The rise in the supervisory wage gap in Western Europe

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Abstract

This article examines the evolution of the supervisory wage gap—the wage difference between supervisory and non-supervisory workers—across 15 Western European countries between 2003 and 2022. Using individual-level data for Western Europe, alongside matched employer–employee data and individual longitudinal data for the United Kingdom, we document a 6–7 percentage point increase in the supervisory wage gap. We then examine three explanations for this trend: worker sorting on unobserved ability, changes in supervisory job content and changes in employment relations. First, worker sorting explains around 20 per cent of the increase. Second, we find limited support for changes in supervisory job content as key driver: the increase occurs primarily within firms and is not confined to firms that grow or expand supervisory span, nor is it systematically related to technological change. Finally, we show that the rise is associated with greater use of digital monitoring tools, outsourcing, offshoring, and weaker wage coordination, suggesting an important role for employment relations.

Keywords: wage distribution, inequality in the labour market, employment relations, labour market institutions, worker sorting, human capital

JEL Codes: J31, J24, J53, M51, L23.

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Introduction

Wage inequality has long been a central concern in research on labor markets and employment relations. A large literature documents widening wage dispersion by skill, task, occupation and firm characteristics (Katz and Murphy, 1992; Lemieux, 2006; Autor, 2014; Kristal, 2020). In contrast, wage differences across workplace hierarchies, particularly between supervisors and non-supervisors, have received comparatively little attention (Rothstein, 2001). This is an important omission because supervisory wage premiums are large—previous studies estimate wage gaps between 6 and 23 per cent across European countries (Leonida et al., 2020) and 10 per cent in the US (Rothstein, 2001). Moreover, supervisory wage gaps may evolve over time as technology, firm organization, and labor market institutions reshape the relative productivity and bargaining power of supervisors and non-supervisors, with important implications for wage inequality.

The limited existing research on supervisory wage gaps has focused primarily on cross-sectional wage differences (Bayer and Kuhn, 2023; Leonida et al., 2020, 2023; Rothstein, 2001). This leaves two important questions unresolved. First, we know little about whether supervisory wage gaps have widened or narrowed over recent decades. Second, previous research has not systematically examined the determinants of these gaps.

This article addresses both questions. We develop a unified theoretical framework that distinguishes three channels through which supervisory wage gaps evolve. The first channel is human capital. Supervisors may earn more because they possess greater education, experience, ability, or other productive characteristics. If higher-ability workers increasingly sort into supervisory roles over time, supervisory wage gaps would widen. The second channel concerns supervisory job content or tasks. Supervisory wage gaps may rise when supervisory responsibilities expand, either because of organizational changes within firms—such as larger firm size or wider supervisory span (Green et al., 2021)—or because technological change

alters supervisory tasks. The third channel is employment relations. Wages depend not only on productivity, but also on bargaining power and institutional context. Changes in worker monitoring, outsourcing, offshoring, and labor market institutions may weaken the bargaining position of non-supervisory workers relative to supervisors, increasing supervisory wage gaps.

Our empirical approach tests the three proposed channels sequentially using three complementary datasets[3]. We first use the European Union Statistics on Income and Living Conditions (EU-SILC), a repeated cross-sectional individual-level dataset to document trends in the supervisory wage gap across 15 Western European countries from 2003 to 2022. We also use these data to examine whether industry- and country-level measures of employment relations are associated with variation in the gap. Second, we draw on longitudinal individual-level data from the UK—one of the countries with the highest supervisory wage gaps in Europe (Leonida et al., 2020)—using the British Household Panel Survey (BHPS) and Understanding Society (USoc) data, to test whether changes in the gap reflect increased sorting on unobserved worker characteristics. Third, we use matched employer-employee data from the UK Workplace Employment Relations Survey (WERS), which follows firms over time and allows us to account for unobserved firm fixed effects. These data allow us to examine whether the rise in the supervisory wage gap is driven by changes in supervisory job content operating through firms, including reallocation towards larger firms, firm growth, and changes in supervisory span within firms.

[3] Longitudinal matched employer-employee data would be the preferred data to analyze our research question, as it allows us to account for both individual- and firm-level determinants of the supervisory wage gap. However, administrative data of this kind does usually not provide indicators for supervisory status, which limits us to survey data. We draw on matched employer-employee survey data for the UK (WERS), which is however limited to two years (2004 and 2011). We therefore use both WERS and individual-level panel data from BHPS to account for firm-level determinants and individual-level factors.

We document a substantial increase in the supervisory wage gap. Between 2003 and 2022, the gap rises by 6.8 percentage points across Western Europe based on harmonized cross-country data, and by 6.3 percentage points in the UK based on longitudinal worker data. Using matched employer-employee data for the UK, we find an increase of 3.6 percentage points between 2004 and 2011, consistent with the longer time trends in the other datasets.

We then show that changes in worker sorting explain only a limited share of this rise. Controlling for sorting on unobserved worker characteristics using supervisor-spell fixed effects reduces the estimated increase by only around 20 per cent, suggesting that the growing gap does not primarily reflect a reallocation of more able workers into supervisory roles. We also find limited support for the job content channel. Using matched employer-employee data for the UK, we show that the rise in the supervisory wage gap is primarily a within-firm phenomenon rather than the result of workers being reallocated across firms with different wage gaps. Moreover, the increase is not confined to firms that grow in employment or to firms where supervisory span increases. Using cross-country data, we also find no systematic relationship between supervisory wage gap growth and measures of supervisory span, task complexity, or ICT intensity, which capture technology-driven changes in job content. These findings cast doubt on the view that changes in supervisory job content are the main driver of the rise. Finally, we show that the rise is associated with changes in employment relations, including the greater use of worker monitoring technologies, increased outsourcing and offshoring, and declining wage coordination. These developments appear to have weakened the bargaining position of non-supervisory workers relative to supervisors, contributing to widening wage gaps.

This article contributes to two strands of literature. First, it extends the labour economics literature on wage structures by focusing on an underexplored dimension: wage differences across workplace hierarchies. Second, it connects labor economics and industrial relations

research by highlighting different channels for supervisory wage gaps, and showing that supervisory wage gaps reflect not only differences in human capital and responsibilities but also changes in bargaining positions and institutional context. The economics literature on wage structures has largely focused on how technological change reshapes skill and task requirements, often through frameworks such as skill- and routine-biased technological change (Acemoglu and Autor, 2011; Autor et al., 2003). By contrast, the role of supervision, job hierarchies, and how they are mediated by labor market institutions and employment relations, has received less attention in economics, although it has been an important focus of industrial relations research (Kristal, 2020; Leonida et al., 2023; Rabensteiner and Guschanski, 2025). Yet, few studies in either literature have examined the supervisory wage gap directly. Analyzing supervisory wage gaps bridges insights from these literatures because wage gaps between supervisors and non-supervisory workers capture not only differences in skills and tasks, but also the distribution of authority and bargaining power within firms. Supervisors occupy a distinctive position within organizational hierarchies, and the value attached to their role is shaped by the broader organizational and institutional conditions. By drawing on insights from both literatures, our analysis contributes to the better understanding of how wage inequality is produced and sustained in contemporary labor markets.

The determinants of supervisory wage gaps

Wage differences between supervisors and non-supervisory workers arise from multiple sources. In this section, we develop a unified framework that organizes the determinants of the supervisory wage gap along three channels: human capital, job content, and employment relations. This framework provides the basis for our empirical analysis.

The human capital channel

A longstanding view in labor economics holds that supervisors earn higher wages because they possess greater human capital, such as specific skills, higher levels of education, experience, and ability. This view is based on the notion that wages reflect productivity, which itself is shaped by individual human capital characteristics such as education, skills, experience, and ability (Mincer, 1958). Early models of hierarchical wage structures suggest that individuals with greater human capital are more likely to hold supervisory positions. Calvo and Wellisz (Calvo and Wellisz, 1979), for example, argue that workers with higher skills and ability tend to be selected into—or self-select into—supervisory roles because firms rely on them to coordinate, organize and monitor production effectively.

In practice, supervisors tend to have higher levels of formal education, more work experience, and stronger cognitive and interpersonal skills than non-supervisory workers. These characteristics translate into higher productivity and, according to standard labor market theory, higher wages (Rothstein, 2001).[4] As a result, changes in worker selection or sorting—such as higher-ability individuals increasingly moving into supervisory roles—would be expected to increase the supervisory wage gap. This mechanism constitutes the human capital channel.

The job content channel

A second explanation for supervisory wage gaps focuses on differences in job content. Supervisory wage gaps may arise not only because supervisors have greater human capital, but also because the tasks they perform differ from those of non-supervisory workers. Supervisory roles typically involve greater responsibility, more complex tasks, and broader decision-making authority than non-supervisory work (Rothstein, 2001). These features may justify

[4] Relatedly, Carmichael (1984) argues that firms may use promotions to supervisory positions and related higher pay as rewards for workers who accumulate specific human capital.

higher wages independent of differences in human capital. From this perspective, supervisors are compensated not only for their skills, but also for the tasks they perform.

Early proponents of this view are Simon (1957) and Lydall (1968), who argue that supervisory wages are a multiple of production worker wages, and that this wage premium is higher for additional layers of supervision. Efficiency wage theory explains why this pay structure emerges endogenously as a response to incentive and monitoring problems within firms (Bowles, 1985; Calvo and Wellisz, 1979; Rosen, 1982; Shapiro and Stiglitz, 1984). To elicit effort from their employees, firms set wages and monitor employee performance. When effort is difficult to monitor and non-performance is costly, firms may pay efficiency wage premia to secure reliability and cooperation (Bloesch et al., 2022). This incentive problem is particularly salient for supervisors, whose strategic and coordinating functions mean that their effort directly affects the productivity of multiple subordinate workers. A reduction in supervisory effort can thus have disproportionate effects on firm performance overall. Consequently, firms have an incentive to offer supervisors a wage premium to secure reliability and align their interests with the firm's objectives (Calvo and Wellisz, 1979).[5] This premium increases with potential losses from supervisory non-performance, which depend on job content characteristics such as the number of supervisees or the complexity of the supervisory tasks. A corollary of this view is that supervisors carry greater responsibility—and hence command higher wages—in larger firms with more complex hierarchies or when they supervise a larger number of workers (Green et al., 2021).

From this perspective, we distinguish two ways in which supervisory job content may change over time: through organizational change and through technological change. First, supervisory

[5] A related argument can also be found in the sociology of work literature, which regards higher wages as an important means of cultivating the loyalty and dedication of upper-class workers (Gil-Hernández et al., 2024). Tournament theory (Lazear and Rosen, 1981; Rosen, 1988) provides a complementary explanation for the supervisory wage gap, suggesting that firms use promotions to supervisory positions and associated wage increases to incentivize worker effort through competition for advancement.

job content may change because firms reorganize production such that supervisors oversee a larger number of subordinates, giving rise to two possible mechanisms. One is a between-firm effect: the supervisory wage gap may rise if workers are increasingly reallocated toward firms in which supervisory responsibilities are greater, such as larger firms or firms with larger supervisory spans. The other is a within-firm effect: the supervisory wage gap may rise if firms themselves grow or increase supervisory span.

Second, supervisory job content may change because technology alters the content of supervisory tasks. Technological change—particularly digitalization and automation—has reshaped task structures in ways that complement higher-order skills (Acemoglu and Autor, 2011; Autor et al., 2003; Firpo et al., 2011). If digital technologies disproportionately augment productivity in tasks characterized by problem-solving and strategic coordination, they may raise relative wages in supervisory roles. Through this mechanism, technological change may widen supervisory wage gaps, even without shifts in worker composition or firm structure.

The employment relations channel

A third, and often overlooked, channel operates through employment relations. Industrial relations research emphasizes that wages do not depend solely on productivity but are also shaped by bargaining power, institutional constraints, and organizational practices (Kristal, 2013; Rabensteiner and Guschanski, 2025; Wilmers, 2017). Institutional features of employment relations shape the distribution of bargaining power between supervisory and non-supervisory workers and, consequently, wage outcomes. We highlight four determinants of employment relations: worker monitoring, outsourcing, offshoring, and labor market institutions (LMIs).

First, the diffusion of digital monitoring and performance-tracking technologies has expanded managerial control over non-supervisory workers, potentially weakening their bargaining

position (Ball, 2021). These tools reduce firms' reliance on efficiency wage mechanisms for less complex and easily observable tasks, as close surveillance diminishes the need to incentivize effort through higher pay. Because supervisory work is more complex and harder to monitor, these developments may worsen the bargaining position of production workers while increasing the relative wage of supervisors. Similarly, Kristal (2013) argues that computerization and monitoring technologies have expanded managerial control and coordination capacities, enabling more effective anti-union tactics such as surveillance, disciplining, and intimidation, that weaken (non-supervisory) workers' ability to organize collectively, and thereby their bargaining position.[6] Consistent with this, Rabensteiner and Guschanski (2025) find that monitoring technologies are associated with rising relative wages in occupations characterized by high autonomy and decision-making, task requirements common in supervisory roles.

Second, outsourcing and the broader fissuring of the workplace into separate production units (Weil, 2014) have redefined firm boundaries and eroded internal pay norms. When firms employ all workers in-house, internal fairness constraints limit wage dispersion. However, outsourcing allows firms to bypass these constraints, resulting in lower wages for outsourced or subcontracted workers (Berlinski, 2008; Dube and Kaplan, 2010; Goldschmidt and Schmieder, 2017; OECD, 2021; Ouyang and Batt, 2026; Weil, 2014). Supervisors, given their strategic role in coordinating activities and their firm-specific knowledge, are less likely to be outsourced. Greater outsourcing intensity is therefore expected to harm non-supervisory workers disproportionately and widen the supervisory wage gap.

[6] Conceptually, it is useful to distinguish between digitalization technologies that enhance productivity and task efficiency and monitoring technologies that alter bargaining dynamics by reshaping information and control structures within firms. The former affects the supervisory wage gap through productivity or job content, while the latter operates through relative bargaining power. Although we distinguish these channels empirically where possible, in practice they may interact. Technologies that expand supervisory control can both raise supervisor productivity and lower non-supervisory workers' bargaining position.

Third, the deregulation of trade barriers and the expansion of global production networks have affected worker bargaining power by increasing capital mobility and reducing offshoring costs (Hanson and Harrison, 1999; Jayadev, 2007; Rodrik, 1997). Offshoring threats can credibly pressure workers to accept wage moderation, a dynamic well established in the literature (Guschanski and Onaran, 2023, 2022). Because supervisory tasks, such as coordination and oversight, are less easily offshored, supervisors face less direct competition from global labor markets. As a result, greater offshoring exposure is expected to increase supervisory wage gaps.

Fourth, LMIs, such as unions, collective bargaining and wage coordination, compress the wage distribution by enhancing the bargaining power of lower-paid workers (Blau and Kahn, 1999; DiNardo et al., 1996; Farber et al., 2021; OECD, 2011; Visser, 2006). LMIs can limit wage dispersion both by lifting lower wages and by constraining top pay (Freeman and Lazear, 1995; Jaumotte and Osorio, 2015). While LMIs may benefit all workers, their effects are typically strongest for lower-skilled and non-supervisory employees (Freeman, 2007; Kristal, 2013; Western and Rosenfeld, 2011). Supervisors, by contrast, often rely on individual negotiations given their strategic positions and the fact that they are less easily replaced due to firm-specific knowledge. Declining union density and wage coordination across many Western economies may thus have weakened the bargaining position of non-supervisory workers, contributing to wider supervisory wage gaps.

Empirical studies

Despite these strong theoretical foundations there is limited empirical literature on supervisory wage gaps. Rothstein (2001) estimates a sizable gap of approximately 9-10 per cent for both men and women in the US. Bayer and Kuhn (2023) document substantial wage differences across job hierarchies in Germany, though without an explicit focus on supervisory status. In the UK, Green et al. (2021) find that firm-size wage premia accrue primarily to supervisors, partly because more able supervisors sort into larger firms and partly because supervisors in

larger firms oversee more subordinates. Leonida et al. (2020, 2023) show substantial cross-country variation in supervisory wage gaps across Europe, with the UK exhibiting the largest gap. They further show that supervisory wage gaps tend to be larger in liberal market economies than in coordinated market economies. The authors argue that this reflects differences in workplace organization: in liberal market economies, such as the UK, flatter hierarchies require more relational and managerial skills from supervisors, whereas these skills are less relevant in coordinated market economies, such as Germany, which are characterized by more hierarchical workplace organization (Cieslik, 2011).

Overall, this literature has made two important contributions. First, it establishes that supervisory wage gaps are economically meaningful and vary across countries and organizational settings. Second, it points to the importance of both worker characteristics (i.e., human capital) and job content (e.g. span of control) in shaping supervisory wages. At the same time, previous studies do not systematically analyze specific institutional drivers of supervisory wage gaps. In particular, existing work has not separately evaluated the importance of worker sorting on unobserved ability, changes in supervisory job content, and shifts in employment relations. Moreover, existing work estimates wage differentials at given points in time, leaving open the question of how they have evolved over recent decades, an important dimension for understanding recent trends in wage inequality.

Hypotheses

We derive three hypotheses regarding changes in the supervisory wage gap:

- H1 (Human capital): Supervisory wage gaps increase when higher-ability individuals sort into supervisory roles.
- H2 (Job content): Supervisory wage gaps increase as supervisory responsibilities expand, either due to organizational change (firm growth or wider supervisory span) or

because technological change increases the complexity and strategic importance of supervisory tasks.

- H3 (Employment relations): Supervisory wage gaps increase when changes in employment relations weaken the bargaining position of non-supervisory workers relative to supervisors, for example through monitoring tools, outsourcing, offshoring, or weaker labor market institutions.

These hypotheses guide our empirical analysis of the rise in supervisory wage gaps.

Data

We draw on three main data sources that include information on supervisory roles as well as wages: EU-SILC, BHPS/USoc and WERS.

European Union Statistics of Income and Living Conditions (EU-SILC)

Our first data source is the EU-SILC, a repeated cross-sectional survey of individuals across European countries.[7] Our analysis of 15 Western European countries from 2003 to 2022 yields more than one million worker-year observations. EU-SILC provides detailed information on wages and employment. We construct gross hourly wages for each individual-year observation by dividing annual gross wage income by the product of the number of months worked, 4.2 weeks per month, and usual weekly hours of work, following Michael and Christofides (2020). The mean hourly wage in our sample is approximately €14.9.

EU-SILC includes a question on supervisory responsibilities: "Are you performing supervisory tasks? Yes/No." An individual is classified as a supervisor if they formally supervise the work of at least one other person. Around 28 per cent of respondents are classified as supervisors. We provide further details on this variable in Appendix A. EU-SILC also includes a range of

[7] EU-SILC provides a panel version, but this version does not provide an indicator for supervisors.

individual-level human capital and demographic variables, including educational attainment, age (as a proxy for experience), gender, migrant status, and marital status. Additional variables include contract type (temporary or permanent), a firm-size indicator, and occupation and industry identifiers. Appendix Table A1 provides details on the variables.

Our sample comprises individuals aged 20 to 65, representing the core working-age population. We exclude self-employed individuals to ensure consistency and to avoid employers who may be recorded in this category. In the cross-country analysis, we also exclude the public administration sector as bargaining processes in the public sector differ significantly by country.[8] To address outliers and measurement issues, we restrict the sample to employees working more than 30 hours per week and trim the top and bottom percentiles of the wage distribution within each country-year cell. To maintain consistency across changes in occupation and industry classifications, we use one-digit International Standard Classification of Occupations (ISCO) codes and aggregate industry codes to eight broad sectors based on the Classification of Economic Activities in the European Community (NACE), as detailed in Appendix A.

British Household Panel Survey (BHPS) and Understanding Society (USoc)

Our second source is the combined British Household Panel Survey (BHPS) and Understanding Society (USoc) dataset, which provides individual-level longitudinal data for the UK. The BHPS is a random sample of up to 16,000 individuals per year, available from 1993 onwards, while Understanding Society is its successor survey, beginning in 2009. Individuals can be tracked across both datasets, except in the first wave of USoc (2009), where the linking identifier is unavailable. Hereafter, we refer to the combined dataset as BHPS/USoc.

[8] For instance, in Germany, civil servants do not have the right to collective bargaining or to strike (Keller, 2020).

We use information on wages and hours to compute hourly wages. The average hourly wage is £12.2. In each wave, employed individuals are asked, 'Do you have any managerial duties, or do you supervise any other employees? Yes/No'. Respondents indicate whether they are a manager, a foreman/supervisor, or neither. We classify individuals as supervisors if they respond positively to either the question of being a manager or a supervisor.[9] BHPS/USoc also includes variables on worker characteristics, employer size, and identifiers for occupation, industry, and region, as detailed in Appendix Table A2. We follow variable choice and sample selection choices in line with our EU-SILC sample, such as including individuals aged 20 to 65 and excluding self-employed individuals. Each BHPS/USoc wave spans September to September, and we analyze waves by survey year.

UK Workplace and Employment Relations Survey (WERS)

Our third data source is the UK Workplace and Employment Relations Survey (WERS), a stratified sample of British workplaces (Van Wanrooy et al. 2013). We use the 2004 and 2011 waves, which allow us to link firms over time. WERS matches questionnaires from senior managers with those of up to 25 randomly selected employees in each establishment.

We use information on wages and hours to compute hourly wages. Gross wages are reported in 14 wage bands for each survey wave. Following Green et al. (2021), we assign midpoints to the wage bands and divide these by hours worked, yielding an average hourly wage of £12.3.[10] Compared with other employer-employee matched datasets, a key advantage of WERS is that it includes a supervisory indicator. Each employee is asked, 'Do you supervise any other

[9] While this may include some managers without supervisory responsibilities, it is plausible that most managers also have supervisory duties (Green et al., 2021). As a robustness check, we analyze the supervisory wage gap both including and excluding managers.

[10] In the 2011 wave, respondents report wage income in 14 bands from 'less than £60 per week/£3120 per year' to '£1051 or more per week/£54,061 per year'. Following Green et al. (2021) we use half the upper bound for the lowest category and for the top we set wages at 1.5 times the lower bound. For robustness, we also present maximum likelihood interval regressions.

employees? A supervisor, foreman or manager is responsible for overseeing the work of other employees on a day-to-day basis. Yes/No'. WERS also includes information on worker characteristics, job characteristics, employer size, and identifiers for occupation, industry, and region, as detailed in Appendix Table A3.

We align variable choices and sample restrictions with those in the other datasets. In particular, we include employees aged 20 to 65 and those working more than 30 hours per week. After dropping observations with missing data, our sample includes more than 10,000 worker-year observations matched to 569 firms. We use the survey weights provided by WERS throughout our analysis (Forth and Freeth 2014; Green et al. 2021).

Industry-level determinants

We use additional data sources to examine the role of job content and employment relations (details in Appendix Table A4). For job content, we rely on information on task complexity and supervisory span (number of supervisees by supervisor) from the European Working Conditions Survey (EWCS), available from 2005 to 2015. To capture technology adoption and digitalization technologies more broadly, we use EU KLEMS data on ICT capital stock relative to value added, following Michaels et al. (2014).

For the employment relations channel, we use data on digital worker-monitoring technologies from the European Company Survey (ECS), which asks managers in firms with ten or more employees whether they use data analytics tools to monitor employee performance. Measures of outsourcing and offshoring are constructed using OECD Inter-Country Input–Output (ICIO) tables. Union density is obtained from the European Social Survey, while wage coordination and collective bargaining coverage information are drawn from the Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS) database.

Methodology

We begin our analysis using repeated cross-sectional data from EU-SILC to document trends in the supervisory wage gap across Western Europe. Our baseline specification is:

$$y_{it} = \alpha_t S_{it} + \gamma_H{}' \boldsymbol{H}_{it} + \gamma_D{}' \boldsymbol{D}_{it} + \gamma_Z{}' \boldsymbol{Z}_{it} + \epsilon_{it} \quad (1)$$

where y_{it} denotes the logarithm of the hourly wage of worker i in year t. The indicator S_{it} equals one if the worker holds a supervisory role at time *t* and zero otherwise. The coefficients α_t capture the supervisory wage gap in each year t relative to the reference year 2003 (the first year in our sample), conditional on the included controls[11]. The vector $\boldsymbol{H}_{it}$ includes measures of human capital, such as educational attainment and age (used as a proxy for experience). $\boldsymbol{D}_{it}$ includes demographic characteristics, such as gender, migrant status and marital status. Controlling for $\boldsymbol{H}_{it}$ and $\boldsymbol{D}_{it}$ helps account for changes in sample composition over time, for example changes in the age structure of employees. The vector $\boldsymbol{Z}_{it}$ includes additional controls, such as occupation indicators, which account for occupational wage gaps, as well as, depending on the specification, contract type, full-time status, and firm size.

In our preferred specifications, we additionally include supervisor-industry-country fixed effects, which control for pre-existing supervisory wage gaps across industries and countries arising from both observable and unobservable factors.[12] We also include industry–country–year fixed effects, which absorb common wage trends at the industry-country-year level.

We estimate equation (1) by ordinary least squares, using EU-SILC survey weights to account for sample design and observable non-response. To ensure that the results are not driven disproportionately by larger countries, we apply equal country weights in the main

[11] Because supervisor–industry–country fixed effects are included as part of $\boldsymbol{Z}_{it}$, 2003 serves as the omitted reference year.

[12] However, because EU-SILC is a repeated cross-section, equation (1) cannot account for changes over time in the sorting of workers into supervisory roles based on unobserved characteristics, as discussed below.

specification but also present an unweighted robustness test. Standard errors are clustered at the supervisor-industry-country level to account for within-group correlation over time.

We next examine the human capital channel (H1), focusing on whether changes in sorting on unobserved ability contribute to the rise in the supervisory wage gap.[13] To do so, we use individual-level longitudinal data from the UK BHPS/USoc and estimate:

$$y_{it} = \beta_t S_{it} + \gamma_i^S S_{it} + \gamma_i^{NS}(1 - S_{it}) + \gamma_H{}' \boldsymbol{H}_{it} + \gamma_D{}' \boldsymbol{D}_{it} + \gamma_Z{}' \boldsymbol{Z}_{it} + \varepsilon_{it} \qquad (2)$$

where β_t captures the supervisory wage gap in each period *t*, and the vectors of control variables $\boldsymbol{H}_{it}$, $\boldsymbol{D}_{it}$ and $\boldsymbol{Z}_{it}$ include the same set of controls. The key difference compared to equation (1) is the inclusion of supervisor-spell fixed effects γ_i^S and γ_i^{NS}, which capture an individual's time-invariant unobserved characteristics, such as ability, associated with supervisory and non-supervisory roles, respectively. This approach allows us to estimate changes in supervisory wage gaps (β_t), while controlling for unobserved worker heterogeneity within supervisory and non-supervisory roles. The approach follows Cortes (2016) and has recently been applied in research on occupational wage gaps (Rabensteiner and Guschanski, 2025; Wang, 2020). For estimations of equation (2), we cluster standard errors at the individual level, in line with these studies.

The longitudinal structure of BHPS/USoc enables us to estimate both equations (1) and (2). Comparing the two specifications allows us to assess the extent to which changes in the supervisory wage gap reflect sorting on unobserved worker characteristics (supervisory-role

[13] Suppose that individuals with higher ability increasingly sort into supervisory roles over time, and that observed characteristics, such as education and age, do not fully capture these attributes. In this case, the estimated coefficient β_t in equation (1) would partly reflect changes in the composition of unobserved characteristics between supervisory and non-supervisory workers.

specific ability). We keep the set of individual-level controls as consistent as possible across specifications to ensure comparability.[14]

We then turn to the job content channel (H2) and begin with organizational determinants of supervisory job content at the firm level. To this end, we use matched employer-employee data from the UK WERS, which follows firms over time and allows us to capture unobserved firm characteristics. We estimate:

$$y_{it} = \delta_t S_{it} + \gamma_H' \boldsymbol{H}_{it} + \gamma_D' \boldsymbol{D}_{it} + \gamma_Z' \boldsymbol{Z}_{it} + \lambda_{sj} + \zeta_{jt} + \epsilon_{it} \quad (3)$$

where δ_t is our estimate of the supervisory wage gap. The key difference compared to equation (1) is the inclusion of supervisor-firm fixed effects λ_{sj}, which capture firm-specific supervisory wage gaps, and firm-year fixed effects ζ_{jt}, which capture firm-specific wage shocks. Relative to equation (1), the inclusion of these fixed effects means that identification of δ_t comes from within-firm changes in the supervisory wage gap over time. In other words, equation (3) absorbs time-invariant firm-specific supervisory wage gaps as well as firm-year wage shocks, allowing us to isolate supervisory wage gap changes within firms.

The firm-panel structure of WERS enables us to estimate both equations (1) and (3), thereby isolating the contribution of firm characteristics to the supervisory wage gap. Again, we keep the set of individual-level controls as consistent as possible to ensure comparability across our data sources.[15]

In extensions of equation (3) we interact the supervisory wage gap with indicators for (within-firm) employment growth and for growth in supervisory span. These extensions allow us to

[14] BHPS provides more detailed information on firm size and education groups than EU-SILC, and we also include regional indicators in our BHPS estimations to account for changes in the regional composition. BHPS does not provide a migration identifier in contrast to EU-SILC. See Appendix Table A2 for variable definitions.

[15] One key difference between WERS and our earlier data sources is that WERS only provides wages in intervals. We therefore use the midpoints of the intervals as our confirmed specification. We then confirm these results with maximum likelihood interval regressions (Steward, 1983), following other wage research using WERS (e.g. Green et al, 2021).

test whether within-firm increases in the supervisory wage gap are concentrated in firms that grow or in firms where span of control expands, as would be expected under an organizational job-content explanation (Green et al. 2021).

Finally, we return to EU-SILC data to examine the technology-related determinant of job content, as well as the employment relations channel (H3), focusing on industry-level variation in these measures. This is appropriate because determinants of employment relations, such as unions or collective agreements, often operate at the industry or country level, and because key indicators are not available at the individual or firm level.

To test H3, we merge EU-SILC data with additional datasets and adapt equation (1) to a long-difference specification. This approach is motivated by two considerations. First, key industry- and country-level variables of interest, such as technology adoption, digital monitoring or labor market institutions, evolve slowly over time, making year-by-year estimates less informative. Second, the long-difference specifications are less sensitive to measurement error. Because our identifying variation for the channels occurs at the industry level, focusing on the average annualized change in the supervisory wage gap yields more stable estimates (see, for example, Michaels et al., 2014).

We therefore estimate the average annualized change in the supervisory wage gap and introduce interaction terms between the supervisor indicator (S_j) and industry- or country-level determinants. These estimations allow us to establish conditional correlations between changes in job content or employment relations and wage trends. Specifically, we estimate models following equation (4):

$$y_{it} = \gamma_1(S_i \times t) + \gamma_2(S_i \times t \times \Delta X_k) + \gamma_H{}'\boldsymbol{H}_{it} + \gamma_D{}'\boldsymbol{D}_{it} + \gamma_Z{}'\boldsymbol{Z}_{it} + \varepsilon_{it} \qquad (4)$$

Here, we replace the annual year dummies from equation (1) with a linear time trend. The variable ΔX_k represents the long difference of a wage gap determinant (for example, union

density in a country-industry). The coefficient γ_1 measures the annualized change in the supervisory wage gap in percentage points. For instance, if $\gamma_1 = 1$, the supervisory wage gap increases by 1 percentage point per year in an industry (k) where the determinant remains constant (e.g. unchanged union density). The sum $\gamma_1 + \gamma_2$ captures the annualized change in the supervisory wage gap in industries where the determinant increases by 1 unit (e.g. a 100-percentage point increase in union density). We include the same set of controls and fixed effects as in our baseline model in equation (1).

Results

The supervisory wage gap in Western Europe over time

We begin by documenting the evolution of the supervisory wage gap (SWG) across Western Europe between 2003 and 2022 using harmonized individual-level data from EU-SILC. Estimates based on equation (1), show a large and statistically significant increase in the supervisory wage gap; the gap rises by 6.8 percentage points between 2003 and 2022 (Figure 1, Panel A, and Appendix Table B1, Model 1).

Our baseline specification includes controls for observed worker characteristics, as well as industry-country-year and supervisor-industry-country fixed effects. Accordingly, the estimated increase is identified within industry-country cells, relative to 2003, conditional on the included controls. This effect is economically significant. A cross-sectional regression for 2003 yields a supervisory wage gap of around 15 per cent conditional on our controls. Our baseline estimate, therefore, implies that the supervisory wage gap increased by more than 40 per cent between 2003 and 2022.

<Insert Figure 1 here>

Our result remains robust when we include job controls, such as contract type and a dummy for full-time employees, as well as firm size indicators (Figure 1, Panel B and Appendix Table B1, Models 2 and 3).[16] The robustness to controlling for firm size also provides preliminary evidence that the rise in the wage gap is unlikely to be driven simply by a reallocation of workers toward larger firms, which pay higher premiums for supervisors (Green et al., 2021).

Figure 2 presents additional robustness tests. For ease of presentation, we report only the cumulative change in the supervisory wage gap between 2003 and 2022, with all estimated coefficients for the supervisory wage gap including the control variables[17], reported in Appendix Table B1. All models are estimated using equation (1). Models 1 to 3 correspond to the specifications shown in Figure 1. Model 4 re-estimates the baseline specification using only observations with non-missing firm size information but without controlling for firm size itself. This allows us to assess whether the smaller estimated increase in the supervisory wage gap in Model 3 is driven by changes in sample composition—since only around 80 per cent of the baseline observations report firm size (see also Appendix Table B1, Model 3)—or by conditioning on firm size itself. In Model 4, the estimated supervisory wage gap increase already falls to around 6 percentage points (Figure 2, Model 4). Including firm size controls only slightly further affects the coefficient (Model 3). This suggests that the smaller coefficient in Model 3 is driven primarily by sample restriction rather than by conditioning on firm size.

Model 5 presents an unweighted regression. Model 6 excludes the top 5 per cent of the wage distribution to address concerns that the increase in the supervisory wage gap is driven by

[16] Firm size is not available in 2021 and 2022 in EU-SILC and hence coefficients are omitted for these years in Figure 1.

[17] The coefficients of continuous variables follow a log-linear interpretation. Overall, the estimated coefficients are in line with expectations. Wages increase with age but at a diminishing rate. The gender wage gap amounts to approximately 11 per cent. Wages increase with education, and native workers earn more than EU migrants, while non-EU migrants receive the lowest wages. Across occupations, wages are highest for managers and professionals and lowest for elementary workers (not reported for ease of presentation, available upon request). Temporary employees earn about 16.2 per cent less per hour, while individuals employed full-time throughout the entire year earn significantly higher wages than part-time workers. Married individuals receive, on average, 4 per cent higher pay, and wages increase with firm size.

workers at the very top of the distribution; the estimated gap increase remains unchanged. Model 7 uses log hourly net wages as the outcome variable. This specification relies on a smaller sample due to missing information in several country-year cells and yields a slightly smaller estimated increase in the gap. Model 8 excludes individuals with the occupational classification 'Managers', to address the concern that results are solely driven by rising wages among managers. All specifications confirm that the supervisory wage gap increased substantially across Western Europe.

< Insert Figure 2 here>

The human capital channel - the role of worker sorting

We next investigate the channels underlying the rise in the supervisory wage gap. To assess the role of worker sorting on unobserved characteristics into supervisory roles, we use individual-level longitudinal data from UK BHPS/USoc.

As a preliminary step, we estimate equation (1) using data from BHPS/USoc and show that the supervisory wage gap in the UK increased by 6.3 percentage points between 2003 and 2022 (black circles in Figure 3; Appendix Table B2, Model 1), a similar estimate as in our cross-country EU analysis. The cross-sectional supervisory wage gap in 2003 was slightly higher in the UK, at around 20 per cent, implying that the supervisory wage gap in the UK increased by around one-third from 2003 to 2022.[18]

<Insert Figure 3 here>

This estimate is also presented in Figure 4, Model 1. We present a set of robustness checks, mirroring the cross-country analysis, all of which confirm our result for the supervisory wage gap. Model 2 excludes firm size and job controls, and Model 3 includes all controls except firm

[18] The higher cross-sectional supervisory wage gap estimated for the UK is consistent with earlier evidence that the UK had the largest supervisory wage gap among European countries in 2007 (Leonida et al., 2023).

size controls. Model 4 drops managers from our sample. The estimate for the change in the supervisory wage gap is almost unchanged compared to our baseline estimate. This addresses measurement errors concerning how supervisory status is captured in BHPS/USoc as discussed in the data section and indicates that the increase in the supervisory wage gap is not solely driven by increasing wages for managers but also by increasing returns to supervisory roles in non-managerial occupations. Overall, these results confirm a substantial rise in the supervisory wage gap in the UK. Estimates of annual supervisory wage gaps and for observed control variables are presented in Appendix Table B2.

<Insert Figure 4 here>

To investigate the contribution of the human capital channel (H1) we account for worker sorting on unobserved ability by estimating equation (2), which includes supervisor-spell fixed effects. This approach controls for time-invariant unobserved supervisor-specific ability and identifies the supervisory wage gap from within-individual wage variation. Using this approach, we estimate a 5.2 percentage point increase in the supervisory wage gap between 2003 and 2022 (grey squares in Figure 3; Appendix Table B2, Model 5).

Comparing our baseline estimate from equation (1) with the estimate including supervisor-spell fixed effects from equation (2) shows a reduction in the overall increase of the supervisory wage gap by around 20 per cent (6.3 percentage points vs 5.2 percentage points). This suggests that supervisor-spell fixed effects account for roughly one-fifth of the overall increase in the supervisory wage gap, leaving the remaining four-fifths unexplained. Figure 3 plots the estimated supervisory wage gap from equations (1) and (2) by year and shows that the two series evolve similarly over time.

These results cast doubt on purely human-capital-based explanations for the rise in the supervisory wage gap and point to the importance of other channels, such as changes in job content (H2) or employment relations (H3).

The job content channel – the role of firm organization and technology

We next examine whether the increase in the supervisory wage gap can be explained by changes in supervisory job content (H2). We have discussed that supervisory job content may change through two mechanisms: through organizational change, such as firm growth or wider supervisory span, or through technological change, such as ICT adoption altering supervisory tasks.

Using WERS data, we first estimate equation (1). The results, reported in Table 1, model 1, show that between 2004 and 2011, the supervisory wage gap increases by 3.6 percentage points in the UK. For comparison, model 2 reports the corresponding estimate from BHPS/USoc over the same period, which reveals a 3-percentage-point increase. The similarity of the estimates increases our confidence in the WERS results.

< Insert Table 1 here>

Model 3 adds firm fixed effects, absorbing time-invariant wage differences across firms. The estimate increases. Model 4 then presents estimates from equation (3), which additionally includes supervisor–firm and firm–year fixed effects and therefore identifies the change in the supervisory wage gap purely from within-firm variation over time. The estimate rises to almost 5 percentage points between 2004 and 2011, indicating that the increase in the supervisory wage gap is primarily a within-firm phenomenon rather than the result of workers being reallocated across firms with different supervisory premia.

We next test whether this within-firm increase is limited to firms that grow in employment or in firms where supervisory span expands. To do so, we extend equation (3) by interacting the

supervisory wage gap with indicators for firm growth and supervisory-span growth. Model 5 shows that the supervisory wage gap increases by around 4 percentage points even in firms that do not grow, and the interaction term for growing firms is not statistically significant. Model 6 reports the analogous specification for changes in supervisory span. Again, the supervisory wage gap rises substantially even in firms where supervisory span does not increase, and the interaction term is statistically insignificant.

Taken together, these findings suggest that the rise in the supervisory wage gap is not driven primarily by reallocation toward firms with different supervisory wage gaps, by firm growth, or by increases in supervisory span. This weakens the case for an organizational job-content explanation based on expanding supervisory responsibilities within firms.

Appendix Table B3 reports further robustness checks for the WERS estimations. First, to address concerns arising from the use of wage bands, we estimate maximum-likelihood interval regressions (see, e.g., Green et al., 2021), both with and without supervisor-firm and firm-year fixed effects, in models 1 and 2, respectively. The estimated coefficients align with our main results. Second, we estimate firm-level panel regressions in which supervisory and non-supervisory wages are first collapsed to the firm level, in model 3. Model 4 reports the corresponding maximum-likelihood interval regression, which yields similar results.

To further investigate the role of supervisory job content, we use EU-SILC merged with industry-level indicators and estimate equation (4). The results are shown in Table 2. Models 1 and 2 examine supervisory span using measures of the average number of supervisees and the share of supervisors with more than ten supervisees. Neither measure is significantly associated with changes in the supervisory wage gap, in line with the results from the UK WERS data.

Next, we turn to the second mechanism within H2 and examine whether broader technological changes are associated with changes in supervisory job content and the supervisory wage gap.

Models 3 and 4 examine task complexity, measured by the share of supervisors performing complex tasks and by the ratio of complex tasks between supervisors and non-supervisors. Again, neither coefficient is statistically significant. Model 5 examines ICT capital stock relative to value added, a standard proxy for technological change and digitalization in the task-based wage literature (Michaels et al., 2014). The estimated coefficient is statistically insignificant. Thus, we find no evidence that changes in ICT intensity are systematically associated with the rise in the supervisory wage gap.[19]

<Insert Table 2 here>

Overall, our analysis provides little support for the job content channel. Neither organizational changes in firm structure nor broader technological changes in supervisory job content appear to explain a substantial share of the rise in the supervisory wage gap.

The employment relations channel – the role of monitoring, outsourcing, offshoring and LMIs

Finally, we investigate whether changes in employment relations are associated with trends in the supervisory wage gap (H3). As for job content measures, our employment relations measures vary at the industry level and we estimate equation (4). Our first result indicates that greater adoption of monitoring tools is associated with an increase in the supervisory wage gap (Table 3, Model 1). Because monitoring tools may capture broader digitalization processes that raise supervisors' productivity through changes in job content or affect relative bargaining power, we control for changes in ICT intensity and value added, which may confound the relationship between monitoring adoption and wage gaps (Appendix Table B4, Models 1 and

[19] In line with our UK-based findings, our previous results in Figures 1 and 2 show an increasing supervisory wage gaps despite controlling for firm size and industry. This provides additional cross-country evidence that explanations for the supervisory wage gap based on changing firm size composition—for example the growth of larger firms, or a shift in employment towards industries with higher wage gaps—cannot account for the rising supervisory wage gap.

2). The positive association between monitoring adoption and the supervisory wage gap remains robust.

Moreover, we also find that increases in supervisory wage gaps are associated with intensified outsourcing (Table 3, Model 2), in line with the literature on the fissured workplace (Weil, 2014).[20] In addition, offshoring is also associated with an increase in the supervisory wage gap (Model 3), in line with the arguments spelled out in Section 2. The findings for offshoring and outsourcing are also robust to additional controls, including ICT intensity and value added (Appendix Table B4, Models 3-6).

In contrast, industry-level measures of union density are not associated with changes in the supervisory wage gap, suggesting that unions were unable or ineffective in countering rising wage gaps (Table 3, Model 4). Finally, Appendix Table B4, Model 7 presents a model including all employment relations variables; the results for monitoring, outsourcing, and offshoring remain robust.

< Insert Table 3 here>

Due to data limitations, we are unable to assess other labor market institutions at the industry level. When turning to country-level data, we find that greater wage coordination is associated with a fall in the supervisory wage gap (Table 3, Model 5), consistent with the notion that collective bargaining in the form of wage coordination benefits non-supervisory workers relatively more than supervisors.

Taken together, these results point to changes in workplace power and institutional context as central factors behind the rising wage gap. This evidence is consistent with Hypothesis 3, which

[20] In the outsourcing regressions, we exclude the financial sector due to concerns about measurement error in value added and intermediate inputs. We also drop Ireland from the analysis, as changes to its tax regime in 2014 substantially altered the reporting of value added, rendering measures of outsourcing unreliable.

posits that employment relations shape the relative bargaining power of supervisory and non-supervisory workers.

Conclusion

This article examines an underexplored dimension of the European wage distribution: the supervisory wage gap. We develop a framework that distinguishes three channels through which this gap may evolve: (i) worker sorting on unobserved ability, (ii) changes in supervisory job content, and (iii) changes in employment relations, and test these channels using a combination of harmonized cross-country worker-level data, longitudinal individual data and matched employer-employee data.

We document a substantial rise in the supervisory wage gap between 2003 and 2022. The gap increased by 6.8 percentage points (40 per cent) across 15 Western European countries, while longitudinal UK data show a similar increase of 6.3 percentage points (33 per cent). Evidence from matched employer-employee data for the UK points in the same direction over the shorter period from 2004 to 2011.

We then assess the drivers of this trend. First, human capital explanations account for only a limited share of the increase. Using longitudinal individual data for the UK, we show that sorting on unobserved ability explains around one-fifth of the increase in the supervisory wage gap. This implies that the growing wage gap does not simply reflect a growing concentration of more skilled or more able workers in supervisory roles.

Second, we find little support for the view that the rise in the supervisory wage gap is mainly driven by changes in supervisory job content, whether through organizational change or technological change. Using matched employer–employee data for the UK, we show that the rise in the supervisory wage gap is primarily a within-firm phenomenon, rather than the result of workers being reallocated to firms with larger wage gaps. Moreover, the rise is not confined

to firms that grow or to firms where supervisory span expands. Lastly, we find no systematic relationship between changes in the supervisory wage gap and measures of supervisory span, task complexity, or ICT intensity using cross-country industry-level data.

Third, our findings point to employment relations as a plausible explanation for changes in the supervisory wage gap. Using cross-country industry-level data, we find that greater adoption of digital monitoring technologies, intensified outsourcing and offshoring, and declining wage coordination are all associated with a rise in the supervisory wage gap. These developments appear to have weakened the bargaining position of non-supervisory workers relative to supervisors, contributing to widening wage disparities. Taken together, our findings highlight the importance of the institutional and organizational context for understanding supervisory wage gaps, and wage inequality more generally, which has not previously been systematically investigated in empirical research on supervisory wage gaps.

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Tables

Table 1: Job content channel - the role of firm organization (WERS data)

	(1) Log wage (WERS baseline)	(2) Log wage (BHPS)	(3) Log wage (Firm FE)	(4) Log wage (Within-firm)	(5) Log wage (Firm size growth)	(6) Log wage (Supervisor span growth)
SWG x 2011	0.036*	0.030***	0.047***	0.048**	0.040*	0.037*
	(0.020)	(0.010)	(0.018)	(0.019)	(0.023)	(0.021)
SWG x 2011 x Firm size (growing)					0.028	
					(0.039)	
SWG x 2011 x Supervisor span (growing)						0.059
						(0.044)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Supervisor-industry FE	Yes	Yes	Yes			
Industry-year FE	Yes	Yes	Yes			
Firm FE			Yes			
Supervisor-firm FE				Yes	Yes	Yes
Firm-year FE				Yes	Yes	Yes
Observations	10337	19478	10335	10215	10215	10215

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Models (1) and (2) are based on equation (1). Model (3) additionally includes firm fixed effects. Models (4)–(6) are based on equation (3), and further include supervisor–firm and firm–year fixed effects to isolate wage changes arising purely from within-firm variation between supervisors and non-supervisors. All regressions include individual-level controls. The sample period spans 2004–2011, corresponding to the availability of WERS data. Standard errors are clustered at the firm level.

Table 2: Job content channel - the role of firm organization and technology (EU-SILC data)

	(1) Log wage	(2) Log wage	(3) Log wage	(4) Log wage	(5) Log wage
SWG	0.151***	0.137**	0.128**	0.135**	0.227**
	(0.055)	(0.059)	(0.054)	(0.054)	(0.042)
SWG x Number of supervisees	0.024				
	(0.018)				
SWG x More than 10 supervisees		0.145			
		(0.312)			
SWG x Complex tasks			0.245		
			(0.357)		
SWG x Complex tasks ratio				0.250	
				(0.297)	
SWG x ICT/value added					-0.652
					(0.692)
Control variables	Yes	Yes	Yes	Yes	Yes
Supervisor-industry-country FE	Yes	Yes	Yes	Yes	Yes
Industry-country-year FE	Yes	Yes	Yes	Yes	Yes
Observations	620830	620830	620830	620830	762989

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Regressions based on equation (4). All regressions include individual-level controls as in Appendix Table A1. Models 1 to 4 include data up until 2015, the last year when EWCS data are available. Model 5 includes data until 2020, the last year when EU KLEMS data is available. All variables included as interaction terms are in long differences. Standard errors are clustered at the supervisor-industry-country level.

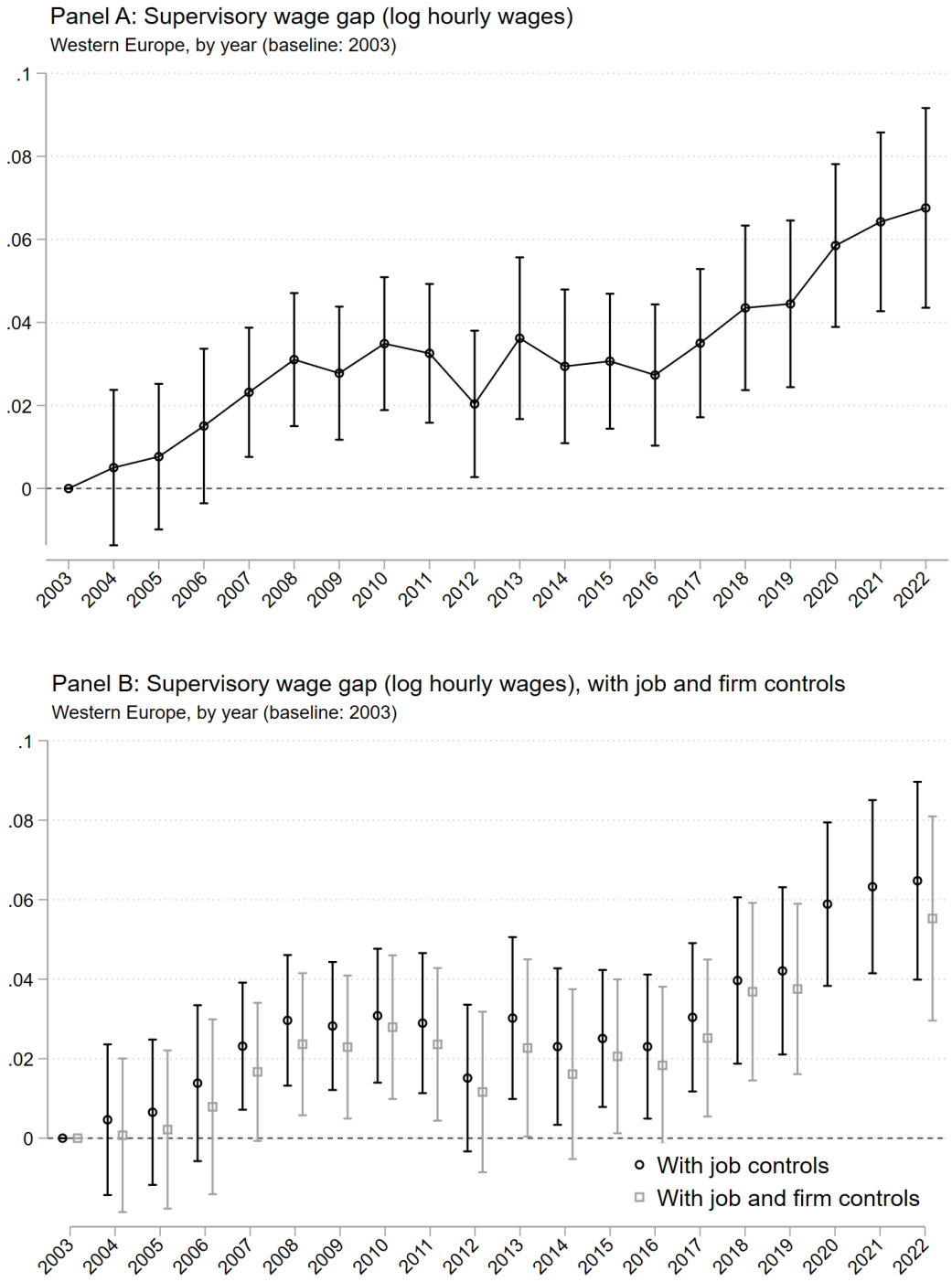
Table 3: The employment relations channel

	(1) Log wage	(2) Log wage	(3) Log wage	(4) Log wage	(5) Log wage
SWG	-0.058	0.182***	0.169***	0.213***	0.108**
	(0.097)	(0.037)	(0.041)	(0.037)	(0.042)
SWG x Monitoring	0.921***				
	(0.310)				
SWG x Outsourcing		0.796*			
		(0.419)			
SWG x Offshoring			0.452**		
			(0.204)		
SWG x Union density				0.096	
				(0.472)	
SWG x Wage coordination					-0.171***
					(0.036)
Control variables	Yes	Yes	Yes	Yes	Yes
Supervisor-industry-country FE	Yes	Yes	Yes	Yes	Yes
Industry-country-year FE	Yes	Yes	Yes	Yes	Yes
Observations	838962	850595	998904	998904	868173
Adjusted R^2	0.571	0.611	0.598	0.598	0.593

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Regressions based on equation (4). All regressions include individual-level controls as in our baseline model of equation (1). Model 1 includes observations until 2019, the year when ECS data on monitoring tools are available. Models 2-5 include observations until 2020. All variables included as interaction terms are in long differences. All interaction terms vary at the industry level, except for Model 5, as wage coordination varies by country. Standard errors are clustered at the supervisor-industry-country level.

Figures

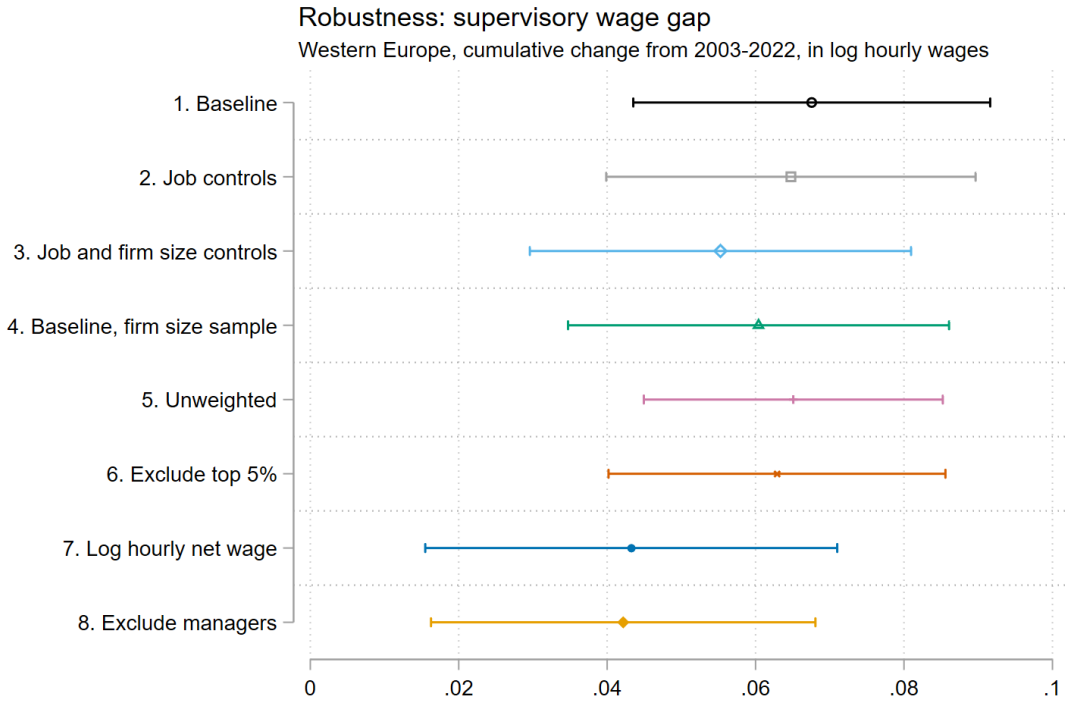
Figure 1: Supervisory wage gap, Western Europe.



Notes: The Figure shows the supervisory wage gap over time, 2003–2022, estimated from equation (1). 95 per cent confidence intervals are shown. Standard errors are clustered at the supervisory-industry-country level. Panel A: Baseline specification. Corresponding coefficient estimates are reported in Appendix Table B1, Model 1. Panel B: Black dots report estimates including job controls (Appendix Table B1, Model 2), while grey dots report

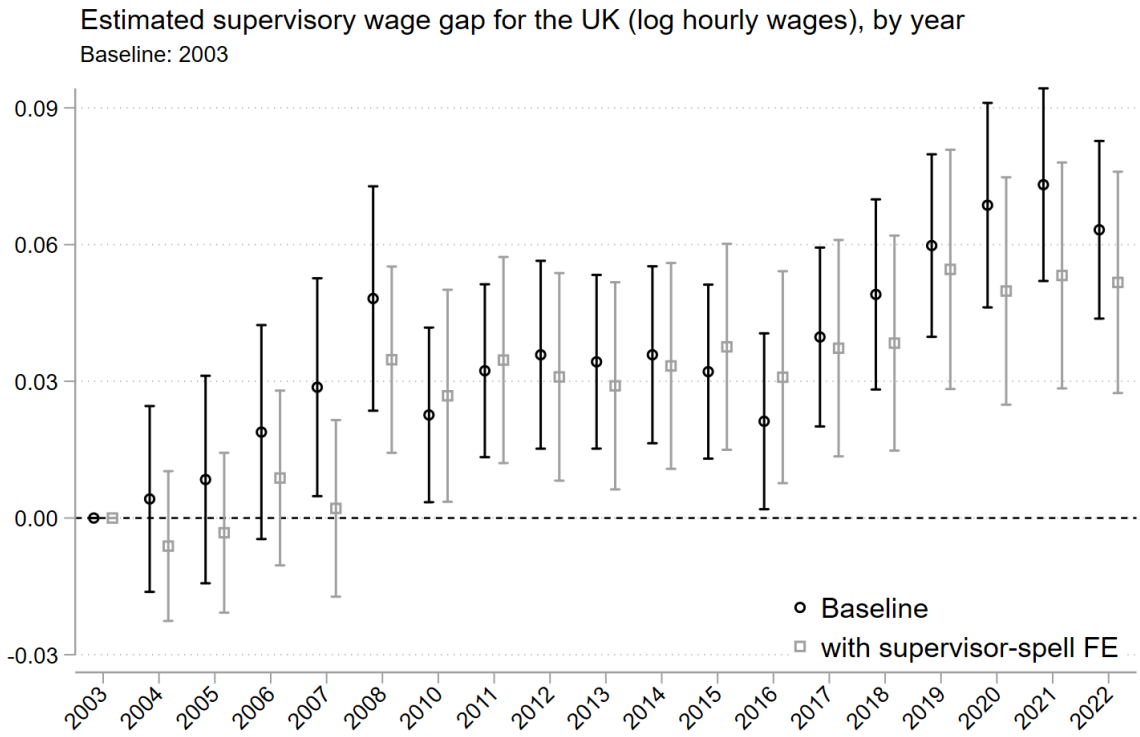
estimates including both job and firm controls (Appendix Table B1, Model 3). Coefficients are missing for 2021 and 2022 because firm size is not available in EU-SILC. Source: EU-SILC.

Figure 2: Robustness for supervisory wage gap, Western Europe.



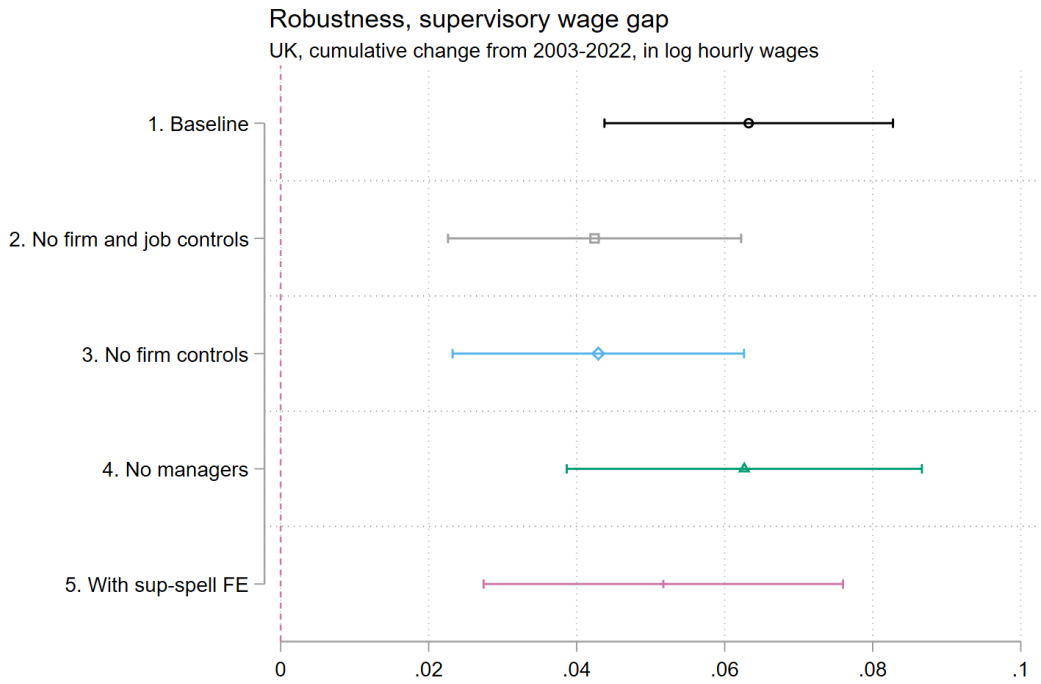
Notes: The Figure shows cumulative supervisory wage gap changes from 2003 to 2022, estimated from equation (1). 95 per cent confidence intervals are shown. Standard errors are clustered at the supervisor-industry-country level. Estimates including all year coefficients and control variables are also shown in Appendix Table B1. Source: EU-SILC.

Figure 3: Supervisory wage gap, UK, with and without supervisor-spell fixed effects



Notes: The Figure shows the supervisory wage gap over time, 2003–2022, for the UK. 95 per cent confidence intervals are shown. Standard errors are clustered at the individual level. The black dots report estimates from equation (1), while the grey dots report estimates from equation (2), which includes supervisor-spell fixed effects. The black dots correspond to the estimates in Appendix Table B2, Model 1, and the grey dots to Appendix Table B2, Model 5. The year 2009 is omitted due to the absence of longitudinal identifiers in that wave. Source: BHPS and USoc.

Figure 4: Robustness for supervisory wage gap estimations, UK



Notes: The Figure shows cumulative supervisory wage gap changes from 2003 to 2022, estimated from equation (1). 95 per cent confidence intervals are shown. Standard errors are clustered at the individual level. Estimates including all year coefficients and control variables are also shown in Appendix Tables B2 and B4. Source: BHPS and USoc.