	(0.0057)
Manual personal (AA)		0.0012
		(0.0008)
Observations	808122	808122
r2	0.5450	0.5450

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A2.2: Robustness check: industries



A.3 Appendix A3

Figure A3.1: Changes in the autonomy wage premium and changes in computer use, country level

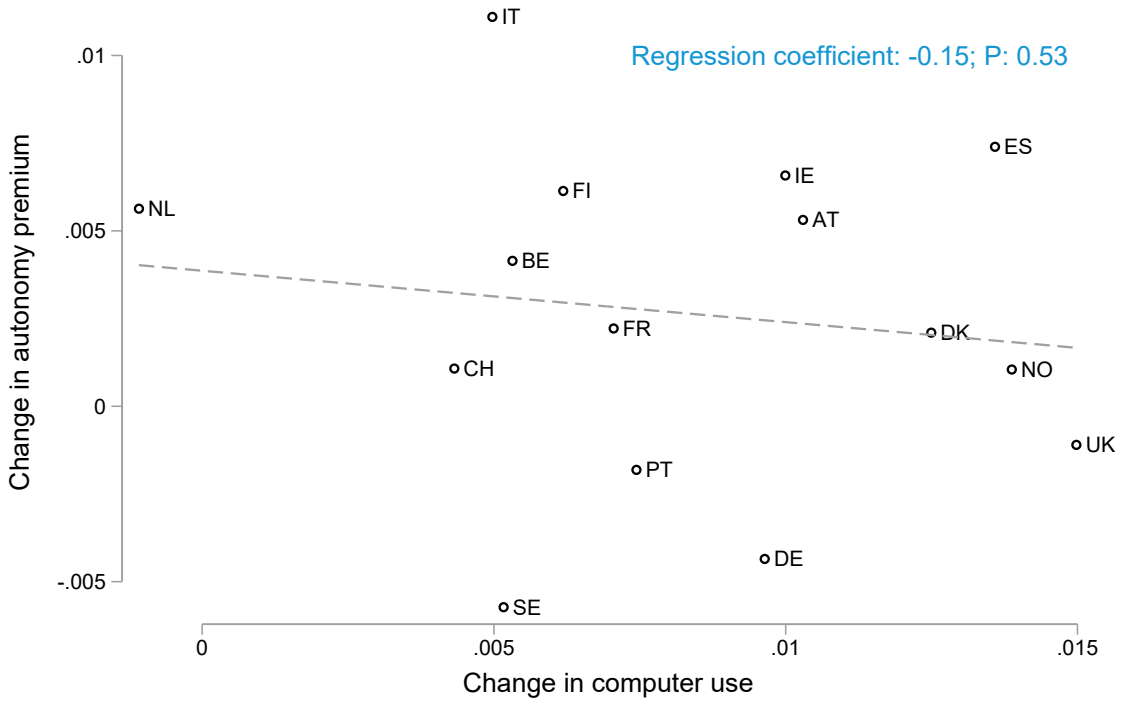


Table A3.1: Collective bargaining variables

Country	Routine involvement of unions in policy-making	Union Density	Coordination of wage-setting	Collective bargaining coverage (private sector)
AT	No	Low	High	High
BE	Yes	High	High	High
CH	Yes	Low	Low	Low
DE	No	Low	High	Low
DK	Yes	High	High	High
ES	No	Low	Low	High
FI	No	High	High	High
FR	No	Low	Low	High
IE	Yes	Low	Low	Low
IT	No	High	Low	High
NL	Yes	Low	High	High
NO	Yes	High	High	Low
PT	No	Low	Low	High
SE	Yes	High	High	High
UK	No	Low	Low	Low

Countries are classified as high (low) if the country value of the respective variable as above (below) the sample mean.

Figure A3.2 illustrates the data availability of our survey wage data for each country.

Figure A3.2: EU SILC data availability across countries

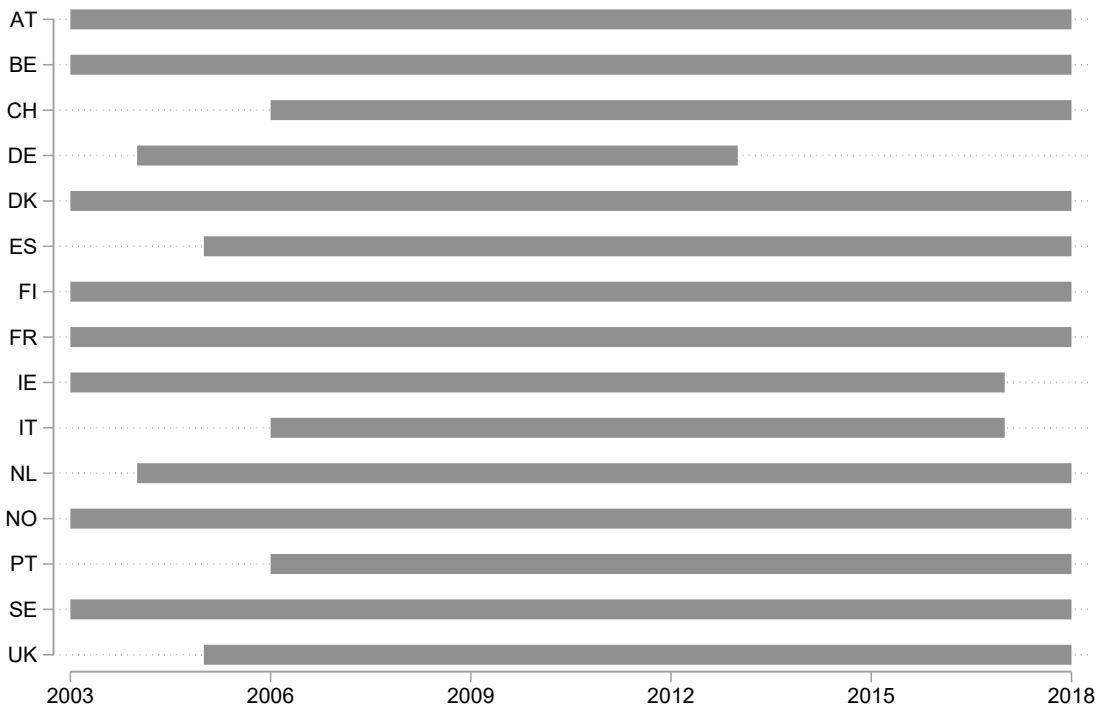
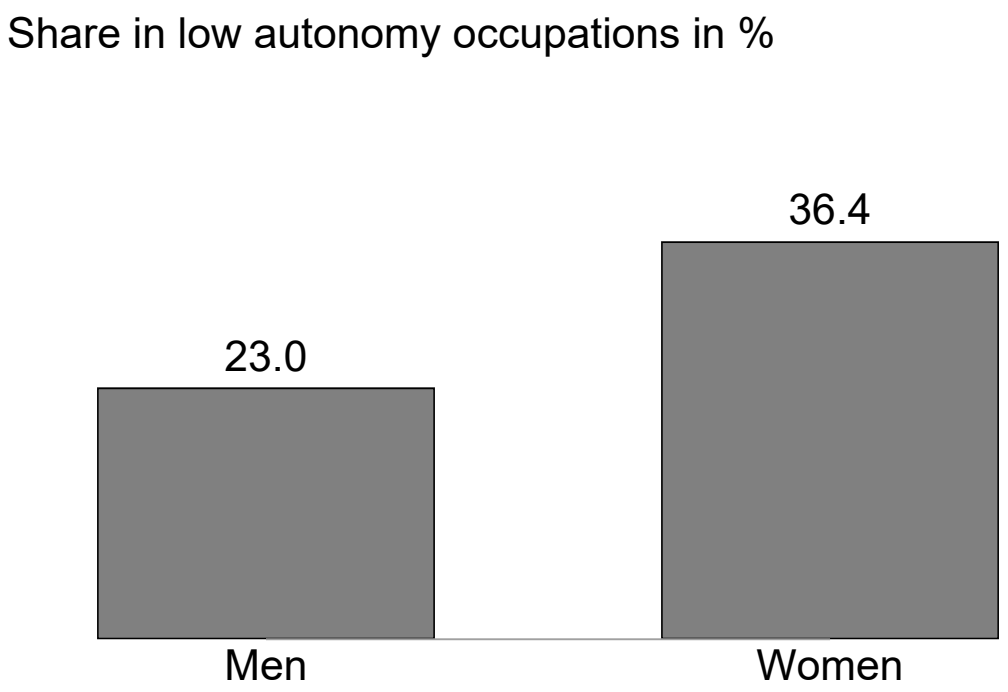


Figure A3.3 shows the composition of men and women in low autonomy occupations, defined as the bottom quartile of the autonomy index.

Figure A3.3: Share of men and women in low autonomy occupations



Note: Low autonomy occupations are occupations below the 25. percentile on the worker autonomy scale.