Worker autonomy and wage divergence: Evidence from European survey data

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Abstract

This paper contributes to the understanding of occupational wage inequality in Western Europe. We assess the effect of worker autonomy, defined as the degree of control workers have over their own work process, on occupational wage growth using data for 15 European countries from 2003 to 2018. We present econometric analyses using individual-level wage data from the EU Survey of Income and Living Conditions and find that real wages in occupations with high autonomy have grown significantly faster than in occupations with low autonomy. We call this finding an increase in the 'autonomy wage premium'. Because workers in high autonomy occupations are at the top of the wage distribution, faster wage growth in these occupations has increased wage inequality. Using additional worker survey data, we conjecture about technological, institutional, and demographic determinants of the autonomy premium. Our analysis suggests that: (i) the autonomy wage premium increases more in industries and countries with faster technological change; (ii) strong collective bargaining reduces the autonomy premium, but the autonomy wage premium rises in countries with strong and weak collective bargaining; (iii) the autonomy wage premium increases more among older and more experienced workers; (iv) the autonomy wage premium rises for men and women similarly, but the increase in the autonomy premium intensifies gender inequality because women are more often employed in low autonomy occupations.

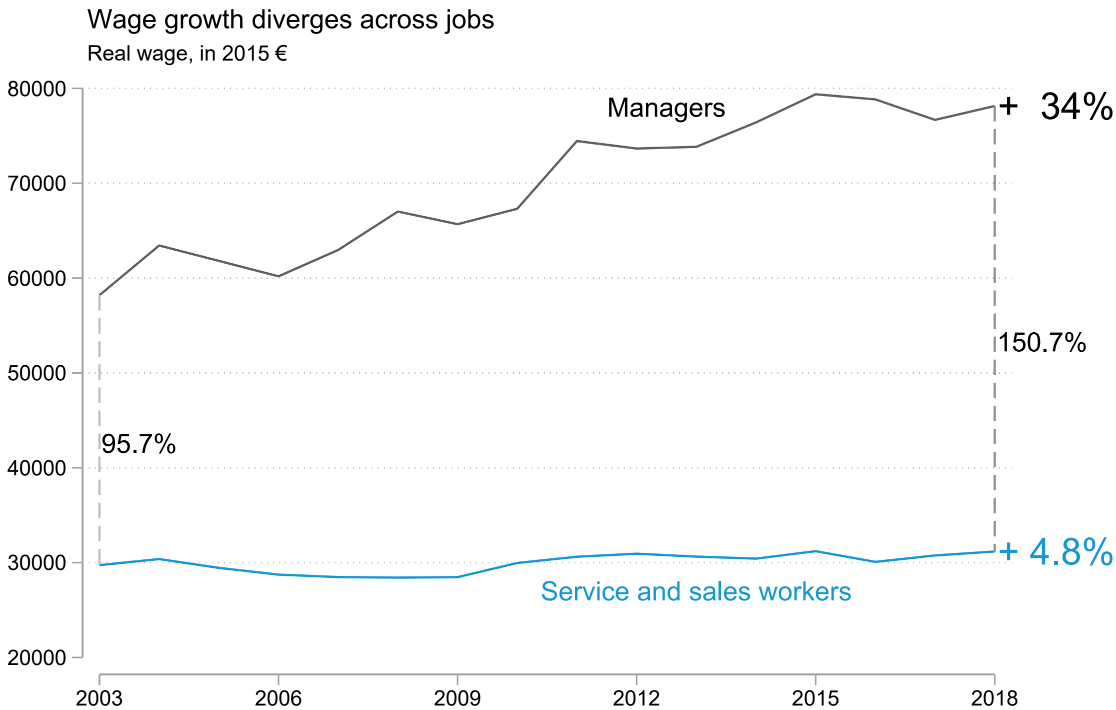
Keywords: worker autonomy, technological change, survey data, collective bargaining
JEL: J31, J50, E24

1 Introduction

In the years preceding the pandemic, wages in Western Europe have diverged across occupations, 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). In the context of a looming cost-of-living crisis, this trend is particularly worrying.

This paper sheds light on the determinants of occupational wage growth in 21st century Western Europe. We ask if worker autonomy, defined as the degree of control and influence workers have over their own work process, can explain wage growth differences across occupations. The main reason why higher worker autonomy relates to faster wage growth is that technological change complements workers in high-autonomy occupations (Deming, 2021). Making use of differences across western European labour markets, we not only conjecture about the technological, but also the institutional and demographic determinants of changes in the autonomy wage premium, which is defined as the wage difference between a high and a mean autonomy occupation.

Figure 1: Wage growth diverges across occupations



Our main contribution is to present the first cross-country analysis of the relationship between worker autonomy and occupational wage growth. We add to the recent literature on the increasing importance of worker autonomy for labour market outcomes, which has thus far focused on single-country studies (Blundell et al., 2022; Deming, 2021). Our second contribution is to investigate the institutional determinants of the autonomy wage premium. While collective bargaining institutions have been highlighted as important determinants of the wage distribution (Farber et al., 2021), they have received less attention in recent applied research on the autonomy premium. We further add to the understanding of technological drivers of occupational wage growth and show demographic subgroup analyses to highlight winners and losers from the change in the autonomy wage premium.

Our econometric analysis uses 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 merge repeated cross-sectional wage survey data from EU SILC with data on occupational tasks from the Occupational Information Network (O*NET) provided by the Bureau of Labor Statistics to empirically test the relationship between autonomy and occupational wage growth. Our main measure for worker autonomy is the worker autonomy index. This index captures characteristics reflecting the degree of control workers in a given occupation exert over their own work process, such as engagement in decision-making, problem-solving, critical thinking or supervising other workers.

We find a statistically significant (at the 0.1%-level) association between worker autonomy and higher wage growth, thereby extending previous findings for the US and the UK to 15 western European countries. A high autonomy occupation (one standard deviation above the

[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.

mean in worker autonomy) is associated with 0.27 percentage points higher annual real wage growth; if annual wage growth in the mean autonomy occupation is 1%, wage growth in an occupation one standard deviation higher on the autonomy scale is 1.27%. After 12 years, the wage level in the high autonomy occupation is 3.3% above the wage level in the mean autonomy occupation if both occupations start at the same wage level. But initial wage levels between high- and low-autonomy occupations differ. For example, in 2005, the average wage of Managers was 109.9% higher than those of Service and sales workers. These occupational groups are roughly three standard deviations apart on the autonomy index. Our estimate suggests an increase in the wage gap between these two occupations to 131.1% until 2017, all else equal, explaining around 54% of the observed wage divergence between Managers and Services and sales workers between 2005 and 2017.

We show that the relationship between autonomy and wage growth is shaped by technological and institutional factors. The autonomy wage premium increases faster in industries and countries with faster technological change, measured as computerisation or ICT investment, suggesting that 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.

Our demographic subgroup analysis reveals winners and losers from changes in the autonomy wage premium and can guide policies aimed at supporting low autonomy workers. We find that the autonomy wage premium is higher for older and more experienced workers in comparison to younger workers. Over our sample period, the autonomy wage premium has increased across all age and experience groups, but the increase in the autonomy wage premium 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 areas with intermediate density. While we do not find differences in the increase of the autonomy wage premium across genders, the overall increase in the autonomy wage premium contributes to the gender wage gap, because women are disproportionally employed in low autonomy occupations.

In additional analyses, we highlight the robustness of our main finding across different measures of worker autonomy. First, we generate alternative worker autonomy indices based on O*NET, in which we change the composition of occupational characteristics. This alternative indices do not change 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 occupational designs. Using this measure in regression analysis yields an even higher coefficient for autonomy on wage growth, suggesting that our main result from above captures a lower-bound estimate for the relationship between autonomy and wage growth. Finally, we use a measure of supervisory tasks of individual workers provided by EU SILC and show that wages of supervisory workers have grown faster than non-supervisory workers even within the same occupation.

For our sample and time period we do not find evidence that the ease the routinise (automate) or offshore an occupation explain occupational wage growth patterns. Splitting our sample in sub periods reveals that routinisation is a wage growth determinant up until 2010, but not after. Changes in the return to education or increasing returns to cognitive analytical occupations (i.e. STEM occupations) can also not explain occupational wage growth patterns in our sample. Instead, worker autonomy emerges as a robust determinant of wage growth.

Section 2 looks at the literature on worker autonomy and wage growth. Section 3 introduces our data and shows descriptive statistics. In section 4, we show our empirical model. Section 5 exhibits the findings of our analysis. Section 6 concludes.

2 Worker autonomy

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.

Recently, worker autonomy has become a pertinent concept in applied labour economics, either explicitly or implicitly through related concepts, such as 'decision-making' (Deming, 2021), 'hold-up power' (Bloesch et al., 2022), 'influence over work decisions' (Blundell et al., 2022) or 'soft skills' (Aghion et al., 2019).[2] While much of the previous literature is concerned with the relation of autonomy and wage levels[3], we focus on the relation between autonomy and wage growth, following a line of labour economics literature that has been concerned with changes in occupational wage inequality.

The most established explanation why autonomy is related to faster wage growth is technological change. 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 to adapt to sudden changes in circumstances. This structural shift in the labour market complements occupations with higher worker autonomy and increases demand and wages for workers with this set of tasks.

Deming (2021) finds that technological change increases demand for occupations with a high degree of decision-making and subsequently raises life-cycle wage growth for these occupations in the US. The return to working in decision-intensive occupations has grown over time and the decision-making premium has grown faster for more able workers. This argument is a version of skill-biased technological change but applied to different degrees of autonomy. Importantly, the causal chain implies that technology leads to a change in labour demand for different occupations, which subsequently results in wage growth divergence. 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 occupations occupied 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).

Earlier research on occupational wage growth has discussed autonomy-related characteristics

[2] We discuss how our autonomy measure differs from previous indicators in section 3.

[3] Autonomy has been emphasised as a wage determinant by the sociology of work literature (Kalleberg, 2003; Wright, 1997), the efficiency wage model (Akerlof, 1984) and research on the Marxist notion of labour discipline (Marx et al., 1981). The main argument is that workers with higher autonomy have higher wages because they are harder to control and monitor or because they have higher disruptive potential in case they withdraw their labour. More recently, Bloesch et al. (2022) investigate the importance of workers' hold-up power for wage levels. They find that workers who play a critical role in the production process and are harder to replace have both higher pass-through of firm productivity and higher pass-through of idiosyncratic outside options to wages.

only implicitly. For example, Autor et al. (2003) use the notion of non-routine cognitive tasks in their work and argue that decision intensity of occupations is one of several characteristics of non-routine cognitive tasks. Firpo et al. (2011) maintain that occupations with decision-making features reduce the likelihood of an occupation to be offshored.

Prior to the recent interest in worker autonomy, the ease to offshore or routinise an occupation have been highlighted as main occupation-level determinants 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) (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 medium-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; Autor and Dorn, 2013; Firpo et al., 2011; Goos et al., 2011), but it is unclear if these factors can explain wage growth patterns for more recent years.

Institutions had long been emphasised as determinants of the wage distribution, but have received less attention in the recent applied microeconometric literature on wage divergence. Collective bargaining institutions allow workers to form alliances across occupations, to negotiate wage increases jointly and to compress wage differences. Freeman (1982) shows that wage dispersion within the group of unionised workers is smaller than in the group of non-unionised workers. Jaumotte and Osorio (2015) find that strong labour unions restrain top management remuneration and reduce wage dispersion. A high level of collective bargaining coverage guarantees that wage gains are shared across occupations (Visser, 2006). If faster technological change increases the autonomy wage premium, strong collective bargaining institutions should reduce occupational wage growth differences.

Occupations differ from each other in their demographic composition, such as the share of women or the average age in an occupation. Demographic subgroups, in turn, differ with respect to their bargaining power or exposure to new technologies. We therefore expect that the relation between autonomy and wage growth differs for workers depending on their gender, age, experience, or location. Lower bargaining power of women might suggest that the autonomy wage premium rises faster among women. Workers in larger cities are often exposed to faster technological change and changes in labour demand (Baum-Snow and Pavan, 2013; Moretti, 2013), which might lead to a stronger relation between autonomy and wage growth in areas with higher density. Previous research has also highlighted that wage growth is different across the life cycle for workers with different degrees of autonomy and that high-autonomy workers have more gradual but longer periods of wage growth (Deming, 2021).

Based on the literature presented in this section, we answer several questions. First, we test whether higher worker autonomy leads to higher wage growth in Western Europe. Second, we assess whether the autonomy wage premium grows faster in countries or industries with faster technological change. In line with the autonomy-biased technological change hypothesis, we expect a faster increase in the autonomy wage premium within industries (and countries) with faster adoption of new technologies, measured, e.g., as computer use or ICT investment. Third, we test whether strong collective bargaining, through trade unions and other employee interest groups, reduces the autonomy wage premium. We conjecture that collective bargaining institutions act as a mediating factor for the autonomy wage premium and use differences in labour market settings to assess this hypothesis. Fourth, we gauge how the rising autonomy wage premium affects different demographic subgroups and highlight winners and losers of recent wage growth patterns.

3 Data and descriptive statistics

Our main 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 the 2003-2018 period 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 include workers who have been employed in a regular occupation, full-time over 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 reliably. 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). Self-employed workers are excluded from our analysis to ensure consistency across countries and because this category includes employers. We focus on private sector wage formation and exclude workers in public sector industries or occupations. 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 occupation characteristics (tasks performed and skills needed) from the Activities and Work Context datasets of the Occupational Information Network (O*NET) database provided by the Bureau of Labor Statistics.[4] The elements of our index are the following:

- 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 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.

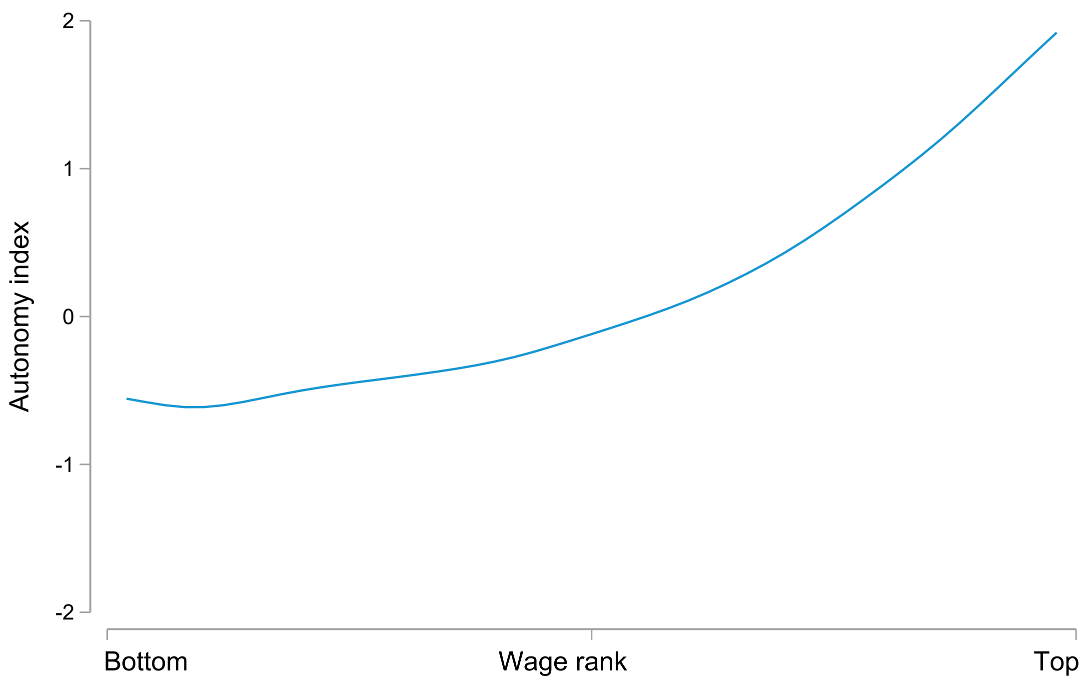
The five characteristics of our index have been used in previous research on occupation-level labour market outcomes. Autor et al. (2003) implicitly use some of these elements in their index of non-routine cognitive tasks, such as problem-solving and communicational tasks. Our index is also related to previous measures capturing decision-making in the work process.

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

Jensen and Kletzer (2010) use measures related to decision-making to capture the potential offshorability of an occupation. Similarly, Firpo et al. (2011) use the elements of our autonomy index as a subcomponent of a broader measure for non-offshorability without interpreting this measure as worker autonomy. We argue that our measure is a good proxy for worker autonomy, as the dimensions captured in this index go beyond mere decision-making (which is the first element) and additionally signal the complexity of the tasks, the freedom to set own goals and how easily the work process can be monitored.

High wage occupations are generally those with higher autonomy, low wage occupations 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



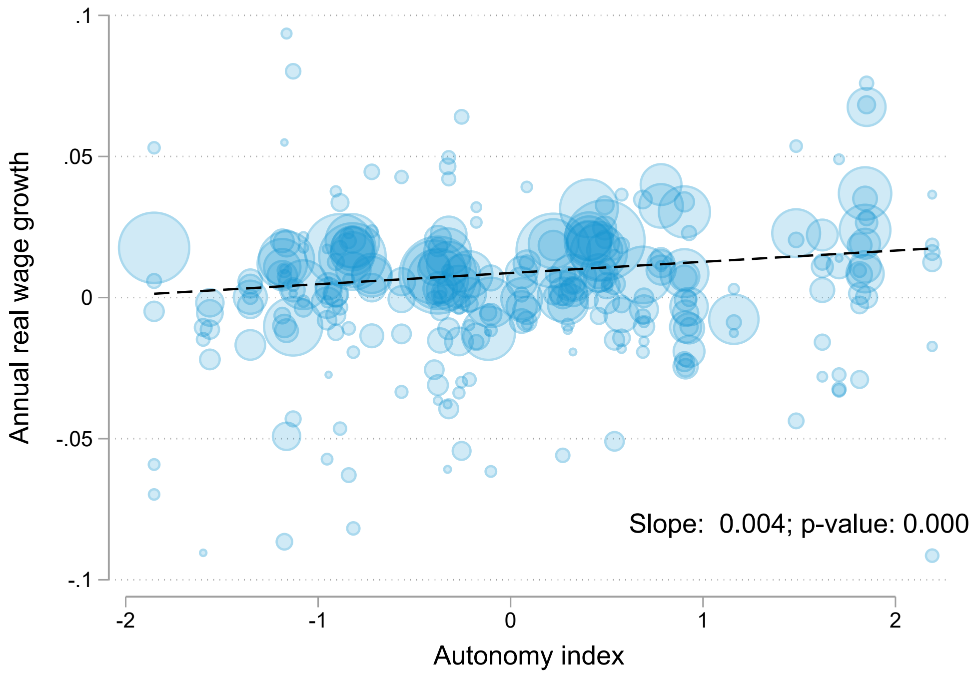
EU SILC, own calculation. Wage ranking is based on average occupation-industry wages across countries.

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

To account for other determinants of wage growth, we generate index measures for the ease to routinise or offshore an occupation from the O*NET database. 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) . Details on the construction of these measures and descriptive statistics are provided in Appendix A1.

The measures for offshoring and routinisation differ in important ways from our autonomy index.

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



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

Many low wage service sector occupationss are neither routinisable nor offshorable because the tasks in these occupations 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, the offshoring and routinisation indices exhibit different patterns when plotted against the wage distribution, as shown in Appendix A1. For example, clerical, administrative support, as well as production and operative occupations are highly routinisable. These occupations are generally in the middle of the wage distribution, yielding the inverted U-shape scatter plot between wage level and routinisation emphasised in the literature on job polarisation (Acemoglu and Autor, 2011). Offshoring is generally proxied with face-to-face interaction and whether the occupation can be done at a remote facility. Highly offshorable occupations are generally related to information and communication technology (ICT) which allows remote work and span from (low skilled) call centre workers to (middle or high skilled) computer programmers, while operative occupations are also highly offshorable. Consequently, offshorable occupations can be found in all parts of the wage distribution.

In addition to our index measures, we use a set of demographic variables on the individual level from EU SILC to account for wage determinants rooted in the Mincerian literature (Mincer, 1974, 1958), which include age, education level, sex, experience, the degree of urbanisation of a workers' residence and migrant status. We show summary statistics for these variables in Appendix A1.

4 Empirical model and methodology

We estimate individual level wage growth regressions based on Acemoglu and Autor (2011) and Altonji et al. (2014) and in line with the Mincerian (Mincer, 1974, 1958) wage determination literature. We model wage growth as a function of worker autonomy and other occupation level measures:

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

where w is the real wage of worker i in an occupation j, industry k, country c, and year t. A_j is the worker autonomy index, which differs across occupations j. $\boldsymbol{X_j}$ is a vector of other task-based measures including *routinisation* and *offshoring*, which indicate 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[5]), age-squared, and country of birth. We log-transform equation 1 to 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 main variable of interest is the autonomy index A_j, which is time-invariant and interacted with a linear time trend t. Our estimated coefficient β_1 captures the effect of a higher autonomy measure A_j on annual wage growth. This estimation equation follows common practice in the task-based indicator literature (Acemoglu and Autor, 2011). We also interact other task-based measures $\boldsymbol{X_j}$ with a linear time trend t. The Mincerian variables $\boldsymbol{M_{ijkct}}$ are not interacted with a time trend, their coefficient captures the effect on changes in these variables on the level of log wages.

We estimate estimation 2 by OLS. We use occupation-industry-country fixed effects λ_{jkc} because our main concern are changes in relative wages across occupations with different levels of autonomy: λ_{jkc} conditions out all pre-existing wage level differences. We further include industry-country-year fixed effects θ_{kct} to condition out all time-variant country- and industry-specific wage growth trends. We cluster standard errors at the occupation-industry-country level. All wage regressions are weighted using the survey weights provided by EU-SILC, rescaled to weight each country equally. This estimation strategy follows Altonji et al. (2014) and builds on prior work by Acemoglu and Autor (2011) and Goos et al. (2014).

Our main coefficient of interest β_1 captures the relation between a one standard deviation increase in worker autonomy and the percentage point deviation of occupational wage growth from the industry-country wage growth trend. If β_1 equals 0.01, a high-autonomy occupation is associated with wage growth 1 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 are multiplied with the time trend t.

The effects of variables included in $\boldsymbol{M_{ijkct}}$ follow a log-linear interpretation; an increase in, e.g., age by 1 year affects wages by B_1%, where B_1 is the coefficient on average age. We include Mincerian variables $\boldsymbol{M_{ijkct}}$ to account for changes in the composition of workers in an occupation. For example, if an occupation profile changes because higher educated workers sort into this occupation, this might subsequently change the average wage in this occupation. Controlling for the level of education (as part of $\boldsymbol{M_{ijkct}}$) accounts for this effect. The inclusion of these variables also accounts for potential outliers in sampling, e.g., if in a particular year many young workers with relatively lower wages were surveyed within an occupation.

[5]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*.

Our fixed effects strategy further eliminates unobserved heterogeneity across occupation-industry cells such as differences in ability or motivation. If, for example, more able workers systematically sort into high autonomy occupations, this will be captured by the occupation-industry-country fixed effect. We assume that this sorting pattern is stable over time.

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 is that a high autonomy occupation (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 occupation grew by 1%, wages in an occupation one standard deviation higher on the autonomy scale grew by 1.27%. If both occupations were to start at the same wage level initially, the high autonomy occupation would have a wage level that is 4% higher than the mean autonomy occupation after 12 years. This difference is strongly increased if we consider that wage levels differ substantially between high and low autonomy occupations.

In 2005, the average wage of *Managers* was 109.9% higher than those of *Service and sales workers* (see Figure 1). These occupational groups are roughly three standard deviations apart from each other on the autonomy index. Our estimate for autonomy predicts an increase of the wage gap between these two occupations to 131.1% in 2017, all else equal. Our estimate explains around 54% of the observed wage divergence between these two occupations from 2005 to 2017.

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

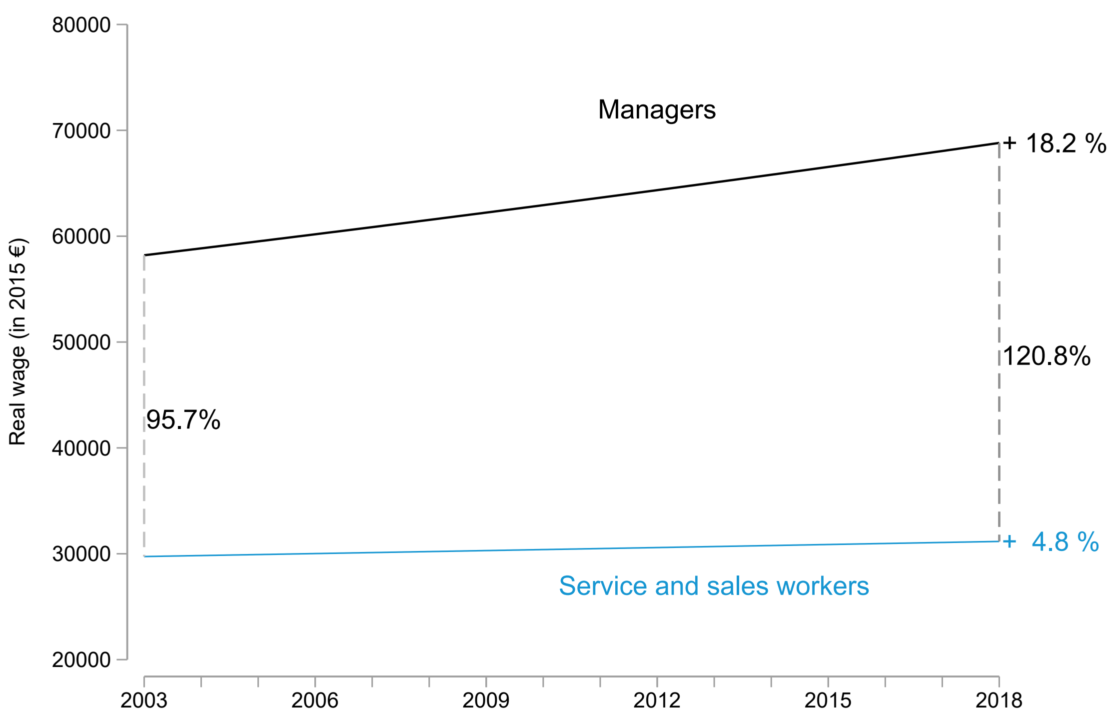


Table 1: Main finding

	(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

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

While this example illustrates only two occupational groups, it highlights an important aspect of the difference between the autonomy index and measures for routinisation or offshoring. *Managers* and *Service and sales workers* are three standard deviations apart in the autonomy index, but both groups have similar routinisation and offshoring values. Our results in Table 1 show that routinisation and offshoring are not able to explain occupational wage growth differences in our sample. The relevance of autonomy for wage growth is also in line with the fact that many low-income occupations which are less likely to be routinised or offshored, such as Service and sales workers, have experienced low wage growth over recent years.

Turning to the control variables based on the Mincer equation, we find that 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, such as whether the worker has managerial responsibilities or the observation that more women than men are in part-time employment and are therefore excluded from our sample, the magnitude of this gap is nevertheless large. EU foreign born workers and other foreign workers have statistically significantly lower wage levels 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 the the effect of autonomy is still significant after excluding routinisation and offshoring. In column 2, we test whether increasing returns to higher education predict occupational wage growth patterns, in line with the canonical model of Katz and Murphy (1992), by adding an interaction term between a dummy for higher education and a linear time trend to our specification. We find that the return to higher education declines after accounting for autonomy. Column 3 includes a variable for cognitive analytical occupations, reflecting STEM occupations. This measure also has a negative effect on wage growth once we include autonomy. Our demographic variables are robust with expected signs across all robustness checks, lending support to our model specification.

Table 3 shows the robustness of our results for alternative autonomy measures, which we introduce in detail in Appendix A1. In column 1 we replace our autonomy measure with an alternative O*NET-based autonomy measure – the decision-making index by Deming (2021). This measure is significant and the coefficient is similar to our main measure. Column 2 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.

Column 3 in Table 3 shows regressions with the worker discretion measure from Menon et al. (2020) based on the European Work Conditions Survey (EWCS) and generated from workers' replies to questionnaires. We show details of the EWCS-based measure in Appendix A1. In contrast to our baseline worker autonomy index which is computed on US data, this EWCS-based measure for worker discretion allows us to generate different occupational autonomy values for each country. The main advantage of the EWCS-based measure is that it can reflect the country-specific institutional context of occupational design. The main disadvantage of this measure is that it the reported level of worker discretion might be endogenous to wage growth. In the regression shown in column 4, the coefficient for the EWCS-based measure is positive, statistically significant and higher than our baseline estimate. An occupation with one standard deviation higher worker discretion has more than 0.4 percentage-point higher annual wage growth. The size of this coefficient suggests that our main regression in column 1 in Table 1 might capture a lower-bound estimate for the effect of autonomy on wage growth.

Finally, we complement our occupation level wage growth analysis with an individual level

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).

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

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

measure of worker autonomy and find that wage growth also differs within workers of the same occupation, between workers with and without supervisory responsibilities. We take this measure from EU SILC, where information about supervisory tasks based on answers to the question 'Does your job include supervising others?'[6] is provided. 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 and interact the supervisory task variable with a linear time trend to capture wage growth differences. We find that the adjusted wage level difference between workers with and without supervisory tasks is 14% and increases by 0.25pp each year. 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 in 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 on wage growth in the period until 2010 (see Table A2.2 in Appendix A2). While routinisation 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. A possible explanation for the positive effect of routinisation on wage growth in recent years is that the least-productive workers in an occupation have already left these occupations because these jobs have already been automated or offshored in the preceding years.

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 routinisation and in row 5 the measure for offshoring. 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 routinisation or automation. Rows 11 to 13 include alternative measures for offshoring. Rows 14 and 15 include task-based measures for non-routine manual occupations.

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 robust, strongly supporting our main finding that worker autonomy can explain wage growth divergence in Western Europe between 2003-2018.

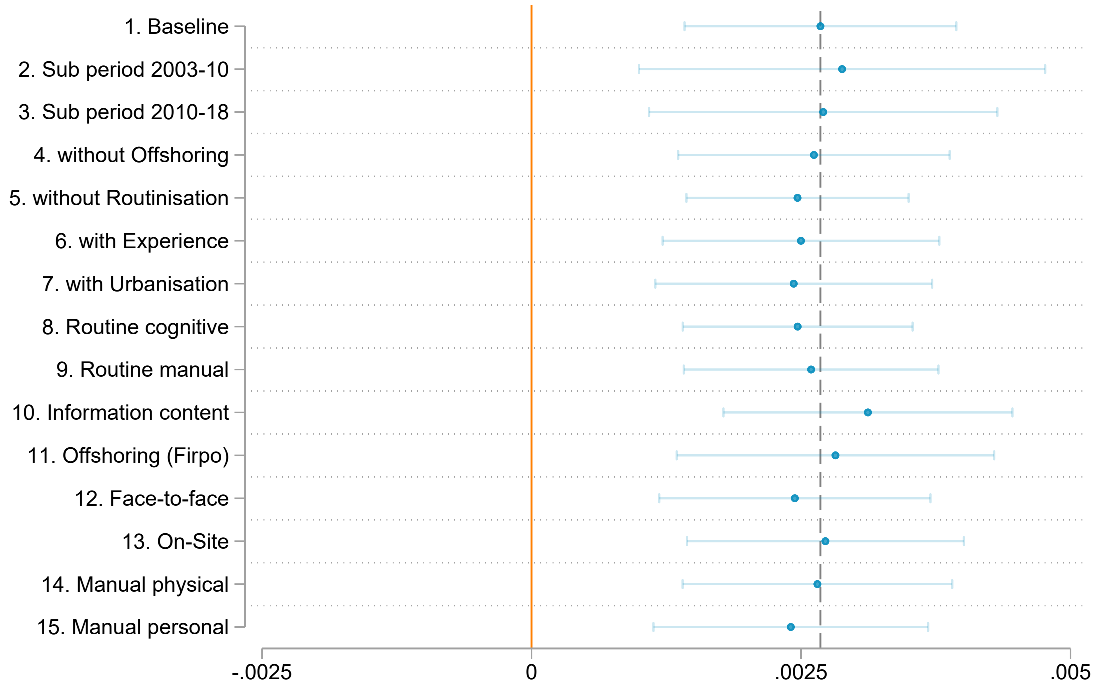
5.3 The drivers of the autonomy wage premium

5.3.1 Autonomy and technological change

To investigate the drivers of the autonomy wage premium at the industry and country level, we extend our empirical strategy. First, we generate the change in the autonomy wage premium for each industry in each country, by estimating equation 2 for each industry-country pair separately. To analyse whether the autonomy premium is higher in industries experiencing faster technological change, we use individual-level data on computer adoption from EWCS and generate the change of computer use within our six industries over our sample period (the

[6] 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.

Figure 5: Further robustness checks



Notes: CI = 95%. The vertical dashed grey line shows our baseline autonomy estimate.

survey is repeated every 5 years). Subsequently, we regress the industry-country autonomy coefficients on the change in computerisation in each industry, in line with equation 3.

$$\text{autonomy wage premium}_{ic} = \beta_1 \times \text{computer use}_{ic} + \kappa_c + \varepsilon_{ic} \quad (3)$$

Column 1 in Table 4 presents the result from estimating equation 3 by OLS with robust standard errors across industries. We include country-specific fixed effects κ_c to adjust for country-specific factors. As expected, the increase of the autonomy premium is higher in industries with faster adoption of computer use. We replicate the same regression at the country-, rather than the country-industry level in column 2, but do not find a statistically significant effect. This could be due to the speed of computer adoption varying more strongly across industries than across countries. However, we find a statistically significant correlation between the ICT investment, measured as the ICT capital stock divided by gross fixed capital formation, and changes in the autonomy wage premium at the country level in column 3. This result lends further support to the impact of technological change on the relation between technology and autonomy. We visualise the result from column 3 in Table 4 in Figure 6 below.

5.3.2 Autonomy and collective bargaining

To test whether strong labour unions reduce the dispersion of wage levels by lowering wages for high-autonomy occupations and/or raising wages for low-autonomy jobs, we split our countries in two groups – those with high-union density and low-union density.[7] Subsequently, we run

[7]Data for labour market institutions at the country level comes from the OECD-AIAS-ICTWSS database. We use the following variables in this section: union density (from administrative data), the degree of collective bargaining centralisation, collective bargaining coverage and the routine involvement of employees in social and labour policy legislation.

Table 4: Computer use and the autonomy wage premium

	(1)	(2)	(3)
Δ Computer use	0.0265*	-0.0052	
	(0.0134)	(0.0160)	
Change in ICT/GFCF			0.0956**
			(0.0345)
Observations	90	15	12
Level	*Industry*	*Country*	*Country*
Country FE	*Yes*		

Standard errors in parentheses

We use robust standard errors in all regressions

Column 3 has only twelve observations becauese ICT and GFCF data in KLEMS is not available for Belgium, Norway and Switzerland.

The start and end period for our measure of computerisation is matched with the start and end period for our wage data. This is 2003-2018 for most countries. Appendix A3 provides an overview of data availability across countries.

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

individual-level wage (level) regressions in each year and add a dummy variable for high or low union density (UD) as well as an interaction term between the dummy and the autonomy index. UD is equal to one for high-union density countries, defined as countries with union density above the median in our sample, and zero otherwise. We estimate the following wage equation by OLS for each year:

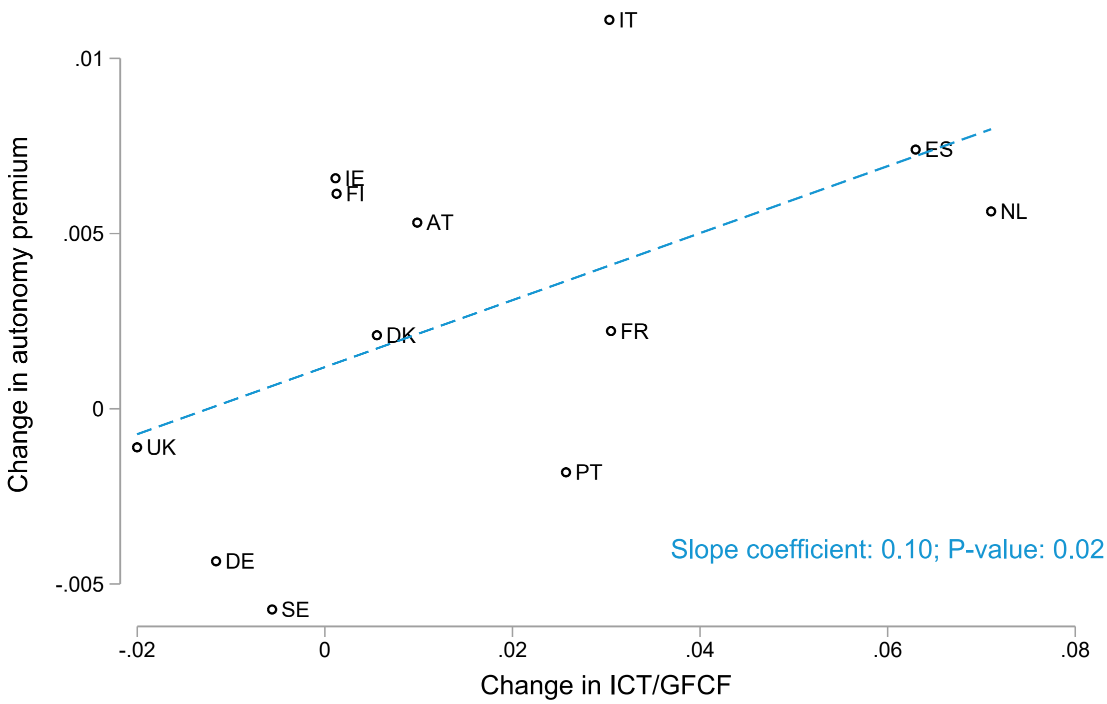
$$ln(w_{ijkc}) = \beta_1 A_j + \beta_2 UD + \beta_3 (A_j \times UD) + \text{controls} + \theta_{kc} + \varepsilon_{ijkc} \quad (4)$$

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. Because we estimate cross-sectional regressions for each year separately, we do not need to interact our index measure index with a time trend. θ_{kc} is an industry-country fixed effect to condition out industry- and country-specific wage premia and we cluster standard errors at the occupation-industry-country level. We include the same control variables as in equation two, which comprise the task measures for routinisation and offshoring and the set of demographic variables.

Estimating equation 4 yields coefficients for the autonomy wage premium for each year, capturing the differences in wage levels between an occupation with the mean autonomy index and an occupation that is one standard deviation above the mean. The interpretation of these coefficients is similar to interpretation of the college wage premium or the gender pay gap. The coefficient β_1 captures the autonomy wage premium in low-union density countries and the sum of coefficients $\beta_1 + \beta_3$ shows the autonomy wage premium in countries with high union density. We plot these coefficients in Figure 7.

We find that the autonomy wage premium is larger in low-union countries, indicating that countries with higher union density display a lower wage-level differences between high- and low-autonomy occupations. This pattern suggests that strong collective bargaining reduces the autonomy premium by improving the relative bargaining power of low autonomy workers. Yet, the autonomy wage premium grows in countries with high and low union density and the rate of this increase is even higher in high union density countries, as visible in Figure 7. This

Figure 6: The autonomy wage premium and ICT investment



finding might indicate that labour unions, while generally able to reduce the autonomy wage premium, were less able to keep wage divergence in check over the last two decades.[8]

In some European countries, collective bargaining power might be better captured by factors such as the level of wage setting coordination (defined as an index measure that increases with more centralised wage negotiations and binding norms regarding wage negotiations), the frequency of the involvement of unions and employer organisations in policy-making, or private sector collective wage agreement coverage (defined as the share of workers covered by wage bargaining agreements). Figures 8A-C reproduce the results reported in Figure 7 after replacing union density with alternative bargaining measures.[9]

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. For both variables we find a higher autonomy wage premium in countries with weaker collective bargaining, suggesting that strong collective bargaining reduces the autonomy wage premium. Countries with a high coordination of wage-setting show a more rapid increase in the autonomy premium (Figure 8C), in line with our findings for union density, whereas countries with higher involvement of unions in policy-making show a slower growth of the autonomy premium (8B). The difference in the autonomy wage premium between countries with and without involvement of unions in policy-making has increased noticeably during the Great Financial Crisis, suggesting that the involvement of worker and employer organisations is particularly important for wage developments in crisis periods.

[8] An alternative explanation might be that unions increasingly bargain for improvements in work quality or reductions in work hours instead of higher wages.

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

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

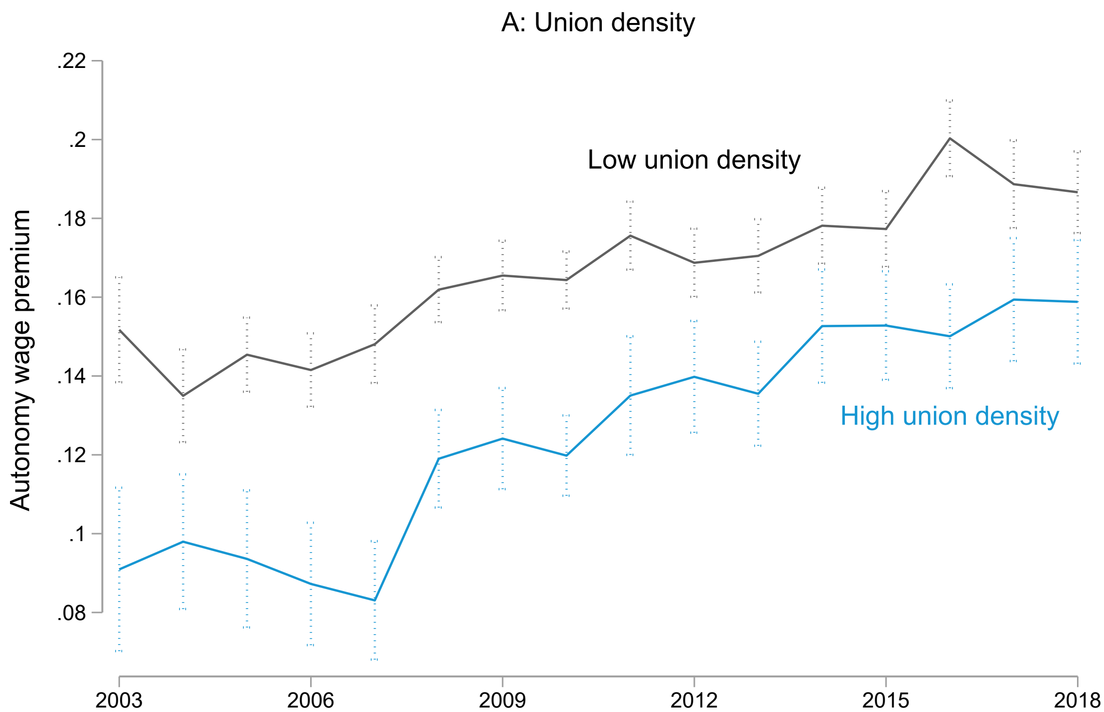


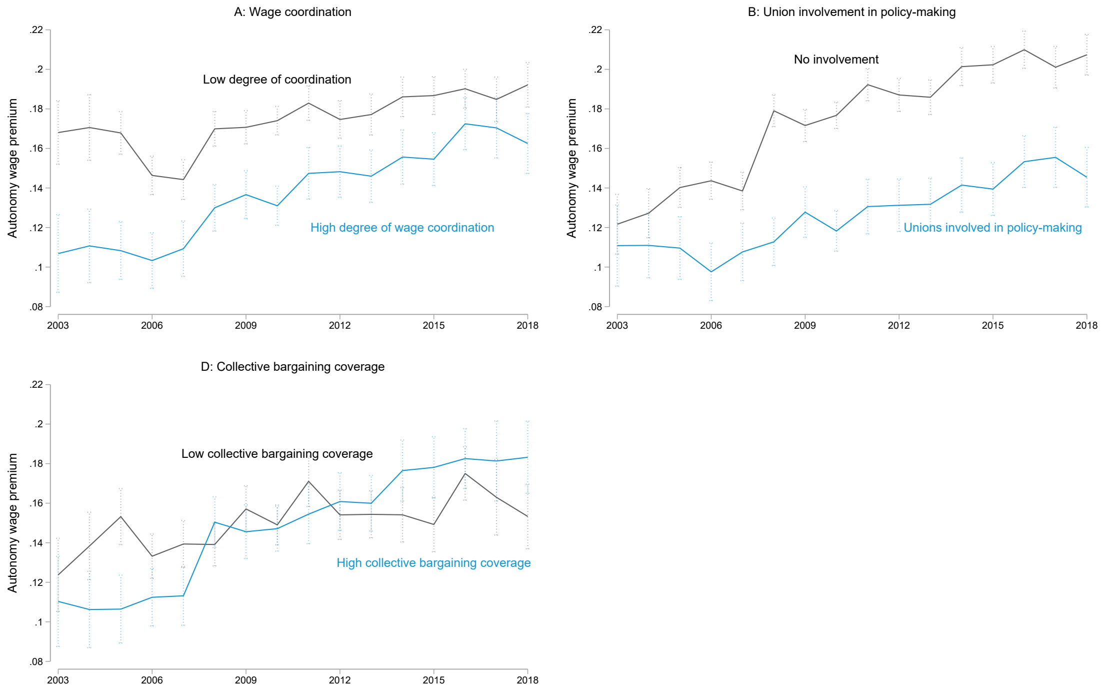
Figure 8C contrasts the autonomy wage premium across countries with high and low coverage of collective wage agreements. While the autonomy wage premium in high collective wage agreement countries is lower until the Great Financial Crisis, it surpasses the premium in low collective wage agreement countries after the crisis, but the difference across both country groups is generally not statistically significant. One potential explanation why collective wage agreements have a smaller impact on occupation-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.

The bottom line from our collective bargaining analysis is that the autonomy wage premium is lower in countries with stronger and more centralised bargaining institutions, in which workers with high and low autonomy bargain jointly for wage increases. While we cannot claim to identify a causal effect of worker autonomy on individual wage levels due to unobserved individual level heterogeneity in ability or motivation, our results suggest that collective wage bargaining institutions play an important role in keeping occupational wage inequality low.

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

Deming (2021) highlights that workers with higher autonomy experience longer and more gradual periods of wage growth in the US. We find the same pattern in the European context as reported in Figure 9A. The solid line exhibits the autonomy wage premium along the age distribution averaged in 2006, chosen because it is the first year when data in all countries is available, the dashed line exhibits the autonomy wage premium in 2017. We generate 5-year age bins and interact them with our autonomy measure, following the estimation strategy in

Figure 8: The autonomy wage premium and collective bargaining



Source: EU SILC, own calculations

equation 4.[10]

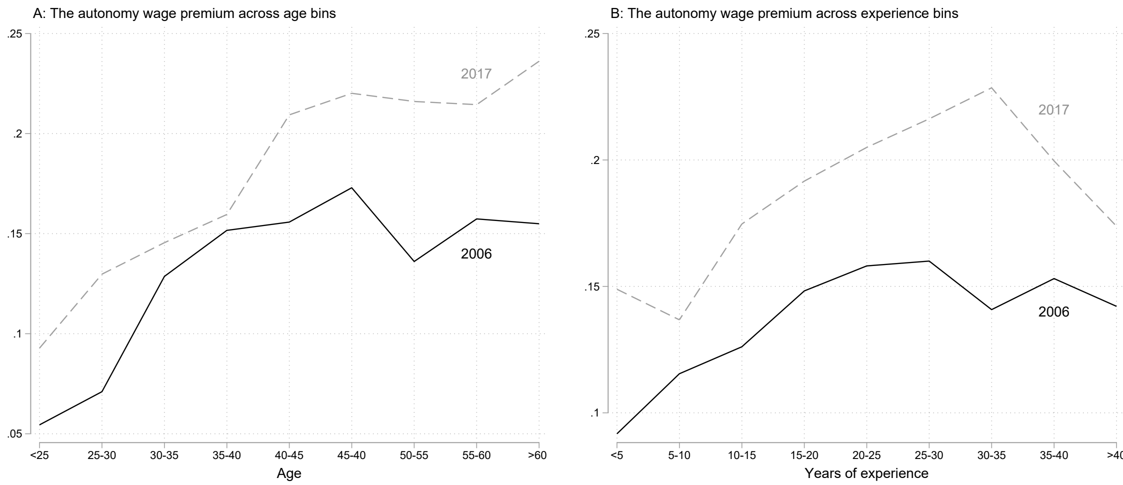
Three facts emerge. First, the autonomy wage premium is higher for older workers in comparison to younger workers. Second, the autonomy wage premium has increased across all age bins. Third, the increase in the autonomy wage premium is most pronounced among workers who are older than 40. One potential interpretation is that many high autonomy workers are not in regular employment for such a long period, due to education, early retirement or because they leave regular employment to start their own companies.

Our findings for changes in the autonomy wage premium across experience bins confirm the overall findings from age, shown in Figure 9B. The autonomy wage premium is higher for more experienced workers and has increased across all experience bins from 2006 to 2017. In 2017, the autonomy wage premium slightly decreases in the highest experience bins (workers with over 35 years of experience). We prefer the age measure because it has larger coverage. For missing experience observations, we impute potential experience as age minus years of education level minus 6, proxying potential experience.

Figure 10A below shows that increase of the autonomy wage premium for men and women separately. The autonomy premium follows the same trajectory 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. 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.[11] Because women are more likely to be employed in low autonomy jobs, the increase in the autonomy wage premium benefits men disproportionally and contributes to an increase

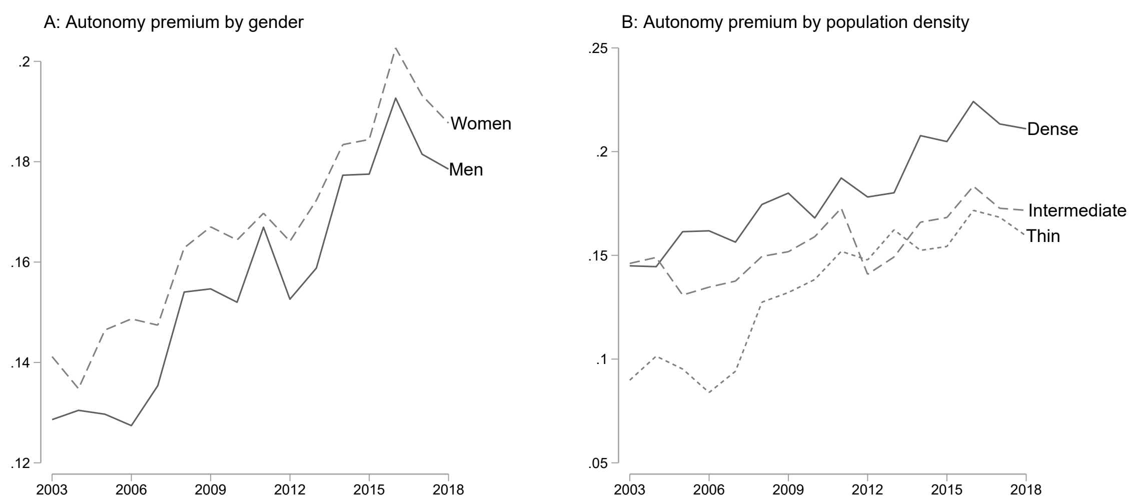
[10]Regression tables from section 5.3.3. are available upon request.
[11]Data shown in Appendix A3.

Figure 9: The autonomy wage premium along age and experience



in the gender wage gap.

Figure 10: The autonomy wage premium over time for gender and population density



In Figure 10B we look at the autonomy wage premium across different levels of population density based on geographic data from EU SILC, and find that that autonomy premium is generally higher in densely populated areas and that the premium increases in both densely and thinly populated areas, but not in intermediate areas. As dense areas might have seen faster technological change and shifts in labour demand (Baum-Snow and Pavan, 2013; Moretti, 2013), our result for dense areas confirms the finding with respect to technological change in section 5.3.1. above. The increase in wage inequality within thinly populated areas is less established, but this result might reflect increasing disparities between prosperous and less prosperous rural areas.

6 Conclusion

We contribute to the understanding of wage inequality in Western Europe by highlighting worker autonomy as an important determinant of wage divergence. Wages in a high autonomy occupation have grown on average 0.27 percentage points faster each year from 2003-2018 than wages in an occupation with an average degree of autonomy. Since high autonomy occupations are generally at the top of the wage distribution, this process increases wage inequality. This finding is robust for various measures of autonomy and different measures of occupational characteristics, the inclusion of a rich set of control variables, and are not driven by single countries or industries.

Our findings imply that technological as well as institutional factors shape wage inequality between high and low-autonomy occupations. The autonomy wage premium increases faster in industries and countries with faster technological change, measured as computerisation and ICT investment. This finding is consistent with theoretical explanations that highlight technological progress as the driver of changes in the wage structure.

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. We infer that collective bargaining can mediate inequalities resulting from technological change and allows productivity gains to be shared more equally. But we also find that the autonomy wage premium is increasing in low as well as high collective bargaining countries, suggesting that labour unions were not able to halt the rise of the autonomy wage premium.

We also shed light on the interaction between demographic factors and the autonomy premium. The autonomy wage premium is larger and increases faster among more experienced workers and among workers in urban areas. We do not find differences in the increase of the autonomy wage premium across genders but the increase in the autonomy wage premium contributes to the gender wage gap, because women are disproportionally employed in low autonomy occupations.

While we only focus on regularly employed workers, future research shall explore the role that changes in the employment structure play on changes in inequality. Over recent years, self-employment has increased, in particular at the bottom of the distribution. In the face of this, our analysis may understate wage growth patterns across worker groups. Our analysis also does not include non-wage income, which is increasingly large at the top of the wage distribution, suggesting that our main result presents a lower bound estimate. 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 whether, for example, the autonomy wage premium at the occupational level rises less in firms with higher worker autonomy in the ownership structure (e.g. cooperatives relative to regular firms).

Policy makers, if concerned about income inequality, should pay particular attention to occupations characterised by low-autonomy, or, considering our results for the subjective autonomy measure, increase the degree of autonomy for workers in certain jobs. Efforts to tackle wage inequality should put a particular emphasis on low autonomy workers in industries with fast technological adoption and low union density. To reduce wage inequality, policies should focus on educational measures and re- or upskilling of workers in low autonomy occupations, allowing them to adapt to technological change and on strengthening collective bargaining institutions that enhance worker power across occupations, such as unions, wage coordination and the involvement of employee organisations in economic policy.

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A Appendix

A.1 Appendix A1

A.1.1 Routinisation and offshoring

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)

The figures below show our measures for routinisation and offshoring along the wage distribution.

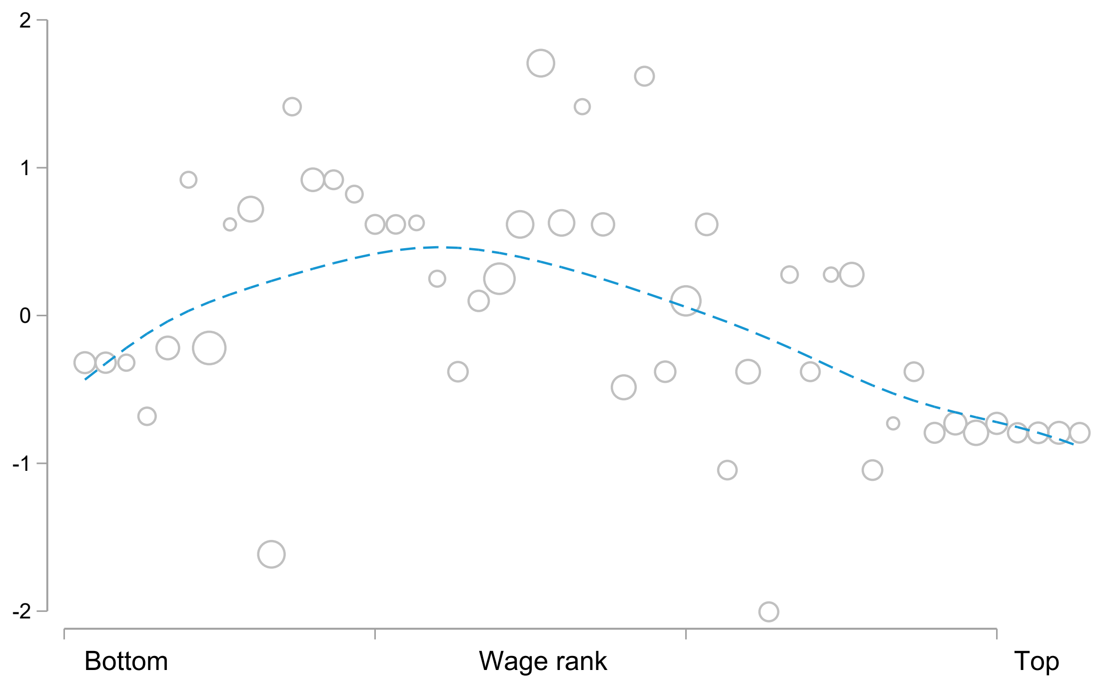
Below we show relations between routinisation (offshoring) and wage growth. The figures do not suggest a relation between these factors and wage growth.

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

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

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

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



EU SILC, own calculation. Wage ranking is based on average occupation-industry wages across countries. Circle sizes reflect employment shares.

A.1.2 Alternative measures for worker autonomy

A.1.2.1 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)
- 4.C.3.a.4 Freedom to make decisions

Below we show correlations between our O*NET based index measures for autonomy.

A.1.2.2 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 advantage of this measure is that the EWCS allows to generate different occupational autonomy measures for each country. This worker discretion measure consists of three binary indicators generated from workers' answers to the following questions: 'Are you able to choose or change?;'

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

EU SILC, own calculation. Wage ranking is based on average occupation-industry wages across countries.

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 polychloric correlation matrix to construct this index. The first component can explain 84 percent of the overall variance, the same share as the 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 each five years from 2005, 2010 and 2015 and we generate a pooled measure for each occupation-industry 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. The table below shoes correlation between different occupation level measures of autonomy.

A.1.2.3 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).

A.1.2.4 Demographic variables

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

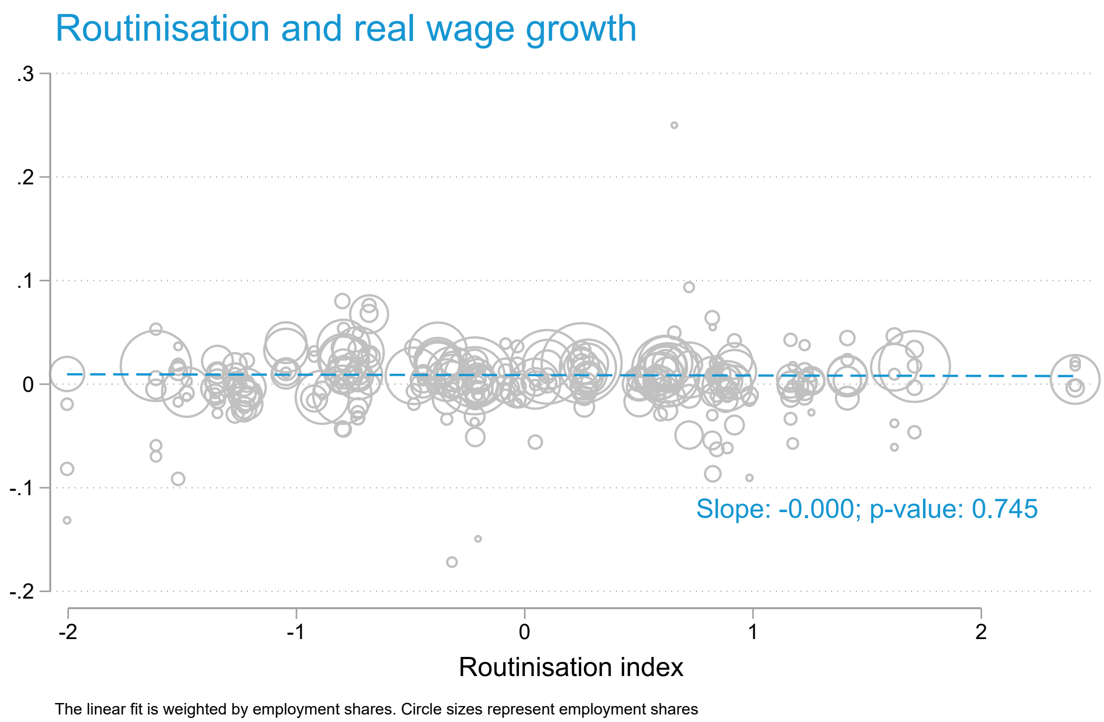
Table A1.2: Autonomy index measures - cross-correlations

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

Table A1.3: Demographic variables

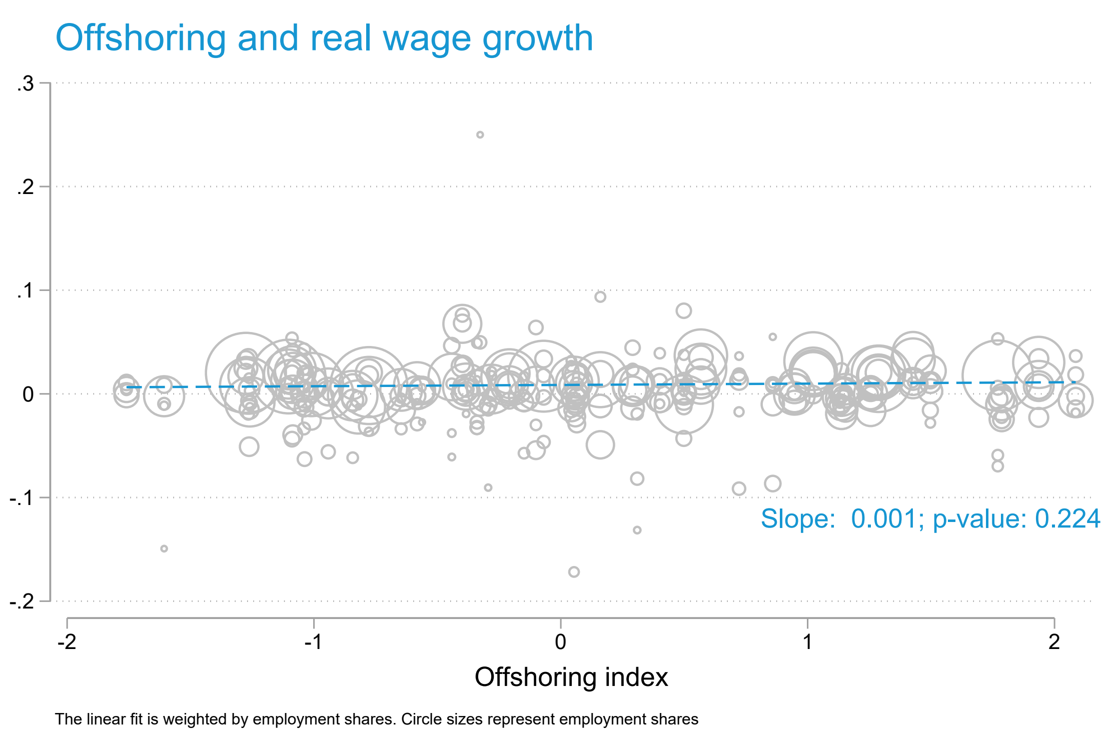
	$Value$
Average age	40.84
Average years of experience	20.23
Average education level (ISCED)	3.43
Share of women	0.36
Share of foreign born	0.13
Share of urban residents	0.48
Share with higher education	0.36
Observations	821974

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



Notes:

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



Notes:

Figure A1.5: Share of workers with supervisory tasks

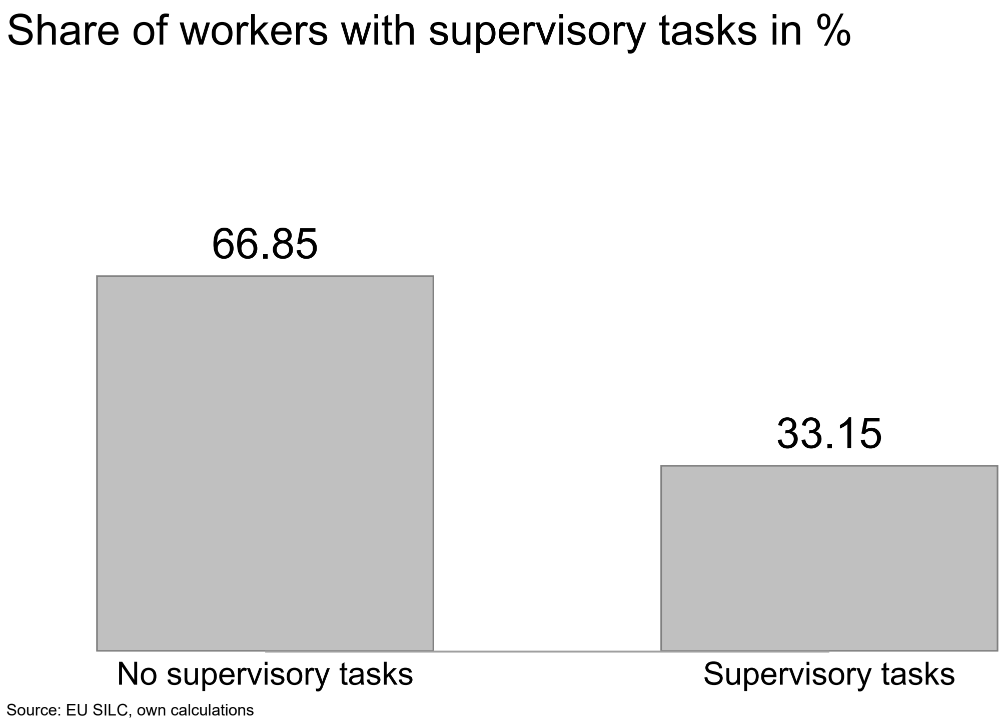
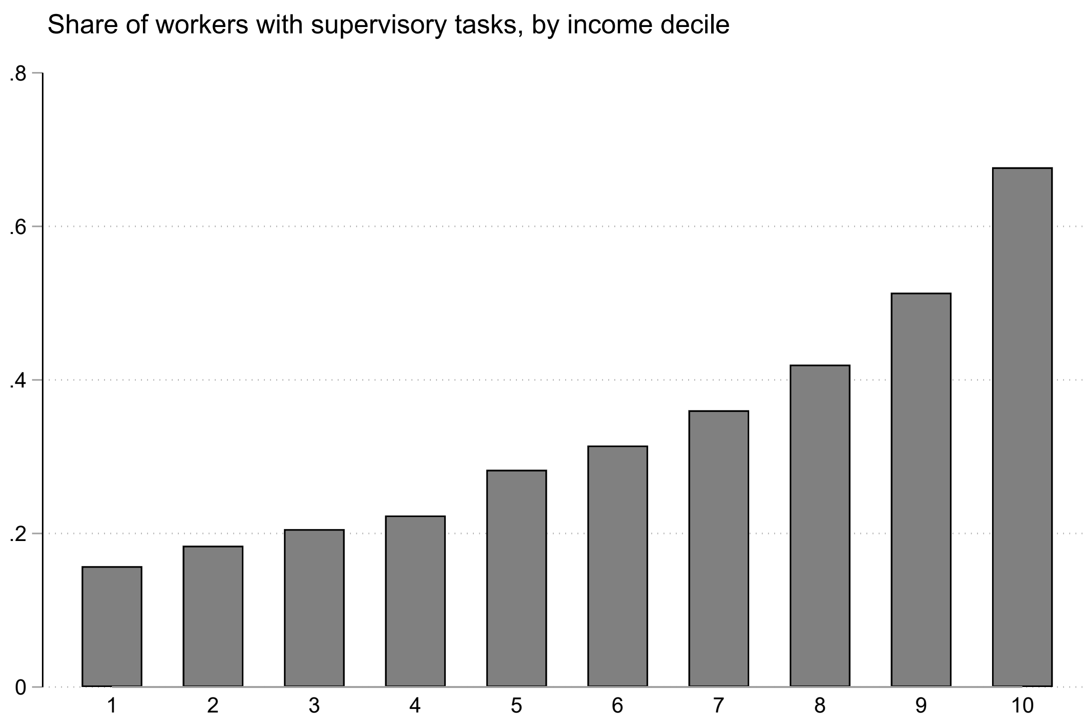


Figure A1.6: Share of workers with supervisory tasks, by income decile



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 for routinisation 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 occupations.

In column 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 regressions mirror rows 4 and 5 in Figure 5.

Table A2.2 reflect 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 regressions 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 function 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 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 manual 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.

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

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

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 A2.1: Robustness check: countries

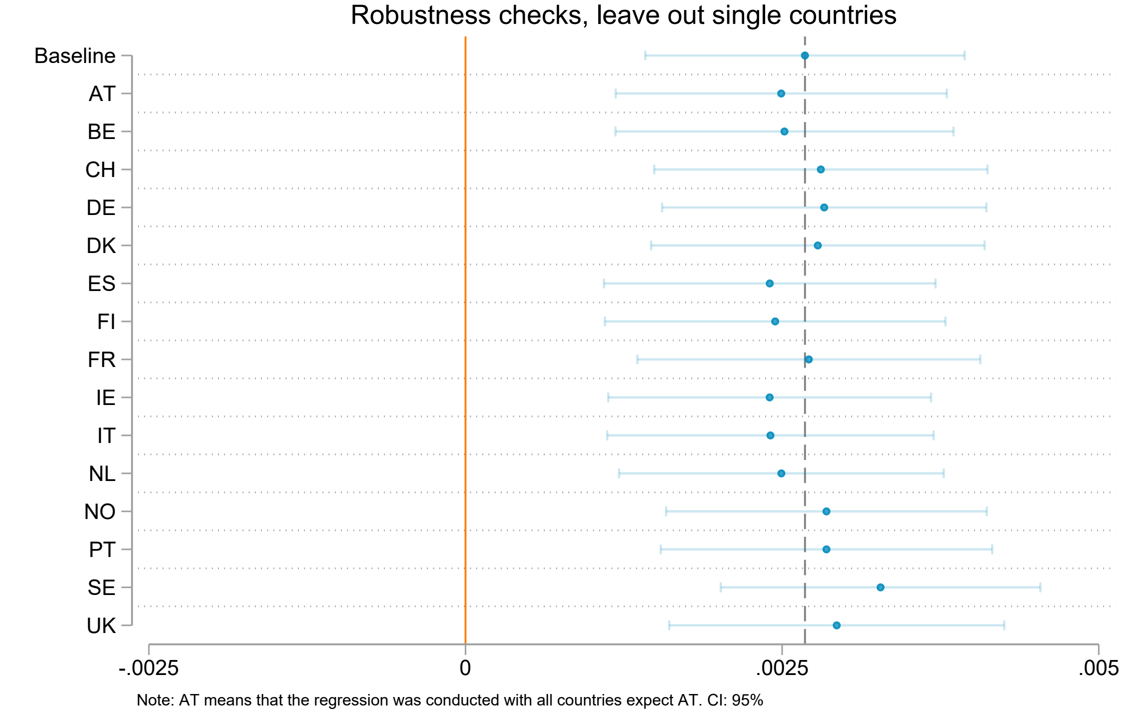
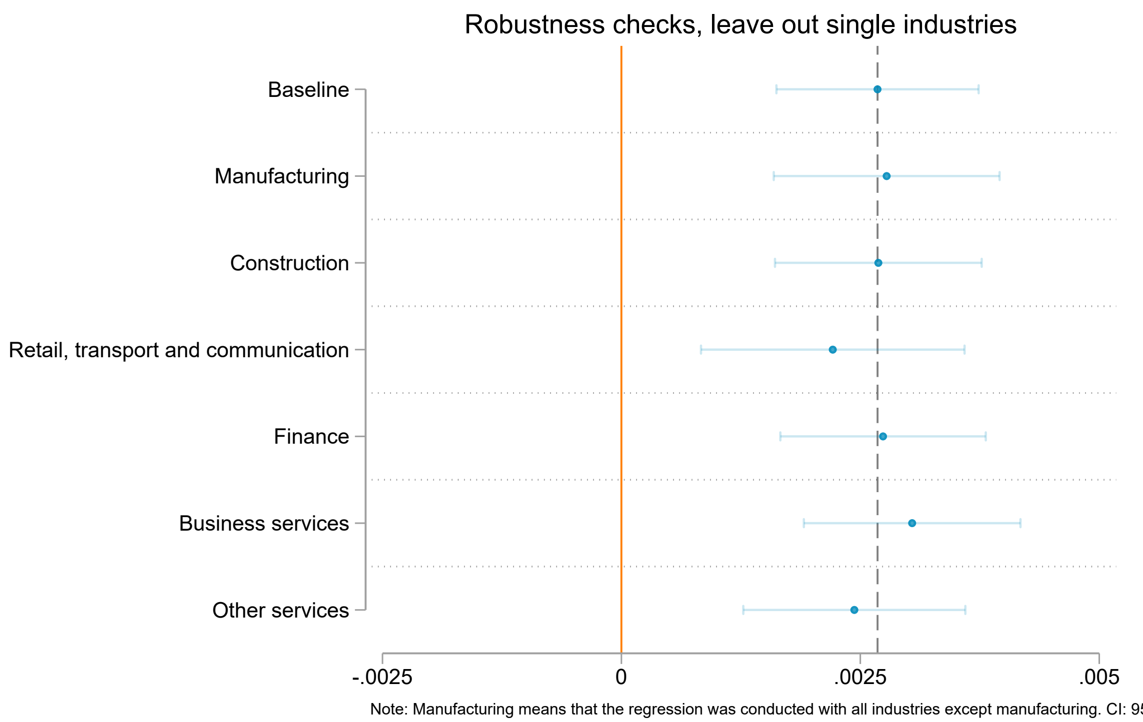


Figure A2.2: Robustness check: industries



A.3 Appendix A3

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

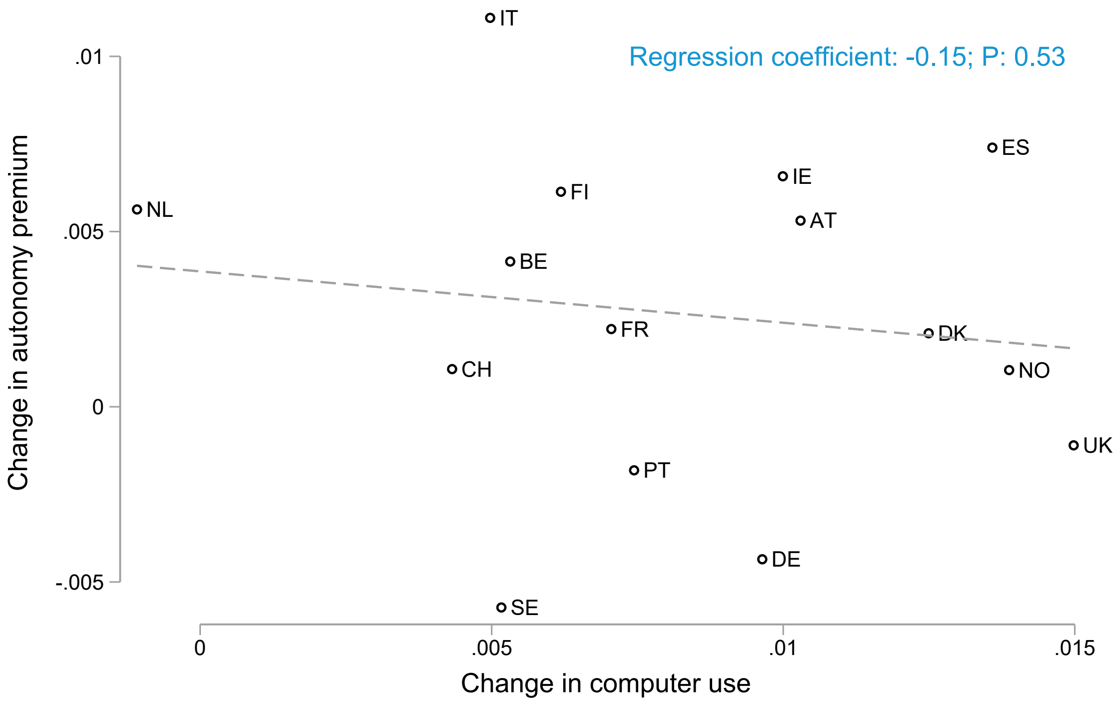


Table A3.1: Collective bargaining variables

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

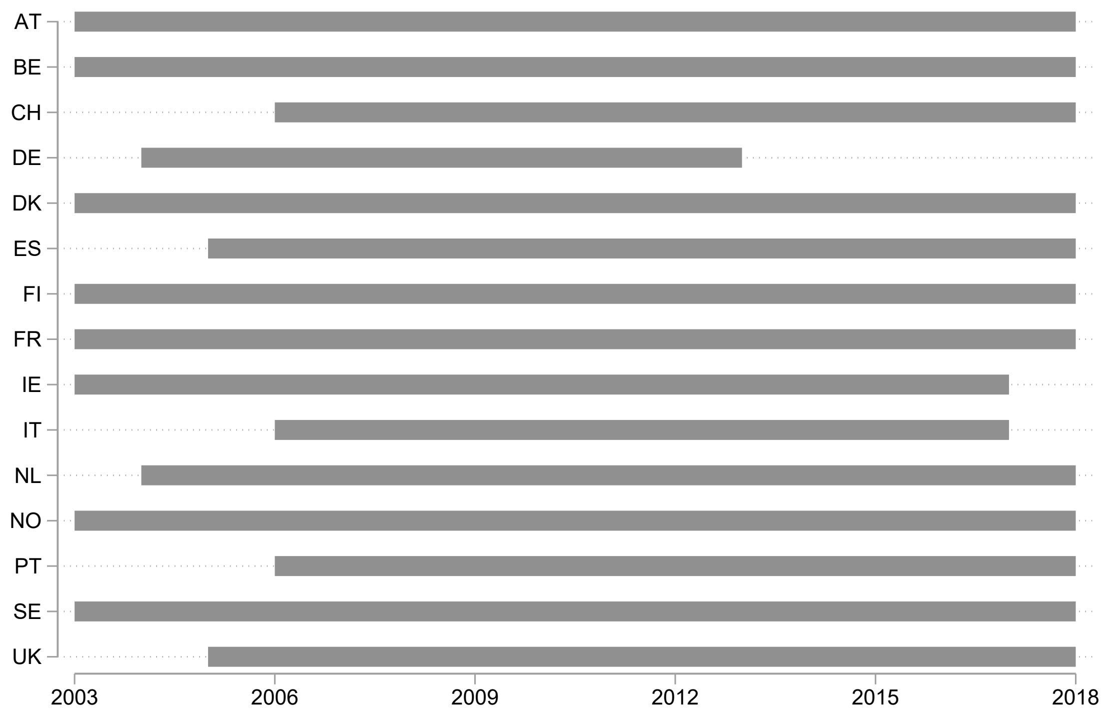
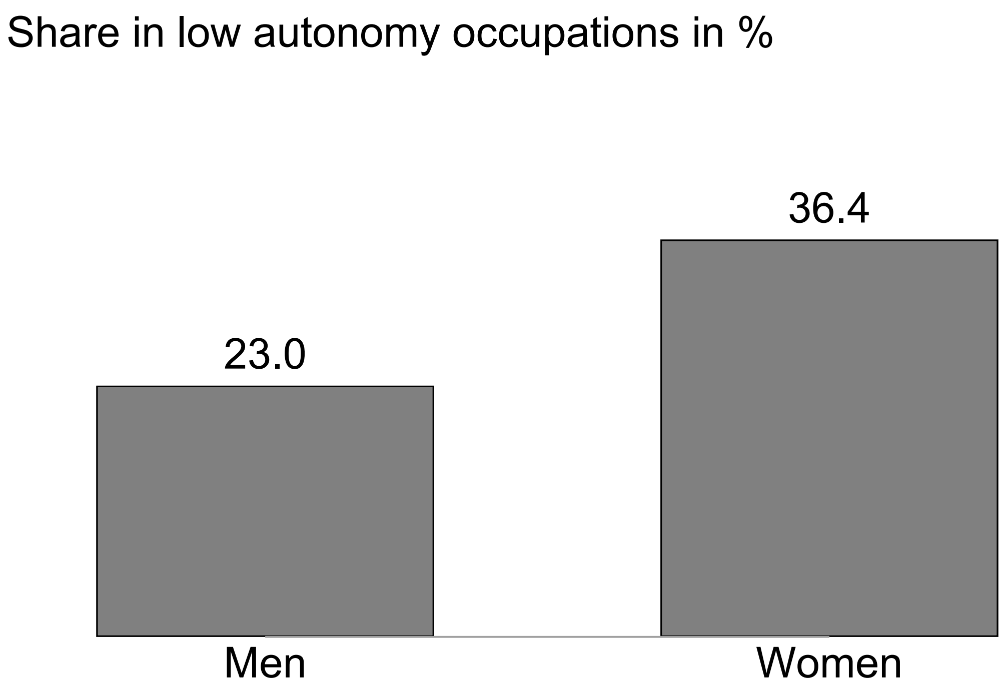


Figure A3.3 shows the composition of men and women in low autonomy occupations, defined as the bottom quartile of the autonomy index.

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.