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Autonomy and wage divergence: evidence from European survey data

Thomas Rabensteiner[1] (University of Greenwich and PEGFA)

Alexander Guschanski (University of Greenwich and PEGFA)

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Abstract

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Keywords: wage inequality, autonomy, employee monitoring, outsourcing, bargaining power, labour market institutions, survey data

JEL Classification E24; J31; J50

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[1] Corresponding author: Thomas Rabensteiner
Email: t.rabensteiner@gre.ac.uk
Address: Old Royal Naval College, Park Row, London SE10 9LS

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Abstract

Wages across occupations have substantially diverged in Western Europe, exacerbating wage inequality. This paper presents a novel perspective on this divergence by identifying occupational autonomy as a crucial determinant of wage growth. We analyse individual-level wage data from the EU Survey of Income and Living Conditions across 15 Western European countries from 2003 to 2018 and reveal that occupations with higher autonomy have experienced markedly faster wage growth compared to those with lower autonomy, thereby increasing the *autonomy wage premium*. Our analysis indicates that the rise in the autonomy premium is more pronounced in countries and industries where employee monitoring and outsourcing are widespread. These findings imply that recent socio-economic shifts are not power-neutral but have eroded the bargaining power of workers in low-autonomy occupations. Conversely, rising minimum wages mitigate the rise in the autonomy premium.

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1 Introduction

Over recent decades, wage disparities across occupations in Western Europe have widened substantially. From 2003 and 2018, real wages of Managers, a major occupational group, grew by 34%, while those for Services and Sales Workers rose only by 4.8% (Figure 1). Given that in 2003, Managers' wages were almost double those of Services and Sales Workers, this growing disparity has exacerbated wage inequality. Wage divergence between these two occupational groups is indicative of a broader trend affecting numerous occupations. Amid the current cost-of-living crisis, which disproportionately harms lower-wage earners, occupational wage divergence is particularly alarming.

Two critical questions emerge: First, which occupational characteristics are associated with stagnant or rising wages? Second, which socio-economic factors drive these wage trends? Prior research has focused on shifts in labour demand, suggesting that wages stagnate in occupations that are susceptible to automation or offshoring (Autor et al., 2006; Acemoglu and Autor, 2011; Firpo et al., 2011), as the increased use of machinery and the globalisation of labour processes reduces demand for certain jobs. However, these explanations fall short for explaining the prevalent wage stagnation in occupations that are neither easily automated (or routinised[1]) or offshored, like cleaning, serving or care work.

This paper introduces a new perspective by focusing on occupational autonomy as a critical determinant of wage growth. We operationalise occupational autonomy through a task-based index capturing worker's control and influence over their work process to compare bargaining power differences across occupations. We conduct the first empirical analysis to explore the relationship between occupational autonomy and wage growth, using wage data across Western European countries. Furthermore, we investigate the drivers of wage divergence between occupations with high and low autonomy. Drawing on insights from the industrial relations literature, we highlight and examine the role of labour market institutions (LMI) (Western and Rosenfeld, 2011; Kristal and Cohen, 2016), power-biased technological change (Skott and Guy, 2007), and the fissuring of the workplace (Weil, 2014) in affecting changes in the occupational wage distribution.

To empirically investigate the wage divergence across occupations, we merge harmonised individual-level wage data from the European Union Survey of Income and Living Conditions (EU SILC) across a sample of 15 Western European countries[2] from 2003 to 2018, with task-content data from O*NET, which allows us to construct an occupation-specific measure of autonomy. Our empirical analysis focuses on occupation-industry-country cells as the primary unit of interest. We conduct our investigation in two main stages: First, we perform regression analyses of occupational wage growth against our constructed autonomy index, while adjusting for several other wage growth determinants. Second, to understand the drivers of the rise in the *autonomy wage premium*, we estimate wage growth trends using interaction terms between autonomy and various industry- or country-level variables, such as employee monitoring, outsourcing, and shifts in LMI.

Our main finding is a sizeable and statistically significant association between occupational autonomy and wage growth. Specifically, an occupation with high autonomy (one standard deviation above the mean) exhibits 0.27 percentage points (ppts) higher annual real wage growth, a trend we describe as a rise in the autonomy wage premium. Over 15

[1]We treat automation and routinisation as synonymous concepts, implying the replacement of human labour with machines or software.

[2]Our sample includes Austria, Belgium, Denmark, Finland, France, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

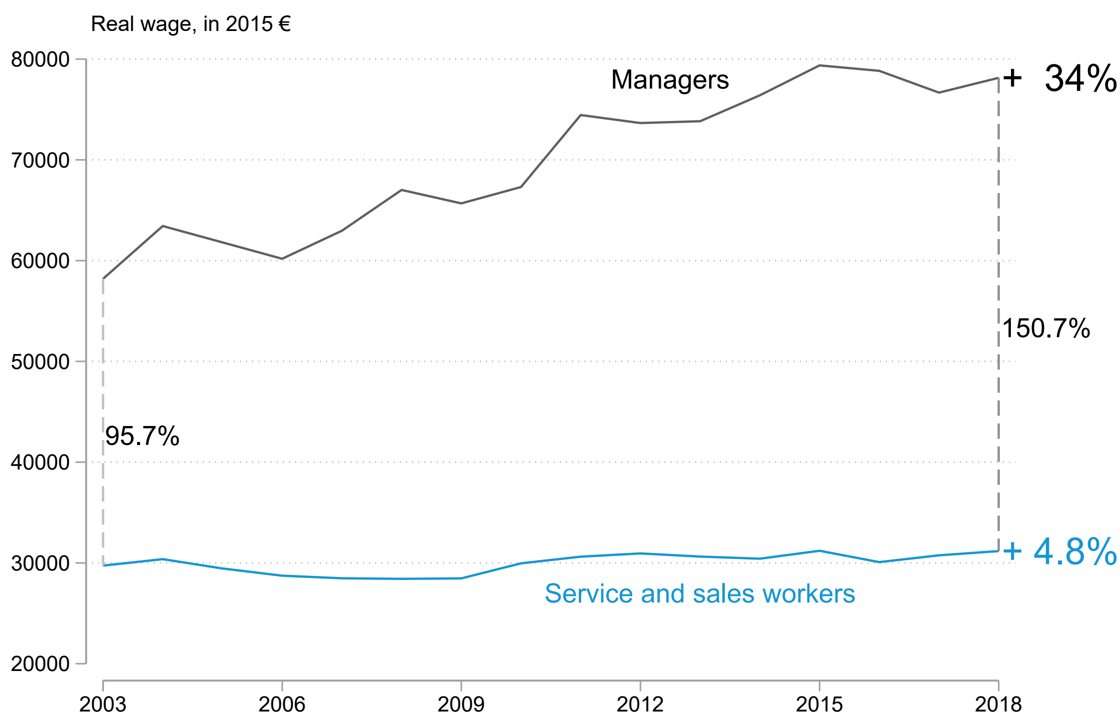
years, this results in a 4.1% higher wage for high autonomy occupations relative to occupations with an average level of autonomy, assuming equal starting wage levels. Considering the existing wage disparities between high- and low-autonomy occupations, our result indicates a considerable increase in occupational wage gaps. For instance, our estimate implies that the wage gap between Managers and Service and Sales Workers (Figure 1) grows from 95.7% to 120.8% between 2003 and 2018, accounting for around 46% of the observed wage divergence between these two groups. Our findings challenge the established view that attributes wage divergence primarily to market factors like the declining demand for routine or offshorable tasks. A sub-period analysis shows that while routineness correlates with wage growth until 2010 this relationship dissipates thereafter. In contrast, occupational autonomy consistently predicts wage growth throughout our study period.

Exploring the factors behind the rising autonomy wage premium, we find it accelerates in countries and industries where a higher share of firms monitor their employees through data analytics. This finding aligns with theories of power-biased technological change, suggesting that new monitoring technologies exacerbate wage inequality by reducing the bargaining power of easily monitored workers (Skott and Guy, 2007). Moreover, we show that the autonomy premium has grown more substantially in countries with increased outsourcing, consistent with literature on the fissured workplace, which posits that the risk of being outsourced depresses wages for certain occupations (Berlinski, 2008; Weil, 2014). Lastly, we show that increases in the minimum wage are correlated with a reduced autonomy premium, suggesting that minimum wages enhance the bargaining power of low-autonomy occupations and contribute to compressing the wage distribution (DiNardo et al., 1996; Grimshaw et al., 2014; Cengiz et al., 2019). However, we find no statistically significant association between shifts in other LMI, such as union density, or collective bargaining coverage, and the autonomy wage premium. This suggests that these LMIs were either unable or ineffective in mitigating the rise in their autonomy premium, possibly due to their limited capacity to enhance the bargaining power of workers in occupations characterised by low autonomy.

Our analysis introduces a political economy perspective to the literature on occupational wage divergence, which has hitherto been dominated by neoclassical explanations focused on shifts in labour demand due to technological change and globalisation. Drawing on interdisciplinary insights from industrial relations, the sociology of work and institutionalist labour economics, the political economy perspective interprets wage distribution through the lens of power relations and offers a counterpoint to the neoclassical view that attributes distributional changes to market forces. Occupational autonomy is strongly linked to bargaining power differences across occupations, and our findings reveal that occupations with greater bargaining power have reaped the benefits from recent socio-economic trends. Conversely, occupations with lesser bargaining power appear to have been adversely affected by monitoring and outsourcing, resulting in lower relative wage growth.

The paper is organised as follows: Section 2 reviews the existing literature, identifies gaps and formulates testable hypotheses. Section 3 introduces our data. In Section 4 we discuss our empirical framework for testing hypotheses related to occupational wage divergence, before highlighting the novel findings of our empirical analysis in Section 5. Section 6 analyses the drivers of changes in the autonomy wage premium and Section 7 concludes.

Figure 1: Wage growth diverges across occupations



Source: EU SILC, own calculations. Managers and service and sales workers refer to 1-digit occupational groups according to ISCO classification. Wage growth is averaged across industries and countries. The figure highlights that the wage gap, measured in annual gross real wages (in 2015 €), between these two occupational groups has risen from 95.7% to 150.7% from 2003 to 2018.

2 Occupational wage divergence: autonomy, routinisation and offshoring

The concept of autonomy - defined as worker's control and influence over their work process - has received considerable attention in labour market research. Autonomy has been investigated from multiple perspectives, including ownership structures (Burdín and Dean, 2009), employment types (Kalleberg, 2003), workplace discretion (Menon et al., 2020), work organization and occupation design (Lopes and Calapez, 2021), and workplace hierarchies (Bloom et al., 2012). This paper focuses on the occupational aspect of autonomy, aligning with the prevailing direction in socio-economic research that emphasises the increasing significance of occupations, characterised by distinct task sets required of workers, for labour market outcomes (Autor et al., 2003; Autor, 2013; Fernández-Macías and Bisello, 2022). Our approach implies that a worker's level of control and influence is intrinsically linked to their specific tasks in the production process, irrespective of the organisational structure of the employing firm[3]. Higher autonomy is characterised by tasks involving decision-making authority, creative problem-solving, task complexity, and strategic responsibility in the workplace.

The link between higher autonomy, higher bargaining power and higher wage *levels* - the autonomy wage premium - is firmly established in the labour discipline variant of the efficiency wage model, the sociology of work, and in recent empirical studies in labour economics (Marx et al., 1981; Shapiro and Stiglitz, 1984; Bowles, 1985; Wright, 1997; Kalleberg, 2003; Bloesch et al., 2022; Bayer and Kuhn, 2023). Because of incomplete contracts, employers must discipline workers by paying higher wages or more intense monitoring - otherwise the workers will shirk. Workers in low-autonomy occupations, performing tasks that lack complexity, creativity, or strategic depth, can be more easily monitored using technological tools such as cameras, software, or GPS trackers. In contrast, workers in occupations characterised by high autonomy are hard to monitor because they perform complex and open-ended tasks. As monitoring is difficult and costly, employers pay higher wages to high-autonomy occupations. Moreover, tasks performed in these occupations are often critical for the production process, and disruption or withdrawal from work is particularly costly for firms, resulting in higher hold-up power (a form of bargaining power) for workers in high-autonomy occupations. Bloesch et al. (2022) show that this bargaining power difference leads to wage premia for high-autonomy occupations in Norway. Moreover, Leonida et al. (2023) observe that supervisory positions, typically characterised by higher

[3]Different dimensions of autonomy are complementary: a low-autonomy occupation, e.g. a Service and Sales Worker, might have more autonomy in workplaces organised as cooperatives than in firms with conventional ownership structures. This has certain implications for our empirical analysis, and we discuss it, along with alternative concepts and measures of autonomy, in more depth in Section 3.

autonomy through greater decision-making authority and control over work processes, receive higher wages than their non-supervisory counterparts and that the UK labour market exhibits the highest wage gap between supervisory and non-supervisory workers for 26 European countries. Using data for Germany, Bayer and Kuhn (2023) show that job roles characterised by higher autonomy are correlated with higher wages, and that autonomy accounts for 75% of the observed wage dispersion between workers.[4]

Wage *level* differences between high and low-autonomy occupations analysed in these studies are unsurprising in the context of hierarchical capitalist organisational structures. The crucial question then becomes whether changes in the autonomy wage premium can explain recent occupational wage divergence, i.e. changes in relative wage levels over time. Existing research highlights three socio-economic drivers of wage divergence between high- and low-autonomy occupations: power-biased technological change, the fissuring of the workplace, and LMI.

First, the power-biased technological change (PBTC) hypothesis (Skott and Guy, 2007) contends that the emergence of employee monitoring technologies disproportionately harms low-skill workers with low bargaining power. This hypothesis builds on the labour discipline model by proposing that advancements in information and communication technology (ICT) have lowered the costs for firms to monitor and control their employees. Consequently, this reduces the need for higher pay incentives to deter shirking, leading to suppressed wages, particularly in occupations that are easily monitored - those with low autonomy. In contrast, high autonomy occupations, characterised by complex tasks and a high intensity of decision making, are less susceptible to monitoring. Thus, technological advances in employee monitoring may reduce the relative wages of low autonomy workers, widening the autonomy wage premium.

Monitoring practices have recently become more widespread and intense across several sectors, including retail, telecommunications, logistics, banking, and care work (see e.g. Newsome et al., 2013; Pierce et al., 2015; Hayes and Moore, 2017). This trend is linked with heightened work intensity and reduced bargaining power for workers in affected occupations (Green, 2004). Examples for the rise in employee monitoring include the use of GPS trackers for truck drivers, sensors in Amazon packaging centres, pervasive video surveillance, keystroke and computer activity tracking, barcodes, or customer interaction recordings. Such examples underscore the broad application of monitoring technologies across different economic activities. The critical empirical question is whether, in line with the PBTC hypothesis, the advancement of employee monitoring technologies has disproportionately affected low-autonomy occupations by easing monitoring, or if its effects are

[4] Their dataset allows them to measure the 'job level' of workers, a variable that captures hierarchies (e.g. 'untrained' vs 'professional') within and between occupations, and thus differs from our occupational measure of autonomy.

uniform across occupations with different levels of autonomy.

A second hypothesis suggests that increased workplace fragmentation, known as the *fissuring of the workplace* (Weil, 2014, 2019), adversely affects low-autonomy occupations. This theory argues that a combination of new technologies, particularly in monitoring, and the enforcement of work standards, alongside legal and institutional changes, have enabled core firms to outsource low-autonomy tasks to subcontractors, who typically pay lower wages. This is evident in practices by companies such as FedEx and Amazon, which subcontract the final leg of delivery. Existing research demonstrates that outsourced workers face a wage penalty because their wages are decoupled from the core firm's equity considerations, allowing the firm to sidestep internal wage pay-equity constraints (Krueger and Summers, 1988; Berlinski, 2008; Dube and Kaplan, 2010; Weil, 2014; Goldschmidt and Schmieder, 2017; Weil, 2019). Outsourcing commonly affects both blue-collar and white-collar occupations with low autonomy, ranging from janitorial and logistics services to clerical, payroll, and basic legal functions (Weil, 2019). Notably, the outsourcing threat might put downward pressure on occupations that are at risk, even when actual outsourcing has not taken place. The empirical question is whether there is a correlation between an increased rate of outsourcing and a rising autonomy wage premium.

The third hypothesis focuses on recent trends in LMI - including trade union density, collective bargaining agreements or minimum wages - and their impact on occupational wage divergence. Despite their recognised role as wage determinants in the industrial relations literature, LMI have been largely overlooked in studies on occupational wage divergence. LMI are known to narrow the wage distribution by enhancing the bargaining power of low-skill workers (DiNardo et al., 1996; Farber et al., 2021) and by capping executive pay (Jaumotte and Osorio, 2015). Unions and collective bargaining agreements typically compress wage disparities by fostering alliances among workers across different occupations and facilitate joint wage agreements. Freeman and Lazear (1995) observed lesser wage dispersion among unionised workers than among non-unionised workers. Furthermore, high collective bargaining coverage ensures shared productivity gains across occupations (Visser, 2006), thereby mitigating overall wage inequality (Blau and Kahn, 1999; OECD, 2011). In Germany, Bayer and Kuhn (2023) show that wage gaps across occupations with varying autonomy levels are smaller among workers covered by collective bargaining agreements. Recent decades have been marked by a decline in union density and collective bargaining coverage across European countries, as detailed in Section 3). This trend suggests a weakened capacity of labour to secure wage increases across different occupations, highlighting a decline in collective bargaining power. Concurrently, individual- or occupation-specific bargaining power, such as occupational autonomy, may have become more important in wage negotiations. This shift potentially contributes to a rise in the autonomy wage premium. In addition, minimum wages, by setting wage floors, are a key policy tool to raise wages at the lower end of the distribution (DiNardo et al., 1996; Lee, 1999; Cengiz et al., 2019). While there has been renewed research interest on the effects of introducing or increasing minimum wages in several countries (Grimshaw et al., 2014; Cengiz et al., 2019; Dube, 2019; Martins, 2021) the relationship between minimum wages and occupational wage divergence remains unexplored. Increases in minimum wages could act as a strategy to mitigate occupational wage divergence.

Building on the discussed literature, we develop two sets of hypotheses. First, our primary hypothesis contents that there will be an increase in the wage gap between occupations with varying degrees of autonomy. We term this an increase in the *autonomy wage premium*. In Section 5, we provide the first empirical test of this hypothesis. Our second set of hypotheses explores the factors influencing trends in the autonomy wage premium. We expect to observe a more pronounced increase in the autonomy premium wage in countries (and industries) where employee monitoring technology are more widely adopted. Similarly, we predict a greater increase in the autonomy premium where outsourcing practices are widespread. Furthermore, we hypothesise that the autonomy premium increases in countries experiencing a decline in LMI, such as reduced trade union density, collective bargaining coverage or lower minimum wages. Section 6 presents the first empirical analysis of how monitoring, outsourcing and changes in LMI mediate the relationship between occupational autonomy and wage growth.

Existing literature on occupational wage divergence: routinisation and offshoring

Prevailing research on occupational wage divergence primarily focuses on changes in labour demand, for instance through the lens of routine-biased technological change (RBTC). The RBTC framework posits that technological advancements displace tasks that are susceptible to automation, consequently reducing demand for occupations characterised by routine tasks (Autor et al., 2003; Acemoglu and Autor, 2011; Goos et al., 2014; Bachmann et al., 2019). Since these occupations are typically situated in the middle of the wage distribution, their decreasing wages are thought to contribute to wage polarisation, with higher wage growth observed at the upper and lower ends of the wage distribution. A related literature has also explored the effects of globalisation, particularly offshoring, on wages. Tasks that are more susceptible to being offshored within global value chains have been identified as most vulnerable to global economic integration, itself influenced by technological change (Blinder, 2009; Blinder and Krueger, 2013). This leads to decreasing demand for offshorable occupations in high-income countries and, subsequently, relative wage decline (Acemoglu and Autor, 2011).

However, the empirical evidence on wage growth patterns in line with the RBTC and task offshoring hypotheses remains inconclusive. While there is some support for the notion that routine or offshorable occupations have experienced relative wage declines in the US (Autor et al., 2006; Acemoglu and Autor, 2011; Firpo et al., 2011), RBTC alone does not adequately explain the stagnant wage growth observed among many low-income occupations whose tasks are neither routine nor offshorable (see e.g., Mishel et al., 2013; Autor, 2022; Mishel, 2022). Furthermore, various studies have failed to confirm these hypotheses in other countries, questioning the universality of the RBTC or offshoring hypotheses in explaining occupational wage divergence (Dustmann et al., 2009; Mishel et al., 2013; Naticchioni et al., 2014; Green and Sand, 2015), or have indicated that these trends are limited to the period before the 2000s, for instance in Germany (Koomen and Backes-Gellner, 2022). This inconsistency raises questions if RBTC and offshoring are adequate explanations for occupational wage divergence.[5] Instead, other factors, such as occupational autonomy, might offer a more comprehensive understanding of wage trends, especially in occupations that are not directly affected by automation or offshoring but where workers' tasks are easily monitorable and prone to outsourcing, or where the decline in LMI reduced collective bargaining power.[6]

3 Data

Wage data

This study uses the gross annual real wage of employees as the main wage measure, employing repeated cross-sectional individual-level data from the European Union Survey of Living Conditions (EU SILC). These data are harmonized across member states, ensuring comparability. Our analysis covers 15 Western European countries from 2003 to 2018, yielding a dataset exceeding 800,000 worker-year observations.[7] We include employees in regular full-time employment throughout the entire 12 months of the reference year and exclude part-time workers who work less than 30 hours per week due to data limitations and the unreliability in calculating their wages accurately. Furthermore, our analysis excludes self-employed individuals to ensure consistency across countries and to avoid employers who

[5] A related literature analyses the return to soft-skills or interpersonal skills. Some studies predict rising wages for workers with high soft skills across different occupations (Deming, 2017; Henseke and Green, 2020). Crucially, this literature is concerned with skills of individuals, measured, for example, by aptitude tests, rather than occupation-specific tasks. It does not directly address occupational wage divergence.

[6] Section 3 discusses the nuances distinguishing occupational autonomy from the extent to which occupations are characterised by routine tasks or are susceptible to offshoring. We highlight the unique attributes of each concept and discuss their respective implications for wage dynamics.

[7] We exclude Greece due to insufficient sample size; further details on data availability are provided in Appendix A.

may be recorded in this category.[8] The focus of our study is on private-sector wage trends, and we exclude public sector industries and occupations from our analysis. Nominal wages were adjusted for inflation using consumer price index data from EUROSTAT to reflect real wage values. The EU-SILC dataset provides occupational information using 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). Due to changes in occupational and sectoral classifications over time, we adjust and link various definitions to maintain consistency in our analysis, as discussed in Appendix A.

Occupational autonomy

Our primary measure for occupational autonomy is an index constructed from task content data obtained from the Activities and Work Context datasets within the Occupational Information Network (O*NET) database. This comprehensive database, which categorises the tasks associated with each occupation based on expert coding, ensuring both accuracy and relevance to occupational task profiles. O*NET data is widely applied in studies both on the U.S. and internationally (Acemoglu and Autor, 2011; Firpo et al., 2011; Goos et al., 2014).

Our measure for occupational autonomy aligns with the conceptual framework outlined in Section 2. Occupations are classified by tasks, and our focus is on tasks that reflect worker's degree of control and influence over their work process, thereby capturing the essence of occupational autonomy. Within this framework, workers in the same occupation are assigned a uniform autonomy index value, regardless of their employer or the country context. This approach allows us to distinctly isolate occupation-specific variation in autonomy and examine its association with wage growth.

Our primary measure of worker autonomy is an index using data on the following five task content variables from O*NET:

- 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

[8] This exclusion is significant given the rise in self-employment, particularly among lower-paid groups, potentially leading to an underestimation of the increase in the autonomy premium. Our findings, therefore, might represent a conservative estimate of the rise in the autonomy premium.

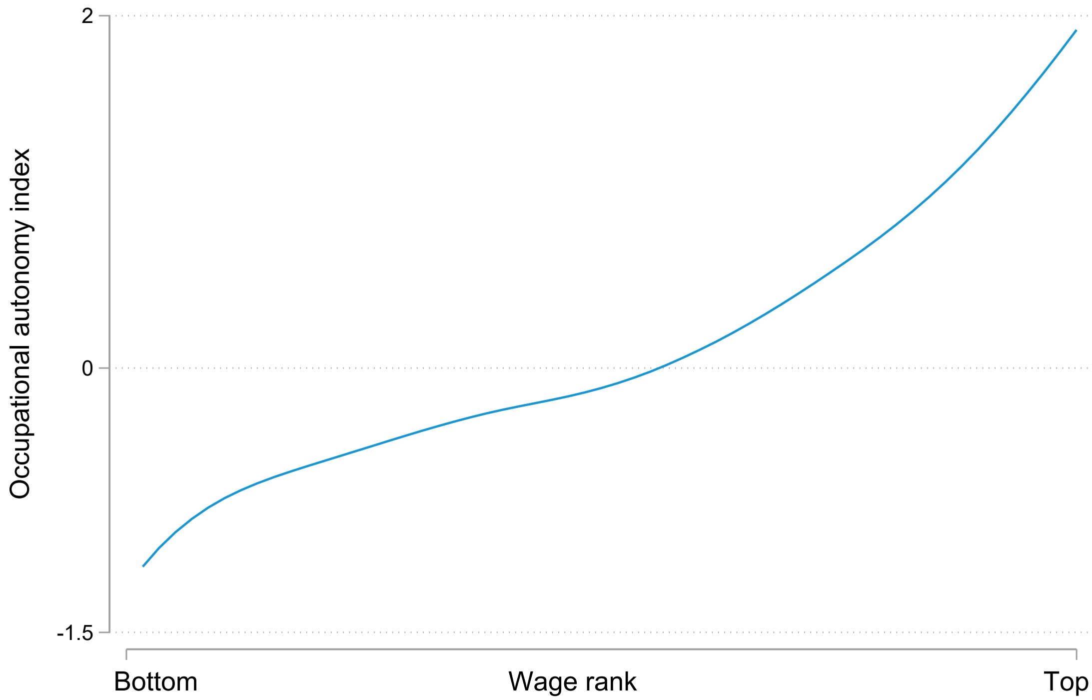
Each occupation receives a score for these variables, each of which reflects crucial aspects of occupational autonomy. For instance, occupations requiring creative thinking or problem-solving inherently provide workers with greater control and influence over their work processes. Drawing on methodologies from leading studies (e.g., Acemoglu and Autor, 2011), we additively combine the variable scores for each occupation and divide the sum by the number of variables to get a single index value. We then undertake several crosswalks to align the O*NET occupational classifications with the ISCO08 and ISCO88 counterparts, and group them into 2-digit occupation categories. This process follows the linking practices established in earlier studies (Acemoglu and Autor, 2011; Autor, 2013; Hardy et al., 2018). Subsequently, we standardise the resulting occupational autonomy index to have a mean of zero and a unit standard deviation. As a result, higher values on our index indicate greater levels of occupational autonomy. The autonomy index scores for a selection of ISCO08 occupations are detailed in Table A1 in Appendix A.

Figure 2 displays the relationship between autonomy and wage levels, averaged across European countries. It reveals that high-autonomy occupations generally command higher wages, whereas low-autonomy occupations are associated with lower wages. This pattern suggests that wage inequality increases if wage growth in high autonomy occupations outpaces that in low-autonomy occupations. As a primary assessment of our central hypothesis - that higher autonomy is related to greater wage growth - we examine the correlation between autonomy and annual wage growth across occupation-industry-country groups in Figure 3. We find a positive and statistically significant correlation at the 1% level, underscoring a robust link between higher autonomy and greater wage growth and implying an increasing autonomy wage premium.

Our occupational autonomy index is predicated on the assumption that differences in task content across occupations are constant over time. We consider this assumption reasonable for the relatively short time span of our analysis, and it also follows common practice in empirical task-based research (e.g. Goos et al., 2014).[9] Another critical assumption of our index is that the task content of occupations is independent of the country-specific institutional context. This might overlook variations in occupational autonomy across different countries, such as differences between the autonomy experienced by cleaners in Germany versus Spain, due to differences in institutional factors (Fernández-Macías and Hurley, 2016; Holman and Rafferty, 2018). To address the potential limitation of this assumption, we also employ an alternative autonomy index derived from the European Working Conditions Survey (EWCS), which provides self-reported task content from workers. Adapting a measure of work discretion from Menon et al. (2020), this alternative index captures autonomy in

[9] We use O*NET version 20.1, published in 2015, to construct our index measures. We also show that our results are unchanged when using an O*NET wave from 2003 in Section 5.

Figure 2: The autonomy index and wage ranks of occupations



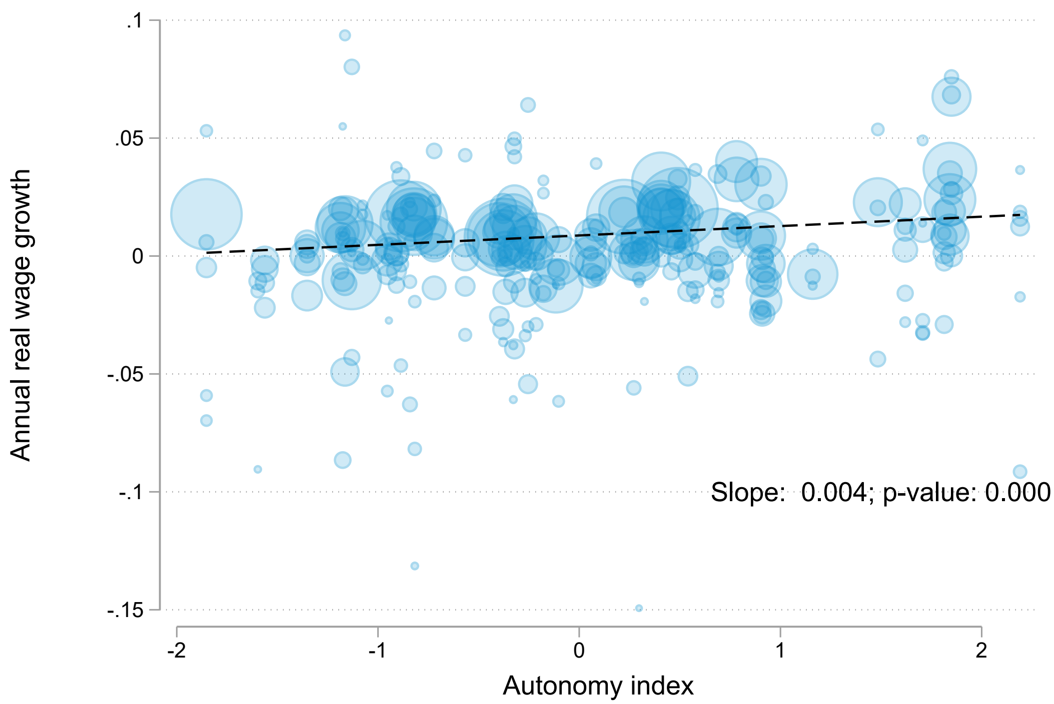
Source: EU SILC and O*NET, own calculations.
The horizontal axis ranks the average wage of jobs (occupation-industry groups) in 2006, the first year when data is available for all countries. The vertical axis displays the autonomy index, in standard deviations. The blue line represents the LOWESS smoothed curve, highlighting the relationship between autonomy and wage ranks.

the self-reported scores workers give to 'the degree of control over tasks, methods, and work pace', and offers the advantage of generating distinct autonomy values for each occupation across different countries.[10] Details on this EWCS-based measure can be found in Appendix A.

Despite the benefits of using self-reported data to account for cross-country variations, our analysis primarily relies on the O*NET-based index for two main reasons. First, self-reported measures concerning autonomy are more prone to measurement errors, particularly in the context of detailed occupation-country cells, which necessitate a large sample size. Second, these self-reports might be influenced by recent wage changes, potentially leading to endogeneity issues. For example, an increase in pay could alter workers' perceptions of their autonomy, reflecting changes in their sense of value or trust from their employer, rather than objective shifts in work conditions. Despite these concerns, employing both

[10]For example, if cleaners in Norway report lower levels of autonomy compared to those in the UK, this difference will be reflected in their respective autonomy indices.

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



Source: EU SILC and O*NET, own calculations.
The linear fit is weighted by employment shares. The size of each circle represents the employment size of the respective group, in proportion to the total employment in a country.

indices — O*NET-based and EWCS-based - yield consistent results (see Section 5).

Other occupation-level measures

Using task content data from O*NET, we also construct index measures on how routine and offshorable occupations are, replicating the methodology from Acemoglu and Autor (2011) to create the 'offshorable' index, and from (Firpo et al., 2011), who updated the initial 'manual routine' index by Autor et al. (2003), to create the 'routine' index. Details on these measures and descriptive statistics are available in Appendix A.

A comparative analysis of our autonomy, routine, and offshorable measures reveals distinct patterns (see Table A1). For instance, many low-wage service sector occupations such as cleaners, hairdressers, care workers, and caterers, exhibit low autonomy levels but are characterised by non-routine tasks and are not easily offshorable, because these roles often require tacit manual skills, direct customer interaction or physical presence. While occupational autonomy increases along the wage distribution (Figure 2), occupations with high routine intensity, including clerical, administrative support, production, and operative occupations, are typically situated in the middle of the wage distribution. This results in the inverted U-shaped pattern of routine intensity along the wage distribution, illustrated in Figure A1. In contrast, offshorable occupations are defined by minimal face-to-face interaction and the potential for remote execution, encompassing a wide range of occupations from lower-skilled roles like call centre workers to higher-skilled positions such as ICT professionals. As a result, offshorable occupations are found in all parts of the wage distribution (see Figure A2). Taken together, each of our task content measures captures distinct aspects of occupational characteristics and we only find a moderate correlation between our measures for autonomy, routine and offshorable (Table A2). While Figure 3 demonstrates a significant positive relationship between higher autonomy and wage growth, our analysis does not reveal a link between routine or offshoring indices and wage growth patterns (Appendix Figures A3 and A4).

Other variables

In alignment with wage determinants established in Mincerian wage studies (Mincer, 1958, 1974), we include demographic variables from the EU SILC in our analysis. These variables encompass age, education levels (classified into five ISCED levels), gender, work experience, and migrant status. We provide summary statistics for these variables in Appendix Table A3.

Turning to the socio-economic drivers of the autonomy wage premium, we use a measure for employee monitoring derived from the 2019 European Company Survey[11] (ECS). This survey asks managers at establishments with 10 or more employees about their use of data analytics tools to monitor employee performance. We calculate the proportion of firms engaging in this practice in each industry (or country) as a proxy for monitoring intensity (Appendix Table A4). In the absence of data for previous years, we rely on the cross-sectional variation observed in 2019 to measure the use of monitoring technology.

We use data on outsourcing practices provided by the ECS wave from 2013. These data allow to distinguish different types of outsourcing: outsourcing of production, outsourcing of sales/marketing, and outsourcing of the design or development of new products or services (Dekker and Koster, 2018). In addition, we construct a measure for the share of firms engaged in at least one type of outsourcing by country. We show the outsourcing intensity measures by country in Appendix Table A4.

We also consider Information and Communication Technology (ICT) investments as an indirect measure of monitoring and outsourcing. Investment in monitoring technologies, such as systems to track workers and evaluate productivity, should be captured by ICT

[11]ECS data is not available for Norway and Switzerland. Earlier ECS waves do not contain information on monitoring, limiting our data to 2019

investment. Similarly, ICT-assisted improvements in oversight of remote or subcontracted work facilitate outsourcing. Our analysis focuses on changes in ICT investments relative to total investment (Gross Fixed Capital Formation, GFCF), using data from EU KLEMS.[12]

Lastly, we use LMI measures at the country level, including minimum wages relative to median and mean earnings of full-time workers (sourced from OECD.Stat), union density and collective bargaining coverage (from the OECD/AIAS ICTWSS database). Detailed statistics are provided in Appendix Table A7 in the appendix. Our data indicate an average decline of 6.4 percentage points (ppts) in union density and a 3.7 ppts decline in collective bargaining coverage between 2003-2018. Meanwhile, the minimum-to-median wage ratio average increases by 4.7 ppts over the study period.

[12]This analysis excludes Norway, Switzerland, and Belgium due to data limitations in KLEMS, focusing on the remaining twelve countries.

4 Empirical model and methodology

We model the relationship between wage growth and occupational autonomy and other occupation-level variables in line with the Mincerian (Mincer, 1958, 1974) wage literature 1.

$$w_{ijkct} = b_0 e^{(\beta_1 A_j + \beta_2 \boldsymbol{X}_j)\mathrm{t} + B\boldsymbol{M}_{ijkct}} \tag{1}$$

where w is the real wage of worker i in an occupation j, industry k, country c, and year t. The growth rate of real wages is a function of our autonomy index A_j and, other task-based measures for routine and offshorable occupations captured by the vector $\boldsymbol{X}_j$. Additionally, we account for a vector of control variables $\boldsymbol{M}_{ijkct}$, based on the Mincerian wage model including sex, education level, age, age-squared, and migrant status.

We transform equation 1 to a logarithmic form to obtain our baseline estimation equation.

$$ln(w_{ijkct}) = \beta_1(A_j \times t) + \beta_s(\boldsymbol{X}_j \times t) + B\boldsymbol{M}_{ijkct} + \lambda_{jkc} + \theta_{kct} + \varepsilon_{ijkct} \tag{2}$$

This estimation equation aligns with previous work in the task-based indicator literature (e.g. Acemoglu and Autor, 2011; Altonji et al., 2014; Goos et al., 2014). Our primary variable of interest is the autonomy index A_j, which is time-invariant and interacts with a linear time trend t. Equivalently, we interact other task-based measures $\boldsymbol{X}_j$ with a linear time trend t. The Mincerian variables $\boldsymbol{M}_{ijkct}$ do not interact with a time trend as their coefficient captures the effect of changes in these variables on log wage levels rather than on the real wage growth rate.

Our empirical strategy consists of estimating equation 2 by OLS, using occupation-industry-country fixed effects λ_{jkc} to condition out pre-existing wage level differences. Additionally, we include industry-country-year fixed effects θ_{kct}, which allow to isolate occupation-specific wage growth factors from industry- or country-specific wage growth determinants. This approach ensures that we identify wage growth differences from variation of wage growth across occupations within the same industry. As a result, our primary coefficient of interest β_1 quantifies the relationship between a one standard deviation increase in autonomy and the percentage point (ppt) deviation of occupational wage growth from average industry-country wage growth. For instance, if β_1 equals 0.01, it implies that an occupation with high autonomy (one standard deviation above the mean) is associated with wage growth that is one ppt higher than the average wage growth in their industry. To contextualise this, consider that the difference between 'Administrative and commercial managers' (Autonomy index: 1.62) and 'Customer service clerks' (-.91) is 2.53 standard deviations, as detailed in Appendix Table A1). This interpretation also applies to the coefficients of other task-based measures $\boldsymbol{X}_j$ interacting with a time trend t.

The estimates for variables included in $\boldsymbol{M}_{ijkct}$ follow a log-linear interpretation; an increase in, e.g., age by 1 year relates to wages being B_1 percent higher, where B_1 is the coefficient on average age. We include Mincerian variables $\boldsymbol{M}_{ijkct}$ to account for observed individual-level heterogeneity and for changes in occupational composition over time. If the composition of workers in an occupation changes, for instance because higher educated workers increasingly sort into this occupation, this might affect observed wage growth in this occupation. Controlling for the level of education (as part of $\boldsymbol{M}_{ijkct}$) accounts for this effect. Including these variables also accounts for potential sampling outliers, e.g., if many young workers are surveyed in an occupation cell in a specific year, resulting in lower wages.

Our fixed effects strategy accounts for unobserved worker heterogeneity across occupation-industry-country cells, such as differences in ability or motivation, as λ_{jkc} conditions out all pre-existing wage level differences (e.g. sorting of more able workers into high autonomy occupations). This rests on the assumption of time-invariance of the unobservable components, which seems reasonable given our relatively short time frame of 15 years. Finally, we cluster standard errors at the occupation-industry-country level and wage regressions are weighted using the survey weights provided by EU-SILC, applying equal country weighting.[13]

5 Autonomy and wage growth

Main result

Table 1 shows our estimation results based on equation 2. Column 1 uncovers a sizeable and statistically significant (at the 0.1%-level) association between occupational autonomy and higher wage growth in Western Europe. The economic interpretation of our finding is that a high-autonomy occupation - one standard deviation above the mean in occupational autonomy - is associated with 0.27 percentage points (ppts) higher annual real wage growth. This means that if wages in the mean autonomy occupation grow by 1%, wages in a high-autonomy occupation (one standard deviation higher) would grow by 1.27% per year. From 2003 to 2018, this estimate accounts for around 46% of the observed wage divergence between Managers and Service and Sales Workers, which represent occupations with a difference of around three standard deviations on the autonomy index. Moreover, our analysis reveals no significant relationship between other task-based measures and occupational wage growth. The coefficients for routine and offshorable are positive but small and statistically not different from zero. These results challenge the prevailing notion that

[13]Weighting countries by their population size yields consistent results (see Appendix Table B2).

routine-biased technological change (RBTC) or task offshoring are major drivers of occupational wage trends. Our control variables, based on the Mincerian model, show the expected signs. Wages increase with education and age (though with diminishing returns), and women and foreign-born workers receive lower wages.

Column 2 underscores the robustness of our result and forms our baseline estimation. Excluding additional index measures for routine and offshorable tasks does not alter our finding for autonomy. In column 3, we replace our primary occupational autonomy measure with an alternative autonomy measure from Menon et al. (2020), based on EWCS data. This 'worker discretion' measure provides distinct autonomy values for each occupation across different countries. Our analysis corroborates the positive association between higher autonomy and greater wage growth, indicating that an occupation one standard deviation higher in worker discretion is linked with a 0.38 percentage-point rise in annual wage growth. This result implies that the baseline estimate, derived from O*NET data, may represent a lower bound of the relationship between autonomy on wage growth. Nonetheless, due to potential endogeneity concerns highlighted in Section 3, we prefer the O*NET-based autonomy measure.

Robustness tests

The association between higher occupational autonomy and greater wage growth persists after considering a range of specification adjustments, including variations in our autonomy measure, control variables, time periods, weighting schemes, and trimming procedures. These specifications are shown in Appendix Tables B1 and B2.

Specifically, our baseline result for autonomy remains robust after using alternative O*NET-based autonomy measures, addressing concerns that our main finding is sensitive to the choice of O*NET task content variables. Column 1 in Table B1 replaces our autonomy measure with a decision-making index by Deming (2021). The result is consistent with our baseline result for autonomy. Column 2 shows that our finding is robust to using an extended autonomy index, consisting of nine task characteristics, with details provided in Appendix A. Addressing potential concerns that our autonomy measure might capture wage growth variations attributable to other task dimensions, we include alternative task-based control measures. The regression in column 3 includes measures for cognitive analytical task content and cognitive interpersonal tasks, other potential determinants of wage growth (Acemoglu and Autor, 2011). The estimate for autonomy remains robust, while cognitive analytical tasks are related to lower wage growth. Column 4 includes measures for routine manual and cognitive tasks, and column 5 includes an alternative offshorability measure from Firpo et al. (2011). Columns 6 adds measures for tasks related to information content, ICT compatibility, and column 7 for manual physical and personal tasks from Acemoglu

Table 1: Main result

	(1) Baseline	(2) Autonomy only	(3) Autonomy (EWCS)
Autonomy	0.0027***	0.0025***	
	(0.0006)	(0.0005)	
Autonomy (EWCS)			0.0038***
			(0.0007)
Routine	0.0004		
	(0.0006)		
Offshorable	0.0003		
	(0.0004)		
Lower sec. educ.	0.0720***	0.0720***	0.0720***
	(0.0071)	(0.0071)	(0.0071)
Upper sec. educ.	0.1704***	0.1704***	0.1705***
	(0.0076)	(0.0076)	(0.0076)
Post-sec. non tert. educ.	0.2358***	0.2358***	0.2359***
	(0.0103)	(0.0103)	(0.0103)
Tertiary education	0.3287***	0.3287***	0.3288***
	(0.0086)	(0.0086)	(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)
Women	-0.1919***	-0.1919***	-0.1919***
	(0.0035)	(0.0035)	(0.0035)
EU foreign	-0.0370***	-0.0370***	-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
Occ.-ind.-country FE	Yes	Yes	Yes
Ind.-country-year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Cluster-robust SE	Yes	Yes	Yes

Notes: Standard errors in parentheses. All regressions include occupation-industry-country fixed effects and industry-country-year fixed effects. Standard errors are clustered by occupation-industry-country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

and Autor (2011). These additions do not affect the significance of autonomy, underscoring the distinct link between autonomy and wage growth. We also address the concern that the trend in the autonomy wage premium is merely a reflection of increasing returns to education. To this end, we add an interaction term between a higher education dummy and a linear time trend to our model. The results in column 8 show that returns to education have not increased in our sample period and our main result for autonomy is unaffected.

Appendix Table B2 shows further robustness tests. Our findings are robust to changes in the ISCO occupational classification. Regressions at the broader 1-digit level (column 1) and a split-sample analysis across two sub-periods due to changes in the 2-digit ISCO classification in 2010 (columns 2 and 3) both affirm the robustness of our estimates for autonomy. Notably, routine occupations had lower wage growth until 2010 but not after. This is consistent with RBTC contributing to wage divergence in previous years but becoming insignificant in the last decade. Concerns related to equal country weighting are addressed by using population-size weighting in Column 4. Our results are unchanged. Next, in column 5, we show that our results are robust to using the 2003 wave of O*NET (version 5.1) for our task-content measures. This underscores that relative differences in autonomy across occupations have been stable over time. Additionally, excluding the top wage percentiles in each country-year (columns 6 and 7) indicates that the autonomy-wage growth relationship not solely reflects higher wage growth at the very top but that it is a broader phenomenon across the wage distribution. Our results are also robust to employing a synthetic panel method (Deaton, 1985), by collapsing our data at the occupation-industry-country level to create a panel where each cell is observed over time (column 8). Finally, a jackknife analyses (excluding countries or industries one by one from the sample) highlights that no single country or industry disproportionately influences our results, shown in Appendix Figures B1 and B2.

6 Drivers of the autonomy wage premium

Next, we investigate the potential drivers of the rise in the autonomy wage premium, as discussed in Section 2: employee monitoring, outsourcing and LMI. To this end, we modify our baseline equation 2 by including interaction terms between autonomy and these potential drivers at the industry- or country-level:

$$ln(w_{ijkc}) = \gamma_1(A_j \times t) + \gamma_2(A_j \times t \times \Delta\text{Drivers}_{ic}) + \text{controls} + \lambda_{jkc} + \theta_{kct} + \varepsilon_{ijkct} \qquad (3)$$

The term $\gamma_1(A_j \times t)$ captures annual wage growth attributable to the autonomy premium across occupations, where the value for a driver is 0 (e.g., no firms monitor their employees).

The term $\gamma_1 + \gamma_2$ evaluates the differential increase in the autonomy wage premium where the value for a driver within a given industry k or country c is 1 (e.g. where 100% of firms monitor their employees).

Autonomy and employee monitoring

First, we test the hypothesis that employee monitoring is related to a rise in the autonomy premium. We estimate equation 3, using a country-level measure of the share of firms using data analytics for employee monitoring. The results, presented in Table 2, column 1, show that at the country-level, an increase in the share of firms using monitoring by 10 percentage points (ppts) increases wage growth difference between occupations one standard deviation apart in autonomy by 0.16 ppts. Similarly, at the industry level (column 2), a 10 ppts higher monitoring share is associated with a 0.09 ppts increase in the growth of the annual autonomy premium.

The economic implication of this finding becomes evident comparing two settings. In Italy, the monitoring share stands at 41%, whereas it is 21% in Portugal. Our results suggest that the autonomy wage premium has increased by 0.32 ppts more rapidly each year in Italy compared to Portugal. When compounded over 15 years, this equates to a 5% higher autonomy premium in Italy relative to Portugal, assuming all other factors remain constant. These findings are consistent with the PBTC hypothesis (Skott and Guy, 2007) and the broader labour discipline literature, asserting that intensified monitoring disproportionately harms workers in low autonomy occupations by reducing the incentive to pay them efficiency wages and, thereby, raising the autonomy premium.

Autonomy and outsourcing

Next, we test if higher prevalence of outsourcing is related to faster increases in the autonomy wage premium. Estimating equation 3 with our measure for outsourcing intensity, we find that the autonomy wage premium has risen more substantially where outsourcing is used more widely. These results align with the argument of Weil (2014) based on pay-equity considerations. Columns 3 to 6 in Table 2 present these findings. Firstly, the regression coefficients in column 3 demonstrate that countries with a higher share of firms engaging in any form of outsourcing activity witness a faster rise in the autonomy premium. This estimate translates into a 0.10 ppts increase in the annual growth of the autonomy premium for every 10 ppts increase in firms using outsourcing. For instance, Austria exhibits an outsourcing share of 49%, compared to 54% in the Netherlands. Our results imply that the autonomy wage premium has increased by 0.05 ppts faster each year in Austria relative to the Netherlands.

When we dissect outsourcing by type in Columns 4 to 6, we find that this result is mainly driven by outsourcing in sales and outsourcing in design and development activities rather than by outsourcing of production. While each outsourcing type is related to a rising autonomy premium, the coefficients for outsourcing sales and outsourcing design activities are large and statistically significant. Taken together, these results suggest that increased workplace fragmentation through outsourcing is linked to occupational wage divergence.

In addition, we employ longitudinal data on ICT adoption to reinforce our findings for the monitoring and outsourcing hypotheses. ICT have become vital in enabling employee monitoring and outsourcing (Green, 2004; Skott and Guy, 2007; Weil, 2019). Our findings indicate a strong correlation between rising ICT intensity, measured as changes in the share of ICT investments in gross fixed capital formation (GFCF), and an increased autonomy premium. Column 7 illustrates that a 10 ppts change in ICT intensity correlates with a 0.5 ppts annual increase in the autonomy premium. This finding supports the hypothesis that technological changes are linked to the rising autonomy premium, likely through enhanced monitoring or outsourcing capabilities.

Table 2: The autonomy premium: monitoring, outsourcing and technological change

	(1) Monitor (cou.)	(2) Monitor (ind.)	(3) Outsourcing	(4) Out. prod.	(5) Out. sales	(6) Out. design/dev.	(7) Δ ICT int.
Autonomy	-0.0016	0.0002	-0.0019	0.0001	-0.0022	-0.0028	0.0024***
	(0.0019)	(0.0014)	(0.0026)	(0.0020)	(0.0024)	(0.0022)	(0.0008)
Autonomy $\times$ Monitoring (country)	0.0161**						
	(0.0064)						
Autonomy $\times$ Monitoring (industry)		0.0094**					
		(0.0046)					
Autonomy $\times$ Outsourcing (any)			0.0100*				
			(0.0053)				
Autonomy $\times$ Out. prod.				0.0078			
				(0.0057)			
Autonomy $\times$ Out. sales					0.0225**		
					(0.0105)		
Autonomy $\times$ Out. design/dev.						0.0236***	
						(0.0088)	
Autonomy $\times$ Δ(ICT/GFCF)							0.0515**
							(0.0252)
Observations	733060	733060	733060	733060	733060	733060	638544
Occ.-ind.-country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-country-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster-robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. All regressions include occupation-industry-country fixed effects and industry-country-year fixed effects. All regressions include demographic control variables in line with our baseline estimation. Standard errors are clustered by occupation-industry-country. All regressions use country-level interaction terms unless stated otherwise. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Autonomy and LMI

Our last analysis examines whether changes in LMI are associated with changes in the autonomy premium. We analyse various LMI measures to account for different institutional and historical contexts of labour representation across European countries. For instance, in Austria from 2003 to 2018, despite a declining union density from 34.6% to 26.3%, collective bargaining coverage has remained at 98%, suggesting that it is a more relevant proxy for collective bargaining power in this context (Appendix Table A7). To examine the relationship between LMI and the autonomy wage premium, we adapt equation 3 by including an interaction term between autonomy and long differences changes in LMI variables from 2003 to 2018. Here, the coefficient γ_1 captures the annual growth rate in the autonomy premium with unchanged LMI, whereas $\gamma_1 + \gamma_2$ reflects the growth rate under a ppts change in LMI.

Column 1 in Table 3 shows that a decline in the minimum-to-median wage ratio correlates with an increase in the autonomy wage premium. Specifically, a 1 ppt rise in this ratio is linked to a 0.02 ppts annual decrease in the autonomy wage premium.[14] The UK experienced a 12.3 ppts rise in this ratio, while France witnessed a 2.3 ppts decline, creating a differential of 14.6 ppts between the two countries (Appendix Table A7). Our estimate implies a 0.34 ppts higher annual increase in the autonomy wage premium in France, everything else constant. Column 2 reinforces this result, using the minimum-to-mean wage ratio in the interaction term. In columns 1 and 2, we limit our analysis to the seven countries with a minimum wage throughout our sample period (see Appendix Table A7 for data availability).[15] In column 3 we also include the remaining countries assigning a zero change in the minimum wage ratio. Our results are consistent.

Columns 4 and 5 in Table 3 reveal no significant link between changes in union density or collective bargaining coverage and variations in the autonomy wage premium. These results suggest that regardless of increases or decreases in these LMI, low-autonomy occupations have lost out, hinting at the possibility that unions and collective bargaining agreements were unable to sufficiently address the unique challenges faced by workers in low-autonomy occupations over recent years.

Summing up, our empirical analysis reveals that recent wage trends can be attributed to the rise in the autonomy wage premium rather than wage declines for occupations susceptible to automation or offshoring. Additionally, our analysis suggests that wage divergence is not primarily caused by shifts in labour demand - the mechanism posited for the impact of routinisation and offshoring on wage growth. Instead, we provide indicative evidence that increased monitoring and outsourcing have contributed to a relative decrease in bargaining

[14] This interpretation is due to the fact that we multiply coefficients for LMI drivers by 100.

[15] Germany introduced a minimum wage in 2016, but Germany is not included in our sample after 2013 (see Appendix Table A5) due to missing 2-digit occupation data from EU SILC after 2013.

power and consequently lower wages for occupations with low autonomy. Meanwhile, rising minimum wages appear to have mitigated this effect. To strengthen the hypothesis that changes in bargaining power, as opposed to shifts in employment demand, are driving wage divergence, we also investigate whether high-autonomy occupations have seen an increase in relative labour demand in Appendix Table B3. The results show no significant correlation between autonomy and employment growth, supporting the notion that occupations with higher bargaining power have been better positioned to to benefit from new technology, unlike those in low-power occupations.

Table 3: The autonomy premium and LMI

	(1)	(2)	(3)	(4)	(5)
Autonomy	0.0032***	0.0032***	0.0029***	0.0031***	0.0031***
	(0.0007)	(0.0008)	(0.0005)	(0.0009)	(0.0006)
Autonomy × Δ (Min. wage/median wage)	-0.0235***				
	(0.0087)				
Autonomy × Δ (Min. wage/mean wage)		-0.0299**			
		(0.0121)			
Autonomy × Δ (Min. wage/median wage), all			-0.0217**		
			(0.0086)		
Autonomy × Δ Union density				0.0096	
				(0.0118)	
Autonomy × Δ CB coverage					0.0188
					(0.0122)
Observations	452013	452013	808122	808122	808122
r2	0.5882	0.5882	0.5450	0.5450	0.5450
Occ.-ind.-country FE	Yes	Yes	Yes	Yes	Yes
Ind.-country-year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Cluster-robust SE	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. All regressions include occupation-industry-country fixed effects and industry-country-year fixed effects. Standard errors are clustered by occupation-industry-country. All regressions use country-level interaction terms unless stated otherwise. Columns 1 and 2: These regression have a smaller sample size becuase countries without a minimum wage are excluded. In column 3 we include the remaining countries and assign these countries a zero change in minimum wage. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusion

This paper offers a new perspective on occupational wage trends and the broader context of wage inequality in Europe. We present four novel findings. First, our analysis reveals that from 2003 to 2018, wage growth in high-autonomy occupations was 0.27 percentage points higher annually compared to occupations with an average level of autonomy, thereby leading to a rising *autonomy wage premium*. Second, we find that higher employee monitoring is associated with an increasing autonomy wage premium, consistent with the power-biased technological change hypothesis. Third, the autonomy premium has grown more substantially in countries with higher levels of outsourcing, consistent with the idea that the fissuring of the workplace reduces the bargaining power of low-autonomy occupations. Lastly, we explore the link between changes in LMI and occupational wage divergence, showing that increases in minimum wages correlate with a reduced autonomy wage premium.

Our findings introduce a political economy view to the debate on occupational wage trends. Previous studies examine occupational wage trends within the neoclassical framework of RBTC or task offshoring, maintaining that wages stagnate in routine or offshorable occupations. We find that neither routine nor offshorable task intensity consistently predicts wage growth; furthermore, there is no evidence of a rising demand for high-autonomy occupations, suggesting that supply and demand factors are not central for recent changes in relative wages.

Instead, this paper shifts the focus to autonomy as an occupational wage growth determinant. The link between higher autonomy and bargaining power is substantiated in socio-economic research that emphasises that high-autonomy occupations command higher wages due to the challenges in monitoring these workers and the significant impact of potential work interruptions on the production process. Considering this, our observation of an increasing autonomy wage premium reflects a growing disparity in bargaining power between high- and low-autonomy occupations. We provide empirical evidence that higher monitoring and outsourcing is related to increases in autonomy wage gaps. However, minimum wages appear to counteract this trend.

Our analysis is based on a specific definition of autonomy tied to occupational tasks. Building on the multidimensional research on autonomy (Kalleberg, 2003; Burdín and Dean, 2009; Menon et al., 2020; Lopes and Calapez, 2021), future studies could analyse how different autonomy dimensions interact, for instance by comparing the autonomy premium in cooperatives versus traditional ownership structures. Another promising research avenue could be an analysis of how minimum wage policy and collective bargaining interact and jointly shape pay bargaining and equity outcomes for low-autonomy workers (Grimshaw et al., 2014; Martins, 2021).

Taken together, our findings offer novel insights on winners and losers from recent changes in European labour markets. Outsourcing and monitoring trends are likely to persist or even intensify, given the enhanced monitoring capabilities enabled by advances in artificial intelligence. Concurrently, occupations with low autonomy will continue to exist unless machines entirely replace human labour. Such occupations, as our analysis shows, are experiencing slower wage growth, further exacerbating wage inequality. To address this issue, policymakers should focus on strengthening the bargaining power of low-autonomy occupations, thus allowing to harness technology in progressive ways (Spencer and Slater, 2020). Our findings indicate that minimum wages are an effective tool to lower the autonomy wage premium. Finally, labour unions, which so far seemed unable or ineffective in countering the rising autonomy wage premium, might need to increase their support for low-autonomy occupations to mitigate wage disparities.

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A Appendix A: Data

Wages

EU SILC provide 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 ISCO classification is part of a framework for organising occupations into a clearly defined set of groups based on the tasks performed in the occupation. We exclude public sector, military and agricultural occupations, following the approach by Goos et al. (2014). Until 2010, our analysis includes 21 occupations classified according to the ISCO-88 sub-major group (two-digit) system in EU SILC. After 2010, the classification shifted to the ISCO-08 system, leaving us with 34 occupations in our analysis (see these occupations in Table A1). To accommodate these changes, we include time dummies in our econometric analysis to account for potential shifts in wages attributable to changes in occupational composition. Additionally, there was a shift in the NACE industry classification during our sample period from NACE Rev.1 to NACE Rev.2. To ensure consistency in our analysis, we categorise industries into six groups: 'Manufacturing and Mining', 'Construction', 'Retail, Transport, and Accommodation', 'Business Services', 'Finance', and 'Other Private Sector Services'.

Autonomy

The five characteristics of our autonomy index have been used in previous research on occupation-level labour market outcomes, but not from the view of autonomy. For instance, Autor et al. (2003) uses some of these elements in their index of non-routine cognitive tasks, which includes problem-solving and communicational tasks. Additionally, 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 in relation to autonomy (see also Jensen and Kletzer (2010)). We posit that the combination of our variables creates a reliable proxy for autonomy since decision-making and other tasks play a crucial role in exerting control and influence over the work process.

Alternative autonomy measures

Autonomy: EWCS-based measure

In addition to our primary O*NET-based autonomy measure, we provide an alternative measure by Menon et al. (2020) based on the European Working Conditions Survey (EWCS). The attractiveness of this measure lies in the fact that it allows to generate different occupational autonomy measures for each country. This worker discretion measure consists of three binary indicators generated from worker' 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 polychloric correlation matrix to construct this index. The first component can explain 84 percent of the overall variance, the same share as Menon et al. (2020). We use this first component as our index measure. The EWCS is conducted each five years from 2005, 2010 and 2015 and we generate a pooled measure for each occupation-country cell. We standardise the index at zero mean and unit standard deviation. 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, and measurement error due to the limited number of observations for some occupation-country groups.

Autonomy: alternative task-based measures on O*NET data

The decision-making index from Deming (2021) uses data on the following task content variables from O*NET:

- 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 ('Autonomy alt.') uses data on the following nine task content variables from O*NET:

- 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

Routine and offshorable

Previous studies have focused on the routine task intensity and offshorability of tasks as 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. 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* (Autor et al., 2006, 2008; Firpo et al., 2011; Goos et al., 2011; Mishel et al., 2013; Koomen and Backes-Gellner, 2022).

Our routine measure, based on Autor et al. (2003) and Firpo et al. (2011) includes the following variables:

- 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)

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.

Our measure for offshorable tasks is based on Acemoglu and Autor (2011), using data on the following task content variables from O*NET:

- 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)

Occupation-specific values for these measures are shown in Table A1.

We have shown that low autonomy workers tend to be at the bottom of the wage distribution (Figure 2). In contrast, our routine measure exhibits an inverted u-shaped pattern across the wage distribution. The most routine occupations are typically in the middle of the wage distribution (Figure A1) and offshorable occupations can be found in all parts of the wage distribution (Figure A2). Moreover, we plot our index measures for routine and offshorable tasks against wage growth trends in Figures A3 and A4, which does not suggest a relation between these factors and wage growth.

Additional task-based measures

In robustness checks, we include additional task-based measures to address potential concerns that our autonomy measure might capture wage growth variations attributable to other task dimensions. These measures include:

- Routine manual (based on 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 et al. (2011), hereafter FFL)
- Face-to-face (FFL)
- On-site (FFL)

- Information content (FFL)

We generate all index measures by adding up all variables and averaging across their scores. All indices are standardised with zero mean and unit standard deviation.

Outsourcing

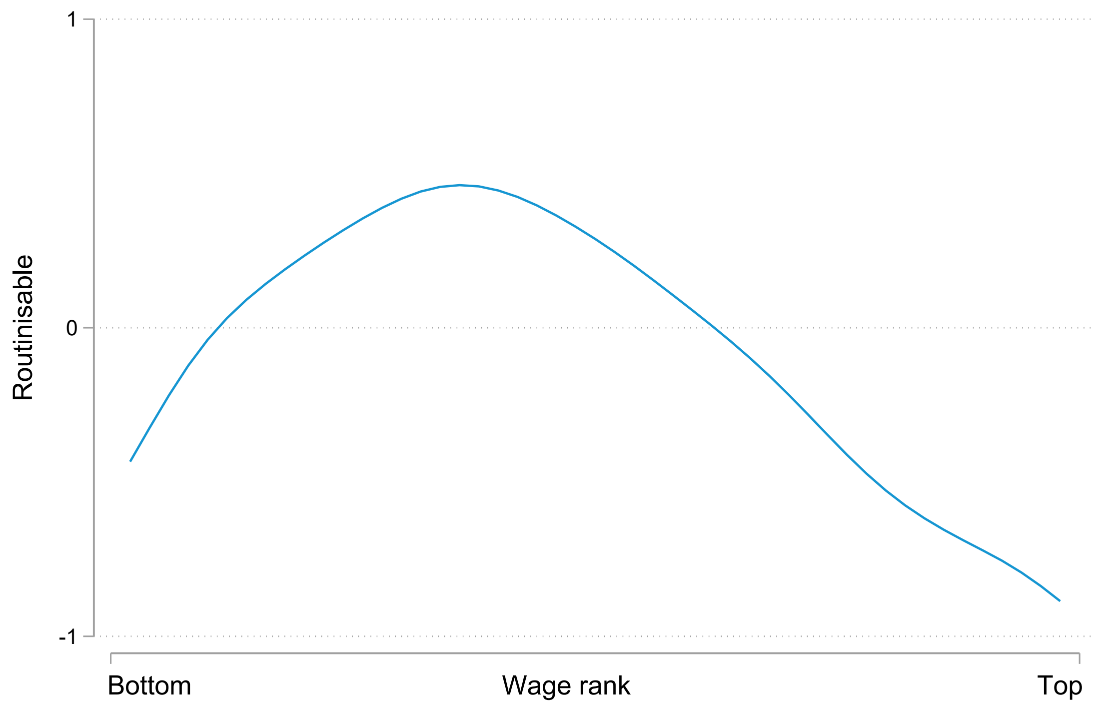
To measure outsourcing, we use data from the European Company Survey (ECS). The ECS questionnaire asks managers, 'Is this establishment partly or entirely outsourcing each of the following activities to a third party that is not owned by your establishment or the company you belong to?'. The activities are first, production, production of goods or services. Second, Marketing: sales or marketing of goods or services and third. Innovation: design or development of new products or services. We use the 2013 version of the ECS, as this is the only version where this survey question is available, and calculate the proportion of firms engaging in this practice in each country to gauge the monitoring intensity there. We cannot do this at the industry level because ECS 2013 does not provide the 1-digit industry classification needed for this.

Table A1: Occupation-level index measures: autonomy, routine and offshorable

Occupation	ISCO 08	Autonomy index	Routine index	Offshorable index
Chief executives, senior officials and legislators	11	2.19	-1.52	.72
Administrative and commercial managers	12	1.62	-1.35	1.5
Production and specialized services managers	13	1.81	-1.27	.06
Hospitality, retail and other services managers	14	1.71	-.73	-.34
Science and engineering professionals	21	.93	-1.22	1.14
Health professionals	22	1.16	-1.48	-1.26
Business and administration professionals	24	.91	-1.23	1.79
Information and communications technology professionals	25	.58	-.03	2.09
Legal, social and cultural professionals	26	.69	-1.36	1.13
Science and engineering associate professionals	31	.32	.58	-.38
Health associate professionals	32	.3	-.2	-1.61
Business and administration associate professionals	33	.06	-.21	.95
Legal, social, cultural and related associate professionals	34	-.18	-.92	.04
Information and communications technicians	35	.08	-.08	.4
General and keyboard clerks	41	-1.35	.5	1.26
Customer services clerks	42	-.91	1.23	.5
Numerical and material recording clerks	43	-.37	.88	1.15
Other clerical support workers	44	-1.18	.82	.86
Personal services workers	51	-.27	-.34	-.65
Sales workers	52	-1.13	-.8	.5
Personal care workers	53	-.12	-.89	-.82
Protective services workers	54	.54	-.22	-1.26
Building and related trades workers (excl. electricians)	71	.27	.05	-.94
Metal, machinery and related trades workers	72	-.21	.59	-.58
Handicraft and printing workers	73	-.32	.66	-.33
Electrical and electronics trades workers	74	.5	-.44	-1.76
Food processing, woodworking, garment and other craft	75	-.95	1.17	-.15
Stationary plant and machine operators	81	-1.08	2.41	-.28
Assemblers	82	-.95	1.26	-.56
Drivers and mobile plant operators	83	-.1	.89	-.84
Cleaners and helpers	91	-1.56	.26	.06
Labourers in mining, construction, manuf. and transport	93	-.57	1.16	-1.04
Food preparation assistants	94	-1.6	.98	-.29
Refuse workers and other elementary workers	96	-.84	.84	-1.04

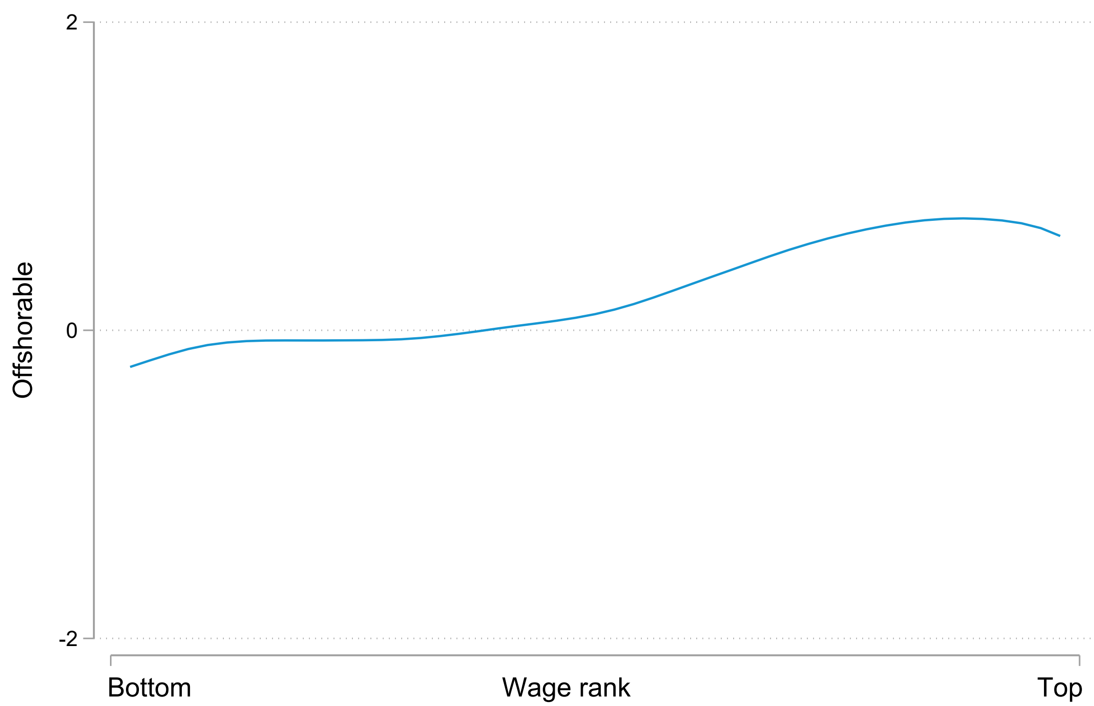
Notes: Index values were created using O*NET data and then mapped onto the 2-digit ISCO-08 occupational classification. All index measures have been standardized to have a zero mean and a unit standard deviation. For the autonomy index, a higher value indicates a greater level of autonomy in the occupation. In the routine index, a higher value indicates a higher intensity of routine tasks. For the offshorability index, a higher value indicates that occupational tasks are more susceptible to being offshored.

Figure A1: Routine index vs. wage rank of occupations, lowess smoothed



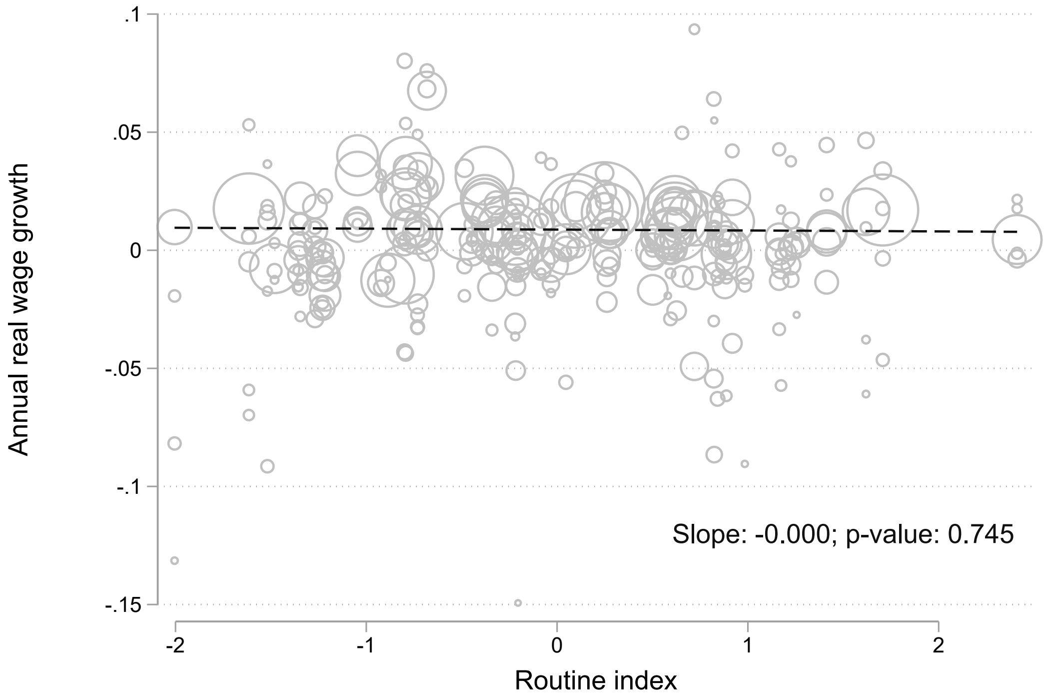
Source: EU SILC and O*NET, own calculations.
The horizontal axis ranks the average wage of jobs (occupation-industry groups). The vertical axis displays the routine index. The blue line represents the LOWESS smoothed curve, highlighting the hump-shaped relationship of routineness across the wage distributio.

Figure A2: Offshorable index vs. wage rank of occupations, lowess smoothed



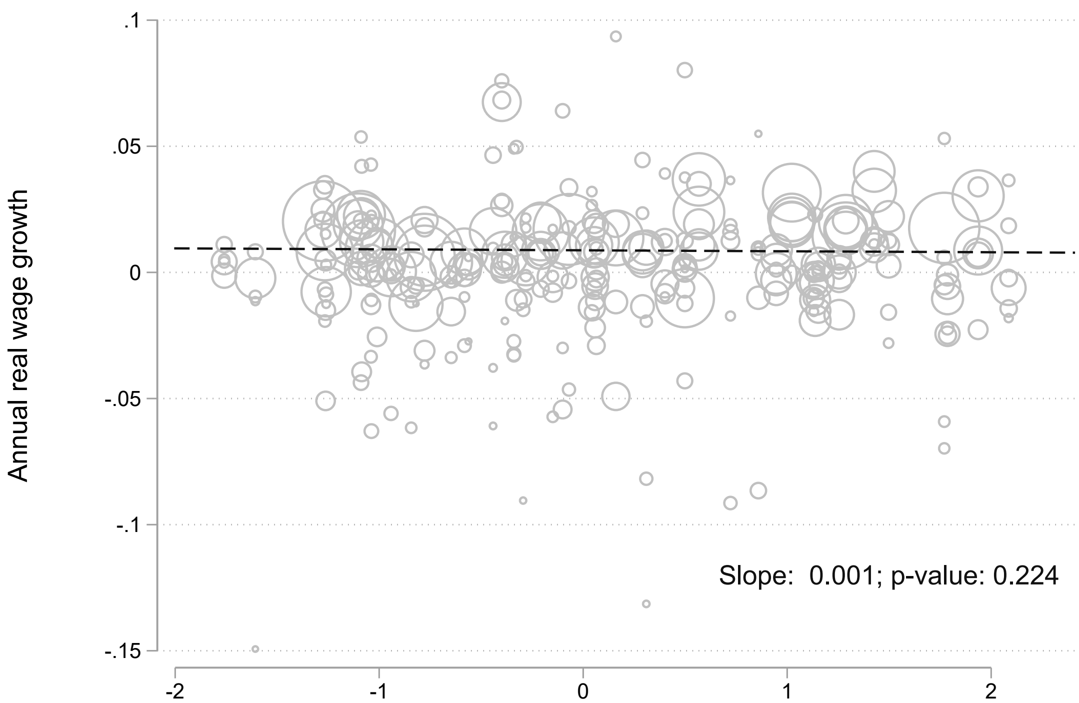
Source: EU SILC and O*NET, own calculations.
The horizontal axis ranks the average wage of occupation-industry-country cells. The vertical axis displays the offshorable index. The blue line represents the LOWESS smoothed curve, highlighting the relationship between autonomy and wage ranks.

Figure A3: Annual wage growth and routine index, 2003 - 2018



Source: EU SILC and O*NET, own calculations.
The linear fit is weighted by employment shares. Circle sizes represent employment shares.

Figure A4: Annual wage growth and offshorable index, 2003 - 2018



Source: EU SILC and O*NET, own calculations.
The linear fit is weighted by employment shares. Circle sizes represent employment shares.

Table A2: Cross-correlation table

Variables	Autonomy	Routine	Offshorable
Autonomy	1.000		
Routine	-0.562	1.000	
Offshorable	0.001	-0.262	1.000

Table A3: Demographic variables

	Value
Average real wage (in 2015 €)	40,523.13
Average age	42.22
Women share	0.37
Native born (share)	0.89
EU 28 foreign born (share)	0.04
Non-EU 28 foreign born (share)	0.06
Primary education (share)	0.06
Lower sec. education (share)	0.15
Upper sec. education (share)	0.42
Post-sec. non-tertiary education (share)	0.03
Tertiary education (share)	0.34
Observations	822663

Notes: All variables from EU SILC. The table shows unweighted summary statistics of our sample over the 2003 to 2018 period.

Table A4: Share of firms using employee outsourcing and monitoring

	Monitoring	Outsourcing (any)	Outsourcing production	Outsourcing sales	Outsourcing design/dev.
AT	0.21	0.49	0.31	0.24	0.20
BE	0.24	0.49	0.36	0.26	0.30
DE	0.14	0.34	0.24	0.14	0.14
DK	0.25	0.50	0.36	0.22	0.21
ES	0.47	0.42	0.31	0.18	0.24
FI	0.39	0.67	0.54	0.31	0.34
FR	0.28	0.41	0.29	0.18	0.21
IE	0.21	0.37	0.19	0.17	0.21
IT	0.41	0.36	0.25	0.15	0.20
NL	0.23	0.54	0.37	0.26	0.29
PT	0.21	0.54	0.43	0.24	0.29
SE	0.18	0.48	0.36	0.22	0.20
UK	0.28	0.35	0.23	0.17	0.15
Mean	0.27	0.46	0.33	0.21	0.23

Notes: Data are from the European Company Survey. The monitoring variable is taken from the fourth wave, conducted in 2019. The outsourcing variables derive from the third wave, conducted in 2013.

Table A5: ICT investments as share of gross fixed capital formation

Country	ICT/GFCF 2003	ICT/GFCF 2017
AT	13.5	14.4
DE	9.1	7.6
DK	12.9	13.5
ES	8.6	14.2
FI	8.2	8.3
FR	13.0	16.0
IE	3.9	4.1
IT	10.2	12.3
NL	12.8	20.5
PT	9.7	12.4
SE	17.8	17.2
UK	13.4	10.6
Mean	11.1	12.6

Notes: KLEMS data are available up to 2017 for most countries. However, for Spain, Ireland, Portugal, and Sweden, the dataset only extends to 2016. For these countries, the values for 2016 are displayed in the second column.

Table A6: LMI variables across countries

Country	Union density 2003	Union density 2018	CB coverage 2003	CB coverage 2018
AT	34.6	26.3	98.0	98.0
BE	55.4	50.0	96.0	96.0
CH	20.4	14.4	41.9	45.0
DE	23.0	16.6	67.6	54.0
DK	72.4	67.5	85.1	82.0
ES	16.5	13.0	78.9	80.1
FI	74.5	60.0	93.3	87.8
FR	9.2	8.8	97.6	98.0
IE	34.9	25.5	42.3	33.2
IT	33.6	32.6	100.0	100.0
NL	20.9	16.5	80.4	76.7
NO	51.8	49.9	75.0	68.0
PT	21.1	13.7	80.1	73.6
SE	77.2	60.1	90.8	88.0
UK	28.5	23.0	35.5	26.0
Mean	38.3	31.9	77.5	73.8

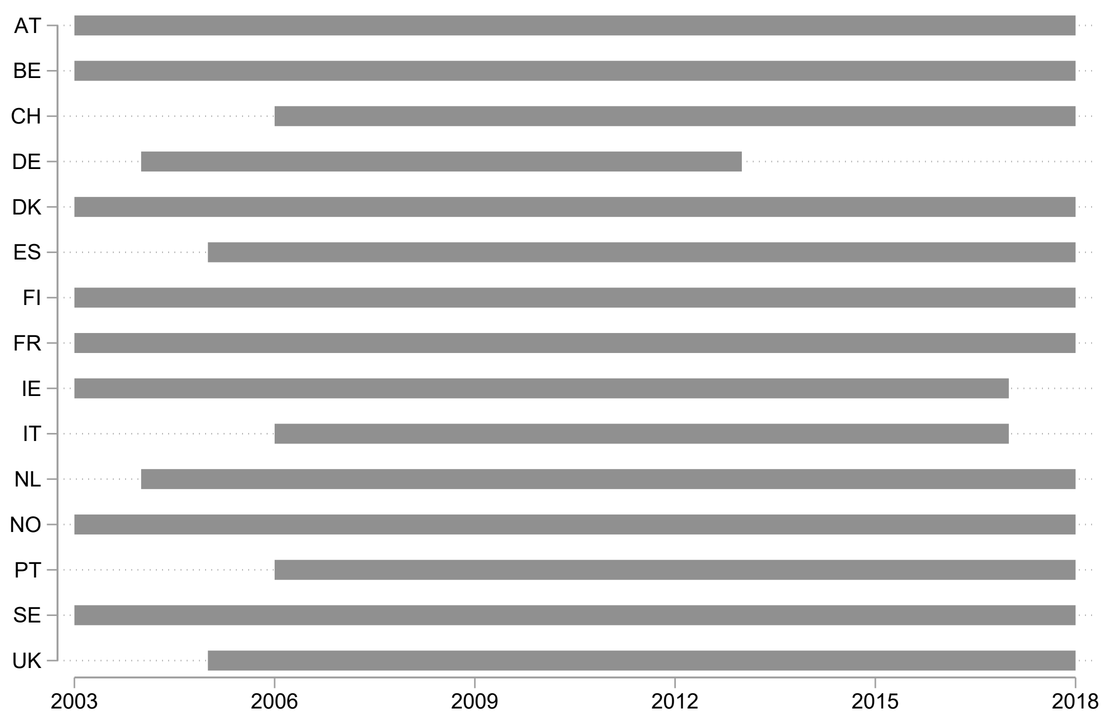
Notes: CB coverage refers to collective bargaining coverage. Data are from the OECD-AIAS-ICTWSS database. Union density and collective bargaining variables are expressed in percentage terms.

Table A7: Minimum wage across countries

Country	Min. wage/median wage 2003	Min. wage/median wage 2018	Min. wage/mean wage 2003	Min. wage/mean wage 2018
BE	48.8	42.7	42.1	39.1
ES	34.6	41.0	27.8	34.3
FR	63.9	61.6	51.7	49.7
IE	36.4	49.7	29.9	39.0
NL	47.5	47.1	42.3	39.6
PT	50.1	63.3	35.5	44.5
UK	42.2	54.5	34.5	44.8
Mean	46.2	50.9	37.7	41.7

Notes: Data on minimum wage are from the OECD Employment and Labour Market Statistics database. Missing countries do not have minimum wages throughout our sample period. All measures are expressed in percentage terms.

Figure A5: EU SILC data availability across countries



B Appendix B: Empirical analysis

Table B1: Robustness 1

	(1) Decision (Deming)	(2) Autonomy alt.	(3) Cogntive tasks	(4) Routine tasks	(5) Offshorable	(6) Information	(7) Manual tasks	(8) Educ. return
Autonomy			0.0029*	0.0025***	0.0028***	0.0028***	0.0021***	0.0027***
			(0.0014)	(0.0006)	(0.0008)	(0.0006)	(0.0006)	(0.0006)
Decision-making (Deming)	0.0027***							
	(0.0006)							
Autonomy altern.		0.0032***						
		(0.0008)						
Routine	0.0004	0.0010			0.0004			
	(0.0006)	(0.0007)			(0.0006)			
Offshorable	0.0003	-0.0003						
	(0.0004)	(0.0004)						
Cognitive analytical (AA)			-0.0016*					
			(0.0009)					
Cognitive interpersonal (AA)			0.0013					
			(0.0011)					
Routine manual (AA)				0.0000				
				(0.0005)				
Routine cognitive (AA)				-0.0000				
				(0.0005)				
Non-offshorable (via FFL)					0.0002			
					(0.0005)			
Information content (FFL)						-0.0005		
						(0.0005)		
Manual physical (AA)							0.0002	
							(0.0006)	
Manual personal (AA)							0.0008	
							(0.0008)	
Return to education $\times$ t								-0.0011
								(0.0008)
Observations	808122	808122	808122	808122	808122	808122	808122	808122
r2	0.5450	0.5450	0.5450	0.5450	0.5450	0.5450	0.5450	0.5450

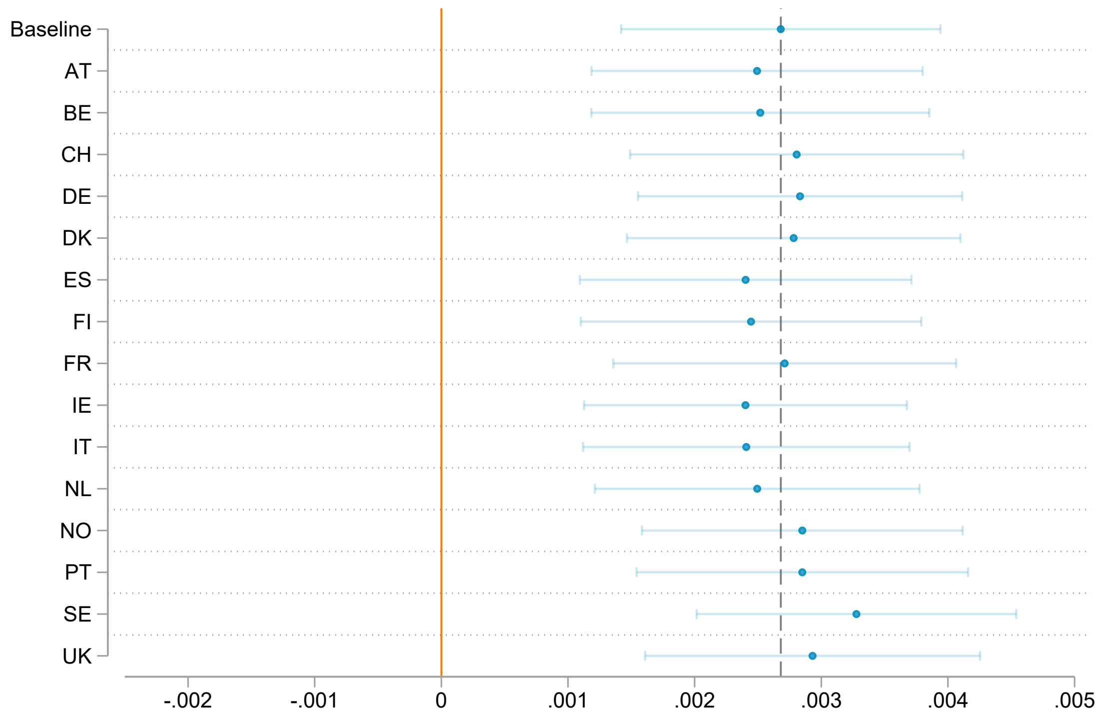
Notes: Standard errors in parentheses. All regressions include demographic controls. All regressions include occupation-industry-country fixed effects and industry-country-year fixed effects. Standard errors are clustered by occupation-industry-country. AA means that the measure is taken from Acemoglu and Autor (2011). FFL means that the respective measure is taken from Firpo et al. (2011). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Robustness 2

	(1) ISCO 1-digit	(2) 2003-2010	(3) 2010-2018	(4) Pop. weights	(5) ONET 5.1	(6) Trim top 1%	(7) Trim top 5%	(8) Synthetic panel
Autonomy	0.0050^{***}	0.0029^{***}	0.0027^{***}	0.0024^{***}	0.0027^{***}	0.0024^{***}	0.0024^{***}	0.0044^{***}
	(0.0007)	(0.0010)	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0016)
Routine	0.0006	-0.0025^{**}	0.0015^{**}	0.0006	0.0004	0.0005	0.0006	-0.0002
	(0.0006)	(0.0011)	(0.0008)	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0017)
Offshorable	0.0001	-0.0002	0.0003	0.0006	0.0003	0.0002	0.0004	-0.0005
	(0.0004)	(0.0008)	(0.0005)	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0010)
Observations	808295	352861	455261	808122	808122	800129	767676	25421
r2	0.5263	0.4524	0.6109	0.4858	0.5450	0.5478	0.5446	0.1707

Notes: Standard errors in parentheses. All regressions include demographic controls. All regressions include occupation-industry-country fixed effects and industry-country-year fixed effects. Standard errors are clustered by occupation-industry-country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure B1: Robustness check: countries



Notes: CI: 95%. In the estimates presented in this figure, 'AT' denotes that Austria was excluded from the respective regression model. All models adhere to the baseline equation as outlined in Equation 2. These analyses also allow us to discern country-specific trends regarding the autonomy premium. For instance, when Austria is excluded from the model, the resulting estimate for the autonomy premium is lower than that of our baseline model. This suggests a steeper increase in the autonomy premium within Austria when compared to the aggregate sample.

Autonomy and labour demand

The labour economics literature suggests that changes in relative wages can be attributed to market forces, particularly changes in labour demand (Katz and Murphy, 1992; Autor and Dorn, 2013). Here, we explore the idea that high-autonomy occupations have experienced a rise in relative labour demand. Table B3 presents employment growth regressions, following the empirical method by Goos et al. (2014), including our measure for autonomy.

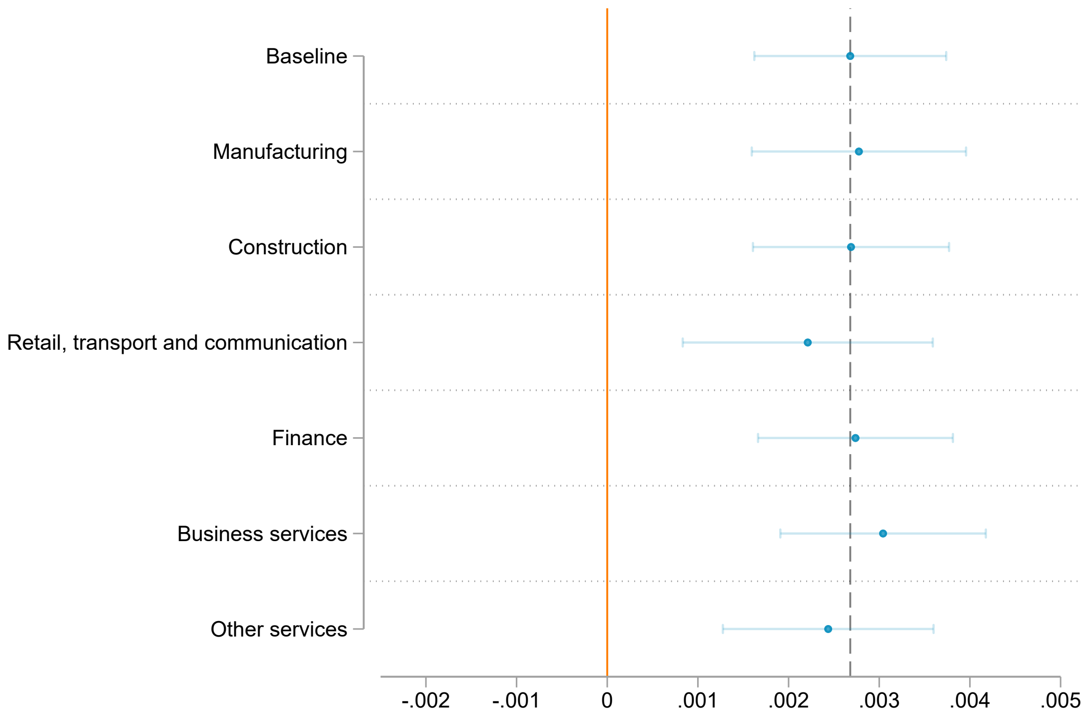
Table B3 presents our results. Our estimates for autonomy are economically small and we can't reject the null hypothesis that autonomy is unrelated to employment growth. Specifically, in column 1, the coefficient for autonomy is both economically and statistically insignificant. The interpretation of this estimate is that employment hours in an occupation one standard deviation more intense in autonomy grow 0.08 percentage points slower annually, compared to an occupation with an average autonomy within our sample, all things equal. Instead, we find that the routine intensity of an occupation is linked to de-

Table B3: Autonomy and labour demand: employment share regressions

	(1) Main	(2) Industry-country-year FE	(3) with FE and controls
Autonomy	-0.087	0.155	0.255
	(0.207)	(0.159)	(0.237)
Routine	-1.195***	-0.653***	-0.473**
	(0.260)	(0.182)	(0.240)
Offshorable	0.254	0.198	0.284
	(0.169)	(0.138)	(0.178)
Education			-0.044***
			(0.010)
Women share			-0.214***
			(0.026)
Age			-0.017***
			(0.001)
Migrant share			0.343***
			(0.031)
Observations	43182	43182	43182
FE	No	ICY	ICY
r2	0.969	0.975	0.921

Notes: Standard errors in parentheses. All regressions include occupation-industry-country fixed effects and regressions where FE is ICY also include industry-country-year fixed effects. Standard errors are clustered by occupation-industry-country. Regression models are based on Goos et al. (2014). The number of observations refers to occupation-industry-country-year cells in our sample. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure B2: Robustness check: industries



Notes: CI: 95%. In the estimates presented in this figure, 'Manufacturing' denotes that the manufacturing sector was excluded from the respective regression model. Manufacturing means that the regression in the respective row was conducted with all industries except manufacturing. All models adhere to the baseline equation as outlined in Equation 2. We can discern industry-specific trends from this analysis. For instance, the estimate for the specification excluding the manufacturing sector is slightly higher than our baseline estimate. This implies that the rise in the autonomy premium in the manufacturing sector was less pronounced compare to our full sample.

creases in employment. Column 2 includes industry-country-year fixed effects to account for industry specific shocks, and column 3 includes additional demographic controls. These findings cast doubt on the notion that wages are increasing in occupations that experience a rise in labour demand. Instead, our analysis suggests that occupations with greater bargaining power have benefitted from recent technological and institutional shifts, unlike low-bargaining occupations.