# When Technology Manages: Workers Demands and Union Responses to AI and Emerging Digital Tools*

Paolo Agnolin† Valentina González-Rostani‡

April 2, 2026

**Abstract**

AI and other digital technologies are reshaping work, yet their effects on labor-market institutions are still not well understood. Research on technology and unions has focused largely on robots, leaving open how newer digital tools influence worker organizing and collective bargaining. We argue that technology matters not only because it can replace labor, but because it changes how work is organized. We distinguish among displacement, augmentation, and monitoring technologies, and show that each type affects workplace interaction, job stability, and managerial control in different ways. These changes, in turn, shape both workers demand for collective protection and their ability to organize. They also create different bargaining priorities, including training, shared implementation, limits on surveillance, and job security. We test these ideas with a two-level design. First, using European Social Survey data from 15 countries between 2012 and 2024, we match occupations to emerging technologies and assess links to union membership, autonomy, job satisfaction, and political attitudes. Second, we analyze over 40,000 Canadian collective agreements from 1993 to 2025 with text analysis and an LLM-based AI exposure measure. Results show varied effects: some technologies raise unionization, while others weaken it and worsen worker outcomes significantly for many employees.

*Key words*: AI, digital technologies, labor unions, working conditions, collective bargaining.

*We thank Michael Becher, Gregorio Buzzelli, Adam Dean, Rafaela Dancygier and workshop participants at the 2026 APSA Comparative Labor Workshop, the Politics of AI Workshop at Nuffield College (Oxford), and Princeton University for insightful comments and discussions. We are also grateful to Wouter Zwysen and the ETUI for sharing the ETUI-IPWS data. Financial support from the Data-Driven Social Science Initiative at Princeton University is gratefully acknowledged. Emmanuela Omole provided excellent research assistance. The usual disclaimer applies.

†Princeton University, paolo.agnolin@princeton.edu.

‡University of Southern California, gonzalez.rostani@usc.edu.

# 1 Introduction

AI and other digital technologies are rapidly transforming work, yet their implications for labor-market institutions - trade unions- remain underexplored. Much research examines how automation affects jobs and wages, and the limited literature on organized labor has focused mainly on robotization. We know far less about how newer digital tools, including platform intermediation, monitoring systems, and AI applications, reshape unions' strength, organization, and political voice. This is a critical gap: by bargaining over wages and working conditions, unions reduce inequality and set labor standards economy-wide (Ahlquist 2017; Becher and Stegmueller 2021b), and by mobilizing workers, they enhance democratic participation (Iversen and Soskice 2015; Becher and Stegmueller 2019; Frymer and Grumbach 2021; Gonzalez-Rostani 2024a). If technological change erodes union capacity, it could weaken not only workplace protections but also equality and civic engagement. This paper addresses that concern by posing two key questions. First, how are emerging digital technologies affecting workers' conditions, union membership, and political preferences? Second, how are trade unions responding to these developments through collective bargaining?

Our core argument is that technology affects unions by reorganizing the labor process, not only by changing labor demand. We distinguish among displacement, augmentation, and monitoring technologies. These forms of technological change shape both the grievances workers experience and whether those grievances can be organized collectively. Unionization is most likely when workers face a common threat but remain in stable employment relationships with coworker interaction and channels of voice. By contrast, technologies that individualize evaluation, fragment workers, or shift jobs into weakly organized settings are more likely to generate alienation than durable organization. The same logic implies distinct bargaining agendas: augmentation encourages bargaining over training and joint implementation; monitoring generates demands for transparency, contestability, and limits on surveillance; and displacement centers bargaining on notice, redeployment, and job security.

To investigate these claims, we combine micro-level survey analysis with textual analysis of union contracts. Using Western European survey data from 2012 to 2024, we measure occupational exposure to six families of emerging technologies and show that their effects are heterogeneous. Exposure to machine learning, embedded systems, remote monitoring, and smart mobility is associated with higher union membership, even as several of these technologies are linked to lower autonomy, lower job satisfaction, and greater political alienation. By contrast, food-ordering platforms are associated with lower unionization and worse worker outcomes. We then examine more than 40,000 Canadian collective bargaining agreements (CBAs) from 1993 to 2025 and show that contractual responses also vary by type of exposure. In the recent AI period, augmentation is associated with more language on training, worker-oriented protections, and joint governance, whereas displacement is associated with fewer proactive safeguards.

This study makes several contributions to the political economy of labor and technology. First, it extends the literature on technology and organized labor beyond robotization by showing that the institutional consequences of technological change depend on what technologies do in the labor process, not only on whether they automate tasks (Agnolin et al. 2025; Agnolin 2025; Leduc and Liu 2024; Gonzalez-Rostani 2024a; Becher and Stegmueller 2025). We show that the impact of new technologies on union membership is not uniformly negative - it varies by technology type and organizational context - thus extending recent arguments that the consequences of automation need not be uniform.

Second, we advance the measurement of technological exposure. Rather than relying on a single aggregate automation risk score, we develop a taxonomy of workplace technologies that extends Prytkova et al.'s work. Our fine-grained approach identifies the specific innovations, from machine learning algorithms to IoT-enabled devices, to which workers are exposed. Because exposure can vary across countries and over time, even within the same occupation, we complement this measure with indicators of the pace of technological adoption. We also introduce a novel LLM-based classification of tasks that evaluates whether AI is likely to displace, augment, or monitor work. Capturing these multidimensional exposures allows us to provide a more detailed account of how technological change shapes workers' daily experiences and collective responses.

Third, we offer one of the first large-scale studies of union strategy as documented in CBAs, getting at the granular textual details of contracts. Labor contracts are a crucial but underutilized source for understanding union influence on workplace outcomes (Freeman and Medoff 1984; Traxler, Blaschke, and Kittel 2001; Arold et al. 2025). Most research on technology and labor relations has relied on qualitative case studies (e.g., Kresge 2025; Rainone 2025); we instead analyze tens of thousands of contracts over three decades. By treating contract texts as data, we show how unions govern technological change through bargaining over training, monitoring, and worker participation, supporting arguments that worker representation can facilitate adaptation to innovation rather than simply resist it (Belloc, Burdin, and Landini 2022; Gingrich, Wu, and Zhang 2026). Together, these contributions deepen our understanding of the link between technology and organized labor, showing that the future of work is not pre-determined by technology alone - it will also be negotiated on the shop floor and at the bargaining table.

## 2 Related Work: Technology, Work, and Unionization

**Automation & Policy Preferences.** Work in political economy has linked exposure to technological change with both voting behavior and mass preferences. Surveys and panel studies show that individuals who feel negatively affected by automation tend to support populist parties, right-wing in the Global North (e.g., Anelli, Colantone, and Stanig 2021; Kurer 2020; Milner 2021; Gonzalez-Rostani 2026, 2024b) and left-wing in the Global South (Boix, Gonzalez-Rostani, and Owen 2025), and exhibit signs of political disengagement (Gonzalez-Rostani 2024a). A second strand connects technological disruption to higher demand for social insurance and redistribution (Busemeyer et al. 2023; Busemeyer and Tober 2023; Kurer and Häusermann 2022; Thewissen and Rueda 2019; Haslberger, Gingrich, and Bhatia 2024) as well as support for policies that slow or redirect change, including trade and technology restrictions (Bicchi, Kuo, and Gallego 2024; Gallego et al. 2022; Chaudoin and Mangini 2025; Gonzalez-Rostani 2024b).

Most of this literature treats automation as a single labor-market shock centered on displacement risk. That perspective has been productive, but it leaves less room to examine how distinct workplace technologies reshape autonomy, evaluation, and social interaction on the job. We build on this literature by connecting political attitudes to differentiated forms of technological exposure and to the working conditions through which those exposures are experienced.

**Measuring Exposure to Emerging Digital Technologies.** A central challenge in this literature is measurement. Most studies rely on a single automation risk indicator, whether based on regional robot exposure (e.g., Acemoglu and Restrepo 2020), occupation characteristics, such as routine task intensity (Goos, Manning, and Salomons 2014; Frey and Osborne 2017; Arntz, Gregory, and Zierahn 2017), cognitive task content (e.g., Autor, Levy, and Murnane 2003), or workers' perceived risk of job loss from technology (Borwein et al. 2025; Busemeyer et al. 2023; Gallego et al. 2022; Kurer and Häusermann 2022; Gonzalez-Rostani and Tober 2025). These measures are informative, but most are tailored to substitution and job loss. They are less well suited to technologies that reorganize work through monitoring, coordination, or platform intermediation, and they compress heterogeneous tools into a single score.

We address this gap with two complementary measures. First, we construct an occupation-level exposure profile across six technology families using text embeddings that link occupational descriptions to patent data (Prytkova et al. 2025). Second, we introduce an original AI exposure measure based on task-level judgments of whether current AI is more likely to augment, monitor, or displace work. This design lets us compare forms of technological change that are usually bundled together under the umbrella of automation.

**The Role of Unions and CBAs.** Trade unions matter because they shape both labor-market outcomes and political voice. Collective bargaining compresses wage dispersion and structures distributive conflict (Freeman and Medoff 1984; Farber et al. 2021; Jäger, Naidu, and Schoefer 2025; Hall and Soskice 2001; Iversen 1999). A broader literature shows that unions also mobilize participation, elevate workplace issues in national politics, and make elected officials more responsive to non-elite workers (Ahlquist 2017; Rosenfeld 2019; Kaplan and Naidu 2025; Kerrissey and Schofer 2013; Hertel-Fernandez 2025; Becher and Stegmueller 2021a), even if the magnitude of these political effects remains debated (Yan 2025). For that reason, technological change matters not only for jobs and wages, but also for the institutions that organize worker representation.

Classic comparative political economy accounts already suggest that technological change can unsettle labor-market institutions. Analyses of the move away from Fordist production argued that widening productivity differences made solidaristic wage bargaining harder to sustain and encouraged decentralization (Pontusson and Swenson 1996; Iversen 1999). In a related model, skill-biased technological change weakens support for unions among workers who bear more of the costs of wage compression (Acemoglu, Aghion, and Violante 2001). Yet the recent empirical literature on technology and unions has focused overwhelmingly on industrial robots. Work on the United States and Europe finds that robotization has negative average effects on union strength, operating in part through employment shifts out of highly organized sectors (Balcazar 2022; Agnolin et al. 2025; Leduc and Liu 2024). Related evidence also shows that unions can buffer some of the broader political fallout from automation shocks (Gonzalez-Rostani 2024a). This evidence is important, but it leaves open whether findings based on robotization travel to other emerging technologies, such as monitoring systems, platform intermediation, embedded digital tools, or newer AI applications.

At the same time, more recent work emphasizes that automation need not uniformly erode organized labor. When new technologies involve fixed capital and reduce firms' ability to relocate, workers' leverage may increase rather than fall (Becher and Stegmueller 2025). Evidence from European establishments similarly suggests that employee representation can facilitate the adoption of advanced technologies through training and organizational adaptation (Belloc, Burdin, and Landini 2022). The institutional effects of technological change are therefore conditional, not mechanically negative.

We build on this literature in two connected ways. First, we extend the analysis from robotization to a broader set of emerging digital technologies, including tools associated with monitoring, platform work, mobility, logistics, embedded systems, and AI, which may affect unions through channels other than labor substitution alone. Second, we shift attention from union density to governance. Union power cannot be inferred from membership alone; bargaining coverage and contract content are also central to labor-market outcomes (Traxler, Blaschke, and Kittel 2001; Baccaro and Howell 2017; Visser 2016; Cazes, Garnero, Martin, et al. 2019; Arold et al. 2025). A growing industrial-relations literature shows that unions bargain over technology through training provisions, consultation rights, limits on monitoring, and rules for algorithmic management (Kresge 2025; Montreuil and Foucher 2023; Rainone 2025; Borelli et al. 2025; Doellgast et al. 2025; De Stefano and Taes 2023; Brunnerová et al. 2024). Yet this evidence is still dominated by case studies, inventories of selected agreements, and survey snapshots. We therefore analyze collective bargaining agreements at scale and relate contractual responses to distinct forms of technological exposure, rather than treating technology as a single shock.

# 3 Displacement, Augmentation, and Monitoring: A Theory of Technology and Unionization

We argue that technologies matter for unions because they reorganize the labor process. They change who performs tasks, how performance is evaluated, how visible managerial control becomes, and whether workers encounter one another as a collectivity or as isolated individuals. This premise is consistent with recent work arguing that workers respond not to technology in the abstract, but to technology as it is governed and deployed in concrete workplaces (Gingrich, Wu, and Zhang 2026; Bankins et al. 2024; Marsh, Vallejos, and Spence 2022). We therefore treat emerging digital tools as heterogeneous interventions in work organization rather than as a single "automation shock." Technological change is not only a labor-demand shock; it is also a workplace-governance shock.

We organize this heterogeneity around three ideal types: *displacement*, *augmentation*, and *monitoring*. Displacement technologies substitute for labor or move tasks out of established jobs. Augmentation technologies complement labor while leaving workers in place. monitoring technologies expand managerial oversight, performance measurement, and algorithmic control. These categories are analytically distinct because they distribute risk, discretion, and interdependence differently across workers. This functional typology is preferable to narrow umbrella labels such as "AI," because the same underlying technology can weaken unions through replacement, strengthen labor's bargaining position through complementarity, or discipline workers through surveillance depending on how it is deployed (Gingrich, Wu, and Zhang 2026; De Stefano and Taes 2023). The key implication is that technological change affects unionization through two linked but separable steps: it first shapes workers' grievances and then shapes whether those grievances can be organized collectively.

At the center of the theory is a distinction between demand for collective protection and realized collective organization. Workers do not unionize simply because conditions deteriorate. Collective action requires at least four conditions. First, workers must perceive a common stake, whether in job security, autonomy, fairness, or privacy. Second, they must retain enough interaction and workplace social capital to solve collective-action problems. Third, they must remain embedded in employment relationships stable enough to sustain mobilization. Fourth, existing channels of voice matter: where workers already have unions, consultation rights, or even informal mechanisms of input, technological change is more likely to become an object of bargaining than unilateral managerial control (Gingrich, Wu, and Zhang 2026; O'Brady and Doellgast 2021; De Stefano and Taes 2023). As Naidu (2022) emphasizes, dense workplace networks are a precondition for successful organizing, while Ferguson (2016) shows how more fragmented organizing environments make mobilization harder. Our core theoretical claim follows directly: technologies that worsen work while preserving common exposure, coworker contact, employment stability, and channels of voice can generate unionization, whereas technologies that worsen work while fragmenting workers are more likely to generate alienation without durable organization.

*First, displacement technologies* primarily affect the *possibility* and *location* of unionization because they alter where and under what terms people work. The aggregate expectation is negative: if automation removes workers from unionized settings or reallocates employment toward more weakly organized sectors, unions should decline. This logic is consistent with evidence linking robot exposure to weaker union presence and lower bargaining power in the United States and Western Europe (Balcazar 2022; Agnolin et al. 2025; Leduc and Liu 2024). But the same threat can have the opposite effect among workers who remain in concentrated and relatively stable workplaces. When exposure to replacement is visible, shared, and not immediately translated into exit, workers may seek unions as a form of collective insurance. Umblijs, Schøne, and Finseraas (2025) provide evidence of precisely this dynamic in Norwegian manufacturing, and Becher and Stegmueller (2025) similarly show that automation can increase organizing incentives where production remains anchored and workers retain leverage. At the same time, unions do not simply react to automation; they can also shape the process of technological change itself, as Kostøl and Svarstad (2023) show in their analysis of how unions affect firms' occupational structure and relative wages, in particular, contributing to raising the relative wage of routine workers over non-routine workers. We therefore expect displacement to depress unionization overall, but to stimulate organizing among protected insiders facing a salient replacement threat.

*Second, augmentation technologies* change the content of conflict more than the existence of employment. When digital tools complement labor, require training, or deepen interdependence across workers, they preserve workers inside the production process while raising the value of their knowledge. Under these conditions, the central issue is less whether workers disappear than who controls implementation, training, classification, and the distribution of productivity gains. This is why augmentation should be the form of technological change most compatible with proactive unionism. Bankins et al. (2024) find more positive worker responses where AI improves job design and learning rather than merely disciplining labor, and Belloc, Burdin, and Landini (2022) show that worker representation can facilitate advanced technology adoption through training and organizational adaptation. Our expectation, then, is that augmentation should be associated less with organizational breakdown than with bargaining over how new technologies are governed.

*Third, monitoring technologies* intensify grievances most directly because they redistribute discretion from workers to management without necessarily severing the employment relation. Surveillance systems, remote monitoring, and algorithmic performance management make control more continuous, individualized, and data-driven. In that sense, they are especially likely to produce demands for collective protection around privacy, due process, pace, and fairness. The empirical literature supports this mechanism: König (2025) reviews electronic monitoring research and finds little consistent productivity gain but more worker strain and weaker job attitudes; Glavin, Bierman, and Schieman (2024) link workplace surveillance to psychological distress and lower job satisfaction through job pressure, reduced autonomy, and privacy violations; and O'Brady and Doellgast (2021) show that collective voice can make monitoring fairer and less exhausting. Yet monitoring also has a second, countervailing effect. Because it individualizes evaluation and can weaken everyday coworker contact, it may make organization harder even as grievances become sharper, a point also emphasized in research on algorithmic management and platform work (Bankins et al. 2024; Marsh, Vallejos, and Spence 2022). We therefore expect monitoring technologies to raise the demand for union protection broadly, but to increase realized unionization only where workers retain shared organizational spaces or occupational communities.

The framework also extends beyond unionization to labor politics. Unions are not only bargaining institutions; they are political intermediaries that mobilize workers, aggregate grievances, and translate workplace conflict into demands for compensation and regulation. When technological change weakens unions, it can therefore erode not only workplace voice but also the organizational infrastructure through which workers seek policy protection. Technological change thus has indirect political effects through its consequences for the organizations that represent worker interests.

These mechanisms also imply distinct bargaining agendas. If collective bargaining is one of the main institutional arenas through which workers can govern technological change, then unions should not respond to all technologies in the same way. Where augmentation dominates, bargaining should center on training, upskilling, job ladders, and joint implementation. Where monitoring expands, unions should seek notice, contestability, data governance, and limits on surveillance or automated evaluation. Where displacement risk is salient, unions should emphasize advance notice, redeployment, retraining, and job security. Emerging evidence suggests that these forms of technological governance are already entering collective agreements (Howe et al. 2026; O'Brady and Doellgast 2021). The broader theoretical implication is that technology does not map mechanically onto union decline: its effect depends on whether it generates shared claims under conditions that still permit workers to act collectively.

Table 1 summarizes these expectations for several technology families and maps each family to its dominant theoretical logic.

Table 1: Theoretical expectations for emerging technologies

| Technology | Dominant logic | Main workplace effect | Expectation for unionization | Expected bargaining agenda |
|---|---|---|---|---|
| Machine learning | Augmentation / monitoring | Decision support, automated classification, and algorithmic evaluation | More compatible with unionization in skilled, stable workplaces where workers remain central to production | Training, skill recognition, transparency, human review, contestability, health and well-being safeguards |
| Embedded systems | Augmentation | Production integration, maintenance, safety, and coordination around automated equipment | Relatively favorable to proactive unionization because workers remain in place and coordination needs rise | Training rights, safety rules, skill classification; often limited contract salience |
| Remote monitoring | Monitoring / control | Surveillance, pace control, autonomy loss, and continuous oversight | Raises demand for protection, with stronger unionization where workers share worksites and stable employment | Notice, consultation, privacy, data governance, limits on monitoring and discipline, retraining |
| Smart mobility | Monitoring / displacement | Routing, telematics, scheduling, and possible task substitution in transport | Can strengthen unionization in organized transport settings despite lower autonomy and job quality | Routing and scheduling transparency, telematics limits, retraining, notice, joint oversight |
| Intelligent logistics | Augmentation / monitoring | Task allocation, warehouse coordination, delivery tracking, and performance management | Ambiguous overall: shared grievances may be offset by precarity, fragmentation, and lower autonomy | Where bargaining exists: workload, staffing, training, and data-use limits |
| Food ordering | Monitoring / displacement with fissuring | App-based coordination, ratings discipline, scheduling volatility, and worker isolation | Least conducive to unionization: despite strong grievances, low worker interaction limits collective organization, while managerial control is reinforced by turnover, dispersion, and precarious employment | Where bargaining exists: safety, scheduling, transparency, data access, pay rules, limits on app surveillance and discipline |

*Note*: The mapping from ESS families to theoretical logics is illustrative, not one-to-one. Families may operate through different channels depending on workplace deployment.

# 4 The Impact of Emerging Digital Technologies on Working Conditions and Unionization

In this section, we examine how different digital technologies are associated with workers union membership and reported working conditions. We consider AI and related tools as heterogeneous, as they reshape tasks and workplace relations in distinct ways that can alter both grievances and incentives for collective action. Using individual-level survey data, we analyze how exposure to these technologies relates to union membership, working conditions, and political attitudes. Section 5 then shifts to the collective and institutional level, exploring whether and how trade unions address these emerging issues in CBAs.

## 4.1 Data and measurement

We use individual-level data from Western Europe covering 2012-2024, drawing on waves 6-11 of the European Social Survey (ESS). The sample includes roughly 130,000 respondents in 15 countries.[1] The ESS provides rich sociodemographic information (including detailed occupation and industry of employment), indicators of objective and subjective working conditions, and political attitudes.

### 4.1.1 Measuring Dependent Variable: Working Conditions and Political Attitudes

We examine two sets of outcomes: (i) unionization and working conditions, and (ii) political preferences and engagement. Table A.1 reports descriptions, coding, and ESS waves for all dependent variables. Unionization is measured with a binary indicator for current union membership (*union member*). To capture workplace power and autonomy, we consider two additional measures: the extent to which respondents can influence firm-policy decisions about organizational activities (*influence on decisions*) and the degree to which they can decide how their daily work is organized (*decide daily work*).

We also include self-reported job satisfaction and life satisfaction (*satisfaction job* and *satisfaction life*). Contractual stability is measured with an indicator for limited-term employment (*limited contract*), distinguishing temporary from permanent contracts. To assess the social context of work, we use the frequency of interactions with colleagues in person and by phone (*interaction in person* and *interaction by phone*). These variables inform us about changing

1. Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, and the UK.

opportunities for social interaction at the workplace, factors that may influence the capacity for collective organization. Finally, we include household income in deciles (*income*).

Political outcomes include self-placement on the left-right scale (*left-right*) and *redistribution* as the agreement that the government should reduce differences in income levels. Political engagement is measured by self-reported turnout in the last national election (*voted*) and *interest in politics*. Satisfaction with the way democracy works in the respondents country (*satisfaction dem.*) serves as an indicator of system support.

#### 4.1.2 Measuring Independent Variables: Exposure to Emerging Digital Technologies

Our measures of technological exposure come from the *TechXposure* project and database by Prytkova et al. (2025), which quantify industry- and occupation-level exposure to emerging digital technologies. The database clusters patents from 2012-2021 into 40 technologies using sentence-embedding similarity of patent titles and $k$-means. Then, matches patents to industry and occupation descriptions via cosine similarity, weights patent-industry links by citations, and aggregates to the technology level. We employ the harmonized occupation scores at the ISCO four-digit level.

Departing from Prytkova et al. (2025), who primarily rely on an overall exposure index, we focus on six technology areas that have clear implications for workplace dynamics.[2] Our first measure, *Machine learning*, captures training techniques, model architectures, and data processing for computer-vision applications. The occupations most exposed to these technologies include photographic products machine operators and chemical and photographic products plant operators, as well as electronics and telecommunications engineers and information technology trainers-workers whose tasks increasingly involve automated image processing or classification. We then construct a composite index for *Embedded systems* –the unweighted mean of exposure to technologies 4-9 in Prytkova et al.[3] High exposure appears among occupations that supervise or interact with automated industrial equipment and digital infrastructure, such as chemical processing plant controllers, process control technicians, power production plant operators, computer network professionals, and even meter readers and vending-machine collectors. We also consider a separate measure for *Remote monitoring and control*. This category refers to

2. See Table A.2 for definitions and illustrative examples of each technology type.

3. This group includes Smart Agriculture, the Internet of Things, Predictive Energy, Industrial Automation, Remote Monitoring and Control, and Smart Home technologies.

real-time supervision in factories, building systems, warehouses, intelligent homes, disaster-management settings, and network security. The most exposed occupations-ICT installers and servicers, computer network and systems technicians, and electronics and telecommunications repairers-regularly work with sensor networks, alarm systems, and digital control panels.

Our *Smart mobility* index (averaging technologies 10-14) captures intelligent logistics, autonomous vehicles, parking management, vehicle telematics, and passenger transportation. This dimension primarily affects transport workers such as car, taxi, and van drivers; transport clerks; and town and traffic planners. Their daily tasks increasingly rely on routing algorithms, fleet-management platforms, and vehicle-telematics systems. We further examine exposure to *Intelligent logistics*, which includes remote-control systems, data-acquisition tools, and mobile-robot applications used in supply-chain management, warehouse operations, and delivery. Occupations with the highest exposure include messengers and package deliverers, freight handlers, and mail carriers and sorting clerks-roles where routing and sorting are tightly linked to digital logistics systems. Finally, we include exposure to *Food ordering* technologies. These systems rely on wireless infrastructure, encryption, monitoring, and remote control for order processing, self-service kiosks, and delivery coordination. Workers most affected include food service counter attendants, fast food preparers, and restaurant managers, who increasingly interact with mobile ordering apps and integrated point-of-sale systems.[4][5]

Each dimension speaks to distinct job-quality risks and opportunities. For example, *Remote Monitoring* relates to pace control and surveillance; *Intelligent Logistics* restructures task allocation and skill demand; *Food Ordering* changes service workflows and scheduling; *Machine Learning* affects evaluation and algorithmic decision-making; *Embedded Systems* alter safety and maintenance routines; and *Smart Mobility* reshapes routes and shifts.

Because the same occupation can face different exposure levels depending on a countrys adoption pace and timing, we scale occupational exposure by the share of firms in the respondents country-year that use enterprise resource planning (ERP) systems (Eurostat). ERP adoption captures the extent of digital integration across production and back-office processes and provides a consistent, comparable measure across countries and over time. In recent years, when national

4. The *Embedded systems* and *Smart mobility* indices are unweighted means of their components; the other four measures are kept separate to preserve conceptual specificity. See Table A.3 for the top five occupations by exposure to each technology.

5. Descriptive summaries of these measures are reported in the Appendix. Figure A.1 and Figure A.2 illustrate how exposure varies across occupations: the first displays the distribution of exposure within major ISCO groups, while the second reports average exposure by two-digit occupational categories. Finally, Figure A.3 displays the correlations among the various exposure indices.

AI adoption data are available, ERP adoption is strongly correlated with AI adoption (Pearson $r = 0.72$), which supports its use as a country-year proxy and allows the analysis to extend to earlier periods.

### 4.2 Empirical Strategy

We study how exposure to specific AI and digital technologies relates to unionization, working conditions, and political attitudes. For each outcome $k$ and each technology $m \in \{$*embedded systems*, *food ordering*, *intelligent logistics*, *machine learning*, *remote monitoring*, *smart mobility*$\}$, we estimate:

$$\begin{aligned} y_i^{(k)} \;=\; \alpha_k \;+\; \beta_k \, \mathit{Technology\ exposure}_i^{(m)} \;+\; \mathbf{X}_{k,i}\,\boldsymbol{\gamma} \;+\; \lambda_{k,\mathrm{region}(i)} \\ +\; \delta_{k,\mathrm{NACE2d}(i)} \;+\; \phi_{k,\mathrm{c,\ t}(i)} \;+\; \varepsilon_i^{(k)} \end{aligned} \tag{1}$$

Here $y_i^{(k)}$ is outcome $k$ for ESS respondent $i$. The vector $\mathbf{X}_i$ includes gender, age, years of education, and firm size. We include fixed effects for two-digit industry (NACE 2), region, and country-year. Standard errors are clustered at the country-year level. Our main regressor is the respondents exposure to technology $m$,

$$\text{Technology exposure}_i^{(m)} = \theta_{j(i)}^{(m)} \times ERP_{\mathrm{c,\ t}}$$

where $\theta_{j(i)}^{(m)}$ is the occupational exposure of occupation $j$ to technology $m$ from Prytkova et al. (2025), and $\mathrm{ERP}_{c,t}$ is the country-year share of firms using ERP. Intuitively, exposure varies with both the inherent technology link of the respondents occupation and the country-time intensity of enterprise digitalization. Unless noted otherwise, exposure measures and continuous outcomes are standardized in the presentation of results for comparability.

### 4.3 Exposure to Emerging Digital Technologies and Working Conditions

Table 2 reports the estimated effects of exposure to different types of AI and digital technologies on the probability of being a union member. The results reveal marked heterogeneity across technology families. Exposure to machine learning, embedded systems, remote monitoring, and smart mobility technologies is positively and significantly associated with union membership. These are technologies that often intensify grievances around autonomy, control, or adjustment while leaving workers inside relatively stable employment relationships and shared organizational settings. These technologies are likely to raise the demand for collective protection without fully destroying the social and organizational conditions needed to realize collective organization.

By contrast, exposure to intelligent logistics shows weak or negligible associations, while food-ordering technologies display a negative and significant effect. This is consistent with our expectation regarding the fragmentation of work. In food delivery and related platform services, algorithmic coordination is paired with individualized workflows, weaker attachment to the firm, and more precarious employment. Even if such technologies generate grievances, they appear less likely to translate into realized unionization because workers are dispersed and collective-action costs are higher.

Table 2: The Impact of Emerging Digital Technologies on Unionization

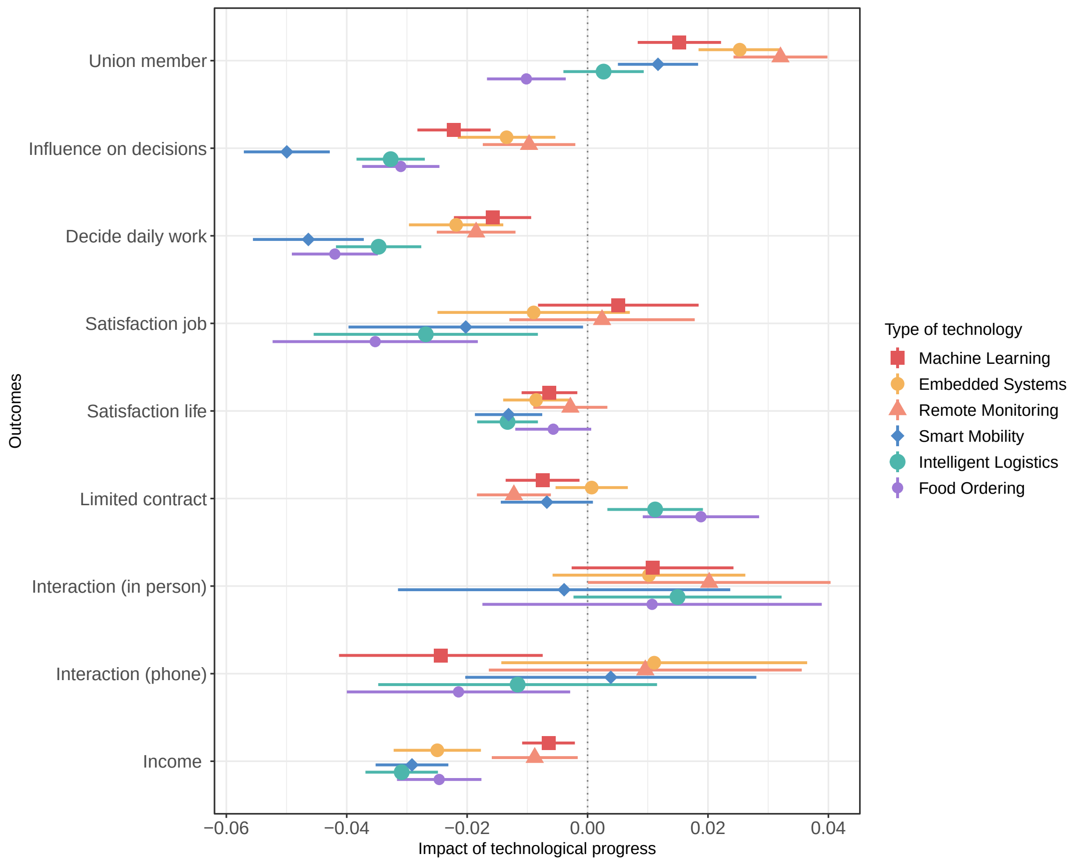
| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var.: | Union member | | | | | |
| Technology exposure | 0.006*** | 0.010*** | 0.012*** | 0.004*** | 0.001 | -0.004*** |
| | [0.001] | [0.001] | [0.002] | [0.001] | [0.001] | [0.001] |
| Technology type | Machine Learning | Embedded Systems | Remote Monitoring | Smart Mobility | Intelligent Logistics | Food Ordering |
| Controls | X | X | X | X | X | X |
| Country-Year FE | X | X | X | X | X | X |
| Region FE | X | X | X | X | X | X |
| Industry FE | X | X | X | X | X | X |
| Observations | 129,129 | 129,129 | 129,129 | 129,129 | 129,129 | 129,129 |
| R-squared | 0.250 | 0.250 | 0.250 | 0.250 | 0.250 | 0.250 |
| Std dev. Y | 0.363 | 0.363 | 0.363 | 0.363 | 0.363 | 0.363 |
| Magnitude | 0.0168 | 0.0261 | 0.0329 | 0.0114 | 0.00272 | -0.0105 |

Standard errors are clustered at the country-year level and are reported in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Two additional exercises assess the stability of the findings. First, the models are re-estimated using the raw occupational exposure measures, without interacting them with country-year levels of technological diffusion. The results in Table A.4 closely align with the baseline estimates. Second, to address the possibility that unobserved country-industry shocks correlate with the interaction of occupational exposure and country-level technological adoption, a specification with country-industry-year fixed effects is estimated. Table A.5 shows that the coefficients remain substantively unchanged.

Figure 1 extends the analysis to a broader set of outcomes related to working conditions. All outcomes are standardized to facilitate comparison. Across technologies, exposure is associated with lower perceived influence over workplace decisions and reduced autonomy in organizing daily work, with particularly large negative effects for smart mobility, intelligent logistics, and food-ordering technologies. These patterns speak directly to how technological exposure often generates grievances by reducing discretion and worsening job quality. Yet the figure also shows why grievance alone is not enough. The same technologies that reduce autonomy do not produce the same organizational response because they differ in whether workers remain in stable, socially connected settings where collective action is feasible.

Figure 1: Effect of technological advance on working conditions across technology types.




*Note:* The figure reports the estimated effects of different forms of technological exposure on multiple outcomes: union membership, influence on policy decisions within the organization, autonomy over daily work organization, job and life satisfaction, having a limited-time contract, frequency of interaction with coworkers (in person or by phone), and income decile. All outcomes and exposure measures are standardized to a normal distribution to allow comparability. The models control for gender, education, age, and firm size, and include fixed effects for region, industry, and country-year. Standard errors are clustered by country-year. Coefficients are shown with 95% confidence intervals.

Exposure to machine learning and remote monitoring is associated with greater employment stability. In contrast, the likelihood of holding a fixed-term contract increases with exposure to intelligent logistics and food-ordering technologies, the same technologies that show weak or negative links to unionization.[6] As expected, when workers remain attached to the workplace,

6. Consistent with the idea that technological change fosters unionization and collective action only when it supports stable employment and workplace organization, we find that declining employment stability is associated

technological grievances are more likely to be organized; when exposure is bundled with precarious contracts, the same grievances are less likely to translate into union membership. Regarding coworker interaction, exposure to both machine learning and food-ordering technologies is correlated with fewer phone contacts among colleagues.

In sum, the worker-level results support the theorys two-step logic. Many technologies generate grievances by reducing autonomy, influence, and satisfaction, but only some are associated with higher unionization. Technologies embedded in established production settings, such as machine learning and embedded systems, appear to create shared pressures while preserving enough stability and organizational contact for workers to respond collectively. By contrast, technologies prevalent in platform and logistics environments, such as intelligent logistics and food-ordering, are more consistent with a fragmentation pathway. They are associated with more precarious conditions and weaker unionization, suggesting that deteriorating work does not automatically produce organization.

### 4.4 Exposure to Emerging Digital Technologies and Politics

We next examine whether changes in working conditions are mirrored in political responses. Figure 2 presents estimates for political preferences and engagement. Exposure to most technologies is associated with a shift toward more left-leaning positions on the ideological scale and with stronger support for redistribution, except in the case of intelligent logistics and food-ordering technologies. These patterns are consistent with higher demands for compensation among affected workers.

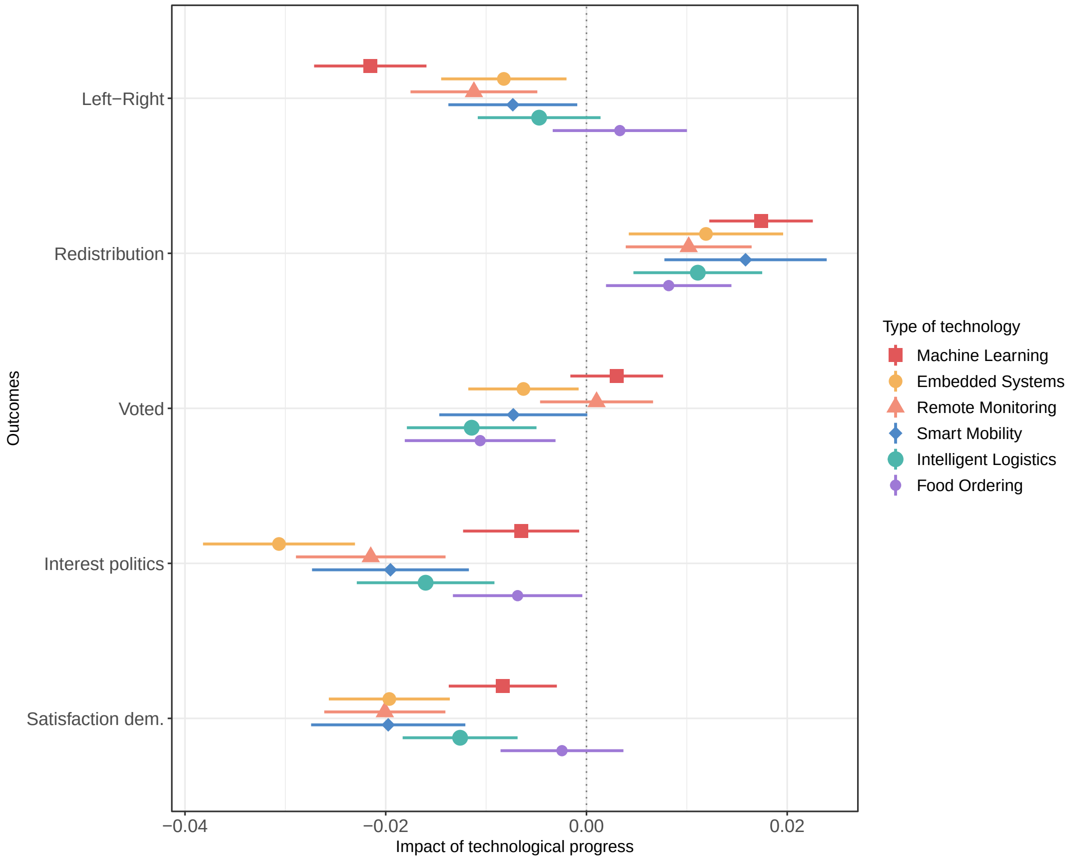
At the same time, technological exposure is also linked to political alienation. Self-reported turnout declines, particularly for embedded systems, intelligent logistics, and food-ordering technologies, while interest in politics falls across technology types, consistent with the alienation pattern documented by Gonzalez-Rostani 2024a. Satisfaction with democracy also declines for nearly all exposures. Together, these findings point to a complex political response: technological change can simultaneously increase demands for protection and weaken democratic engagement.

When technological change reduces workers control without generating effective collective

with lower unionization. We estimate a model in which technological exposure is interacted with fixed-term contract status. As expected, the interaction term is negative and significant, indicating that the push toward unionization associated with technological exposure is weakened by precarious employment. Results are shown in Table A.6. These findings, however, should be interpreted with caution. The estimated coefficients are likely affected by post-treatment bias, because employment contracts are themselves endogenous to technological exposure. See (Agnolin, Colantone, and Stanig 2025) for a discussion of the required assumptions.

organization, its effects extend beyond the workplace. In those settings, grievances appear less likely to be channeled through collective voice and more likely to spill over into broader disengagement from political and democratic institutions. This combination of material demands and democratic alienation is also consistent with prior evidence linking technological disruption to populist backlash (Anelli, Colantone, and Stanig 2021; Gonzalez-Rostani 2026; Kurer 2020).

Figure 2: Effect of technological advance on political outcomes across technology types.




*Note:* The figure reports the estimated effects of different forms of technological exposure on political outcomes: support for redistribution, self-placement on the left–right ideological scale, having voted in the last election, interest in politics, and satisfaction with how democracy works. All outcomes and exposure measures are standardized to a normal distribution to allow comparability. The models control for gender, education, age, and firm size, and include fixed effects for region, industry, and country-year. Standard errors are clustered by country-year. Coefficients are shown with 95% confidence intervals.

## 5 Union Responses to Technology in CBAs

We now turn from individual-level evidence to how unions address technological change in collective bargaining. Our analysis draws on a new corpus of Canadian CBAs spanning 1993-2025. Using bilingual dictionaries, we identify clauses related to training, governance, health and safety, mitigation, and actor language, and we link these topic shares to industry-level exposure to six emerging digital technologies, as well as to a task-based AI measure that distinguishes between augmentation, monitoring, and replacement. After examining the Canadian case, we complement the analysis with a review from other regions and sectors that reveal recurring contractual responses-such as clearer definitions of AI use, information and consultation rights, limits on monitoring, and commitments to training and transition pathways.

Canada offers an especially suitable context for this analysis. It provides extensive and publicly accessible bargaining records, allowing for a fine-grained examination of how unions adapt to technological change. Like the United States, Canada follows a common-law system and features decentralized, firm-level CBAs. These agreements are regulated at the jurisdictional level –typically by province– creating meaningful within-country variation. The countrys labor movement spans a wide range of sectors, from heavy industry and public services to high-tech industries, likely displaying diverse strategies. Moreover, Canada has experienced patterns of labor-market de-routinization similar to those observed in several Western European countries (e.g., Sweden, Great Britain, Norway, Denmark, Finland) and the United States, making it a valuable comparative case (De La Rica and Gortazar 2016).[7][8]

### 5.1 Data: Collective Bargaining Agreements

We use Canadian CBAs to map how contracts address digital technologies. We built a custom scraper to collect agreements from Employment and Social Development Canadas repository and harvested all available records from 1993–2025. For each agreement we downloaded the PDF and produced machine-readable text (using OCR when needed). The corpus contains more than 40,000 agreements in English and French.[9] We retain ESDC metadata (employer, union, location, NAICS industry, sector, employees, and signing/effective/expiry dates), which permits measures of duration and timing. We remove exact and near-duplicate files. The unit of analysis is the agreement document. Our aim is to quantify how unions regulate emerging digital technologies by counting governance, protection, and adjustment clauses, rather than tallying generic technology terms.

7. Existing political science research has also begun to document how AI exposure shapes individual attitudes (e.g., Magistro et al. 2024; Magistro et al. 2025).

8. See subsection A.4 for additional background on Canada.

9. See subsection A.5 for dataset details.

## 5.2 Measuring Dependent Variables: Topics in CBAs

The dependent variables are shares of text devoted to specific contract themes.[10] All texts are lowercased, and tokenization uses a word-character regular expression that removes punctuation. We remove stopwords and compute document length as the number of non-stopword tokens. Dictionary matching proceeds on the normalized token stream under two rules. We rely on a dictionary approach as it is a tool that is scalable and can be used with recognizable bilingual terminology. For single tokens and ordered multiword phrases (e.g., "artificial intelligence"), matches are literal with phrase boundaries enforced. For unordered multiword sets (e.g., {notice, date, change}), we apply a conservative co-occurrence rule: a hit requires that every keyword appears in the document, and the count equals the minimum per-keyword frequency. Counts for auxiliary categories such as modal verbs and negations come from the full token counts before stopword removal so that items like *not* or *may* are not dropped. Denominators for share measures use the non-stopword length.

The categories align with expected union responses to technological change: capability building (*Training and Retraining*); governance and information rights (*Notice and Content Requirements*, *Joint Committee*, *Union Notice*); protection of conditions and health (*Working Conditions and Protection*, *Health, Safety, and Well-Being*); and mitigation and adjustment (*Remedies and Mitigation*, *Displacement Rights and Bumping*, *Retirement Allowance*), with *Exceptions and Limits* marking carve-outs. Language-of-rights measures distinguish active (*receive*, *gain*, *earn*) from passive (*entitle*, *give*, *offer*, *provide*, *compensate*). Agency terms (*Union as Agent*, *Worker as Agent*, *Firm as Agent*) track which actor is named. For additional details on how the topics were constructed, see Appendix A.6.

As an illustration, Figure 3 plots the 12-month moving-average share of words tied to monitoring and surveillance in technology-related clauses. Levels are small through the 1990s, rise in the 2000s, and step up again in the mid-2010s. The most pronounced increase occurs after 2020, with a sharp jump beginning in 2023. By 2024–2025 the average share is roughly five times its early-1990s level, indicating growing contractual attention to electronic monitoring, data collection, and supervisory tools.

10. Constructed as $\mathrm{DV}_{dc} = \frac{\mathrm{hits}_{dc}}{N_d^{\mathrm{nonstop}}}$, where $\mathrm{hits}_{dc}$ is the dictionary count for category $c$ in document $d$, and $N_d^{\mathrm{nonstop}}$ is the document length after stopword removal.

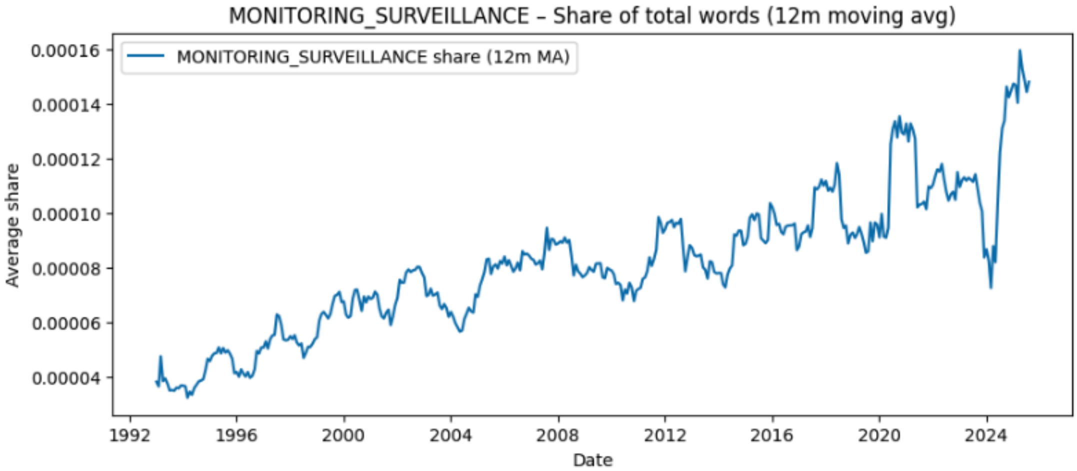



Figure 3: Salience of Monitoring and Surveillance in CBAs, Canada 1993–2025.
*Note*: 12-month moving average across agreements with technology-related clauses.

### 5.3 Measuring Independent Variables: Exposure to Emerging Digital and AI Technologies

Our main exposure measures come from the *TechXposure* database (Prytkova et al. 2025), which scores industry exposure to emerging digital technologies (refer to Section 4.1.2).[11] We focus on six areas: *embedded systems*, *smart mobility*, *remote monitoring*, *intelligent logistics*, *food ordering*, and *machine learning*.

As a second approach, we construct an AI exposure score at the industry-occupation level. A large language model scores task-level exposure along three pathways-augmentation, replacement, and monitoring-with four 1-10 components (AI capability, replacement, augmentation, monitoring) and corresponding 1-10 certainty scores, plus four binary exposure flags (E0-E3). We form certainty-weighted components and indices (e.g., `ai_exposure_index` as the mean of the four weighted components; a negative version excluding augmentation) and summarize the E-flags into an index. Full details about the index and prompt are provided in subsection A.7, and descriptive statistics are available in subsubsection A.7.3. This measure complements TechXposure by distinguishing replacement, augmentation, and monitoring channels, and is specific to AI and LLMs.

### 5.4 Model Estimation

We estimate OLS models at the agreement level that relate the share of contract text on topic $k$ to a single exposure measure $m$. For each outcome $k$ and exposure $m \in \{$*embedded systems*, *remote monitoring*,

11. We rely on 4-digit industry-level indicators.

*smart mobility*, *intelligent logistics*, *food ordering*, *machine learning*}, we run a separate regression with a linear time trend (year), firm size (employees), and fixed effects for two-digit industry (NAICS 2) and location. Inference uses standard errors clustered at the employer level.

$$\begin{aligned} y_i^{(k)} \;&=\; \alpha_k \;+\; \beta_{km}\,\text{Technology Exposure}_i^{(m)} \;+\; \rho_k\,\text{year}_i \;+\; \theta_k\,\text{employees}_i \\ &\quad+\; \delta_{k,\text{NAICS2}(i)} \;+\; \lambda_{k,\text{location}(i)} \;+\; \varepsilon_i^{(k)}. \end{aligned} \tag{2}$$

Here, $y_i^{(k)}$ is the share of non-stopword tokens in agreement $i$ assigned to topic $k$, Technology Exposure$_i^{(m)}$ is the standardized exposure $m$, and $\delta_{k,\text{NAICS2}(i)}$ and $\lambda_{k,\text{location}(i)}$ denote two-digit NAICS industry and location fixed effects, respectively. The coefficient of interest, $\beta_{km}$, measures the change in the outcome share (on a 0-1 scale) associated with an increase in exposure $m$.

## 5.5 Exposure to Emerging Digital Technologies and CBAs

Figure 4 summarizes how industry exposure to emerging technologies relates to the content of CBAs. Exposure to *machine learning*, *smart mobility*, and *food ordering* technologies is associated with a greater emphasis on health, safety, and well-being provisions, consistent with technologies that intensify control, pace, or uncertainty on the job. Exposure to *smart mobility* and *remote monitoring* is also linked to increases in training and retraining language, suggesting that unions respond not only to displacement risk but also to the need to govern technological transitions inside ongoing employment relationships. Most clearly, exposure to *remote monitoring*, *smart mobility*, and *food ordering* coincides with more procedural safeguards, including joint committees and notice requirements. As we expected, when technology directly restructures day-to-day work, unions bargain for information, oversight, and a role in implementation. Overall, these agreements shift away from purely ex post compensation and toward ex ante regulation.

By contrast, technologies such as *embedded systems* and *intelligent logistics* are associated with weaker or even negative coefficients across most topics. These exposures appear less likely to generate a clear, shared bargaining agenda, either because their effects are more indirect or because they are more compatible with fragmented or weakly organized employment settings.

Regarding other explanatory variables, Figure A.13 in the Appendix shows that more recent years are associated with a higher likelihood of including clauses on health, safety, wellbeing, training and re-training, and notice provisions. Likewise, unions representing a larger number of employees-an indicator of union strength-are more likely to include terms related to notice

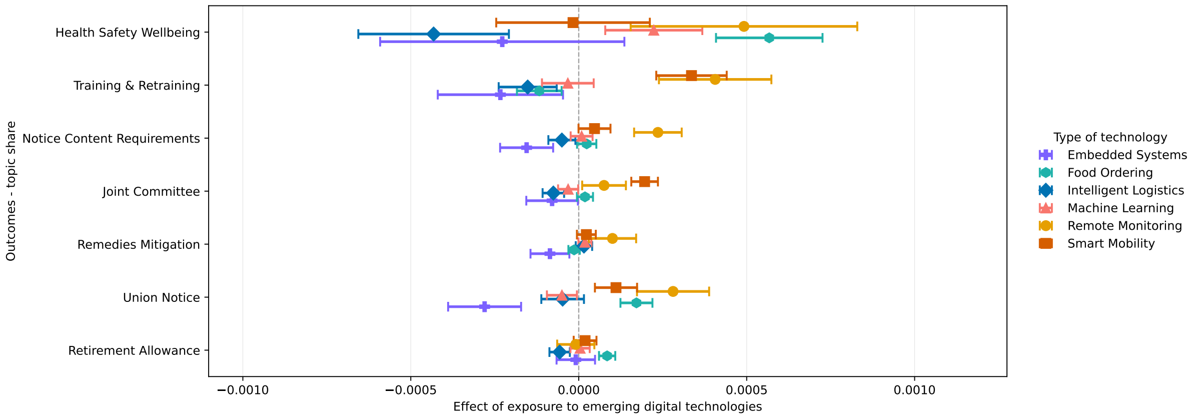



Figure 4: Exposure to Emerging Digital Technologies and CBAs (1993-2025)
*Note*: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words in each topic relative to the total document length (average length: 13,239 words). In this case, topics refer to the inclusion of clauses related to health and well-being, training, notice, union participation, etc. The independent variables capture exposure to emerging technologies, measured using related patent data at the four-digit NAICS level. All models control for the number of employees and include fixed effects for year and location. The sample of CBAs covers all agreements signed between 1993 and 2025 (N = 40,742). Standard errors are clustered at the employer level. Each panel displays coefficient estimates with 95% confidence intervals.

requirements, training, co-governance, and remedies or mitigation, while being less likely to rely on passive rights.

Overall, these results reveal a clear pattern of adaptation in collective bargaining. The CBA evidence supports our expectation that unions do not respond to all technologies in the same way. Where technologies monitor workers or visibly reorganize workflow, agreements prioritize preventive protections and governance rights. Where technologies are more diffuse or less easily translated into a common workplace claim, bargaining responses are weaker. The main empirical implication is that technological change enters collective bargaining most strongly when workers remain in place and can press for rules governing how new tools are introduced, monitored, and contested.

## 5.6 Exposure to LLMs, AI, and Collective Wage Bargaining

We next examine the current wave of AI and LLMs. We restrict to post-2021 CBAs ($N = 788$) and use the LLM-based AI exposure described in subsection 5.3. We relate exposure along three pathways-augmentation, monitoring, and replacement-to topic shares and actor language in AI-relevant clauses. Figure 5 shows clear differences. Where exposure points to *augmentation*, agreements devote more language to worker-oriented provisions. Health, safety, and well-being rise the most; training and retraining, joint committees, notice-content requirements, union notices, and remedies or mitigation also tend to increase. This is the bargaining pattern we would expect when workers remain central to production and seek to govern implementation rather than defend against immediate exit.

Under *monitoring*, governance-related language expands: notice-content requirements and union notices are positively associated with monitoring exposure, though estimates are less precise. Monitoring does not necessarily remove workers from the workplace; instead, it makes control more continuous and contestable, so bargaining shifts toward disclosure, oversight, and limits on managerial discretion.

By contrast, *displacement* exposure is associated with reduced attention to worker-protective topics. Mentions of health, safety, and well-being fall, as do references to union notices and joint committees or mitigation. In agreements where job-loss risk is salient, we do not see an expansion of skill-investment or individual protections. To put it simply, where workers are more replaceable, unions appear to have less room to secure proactive safeguards.

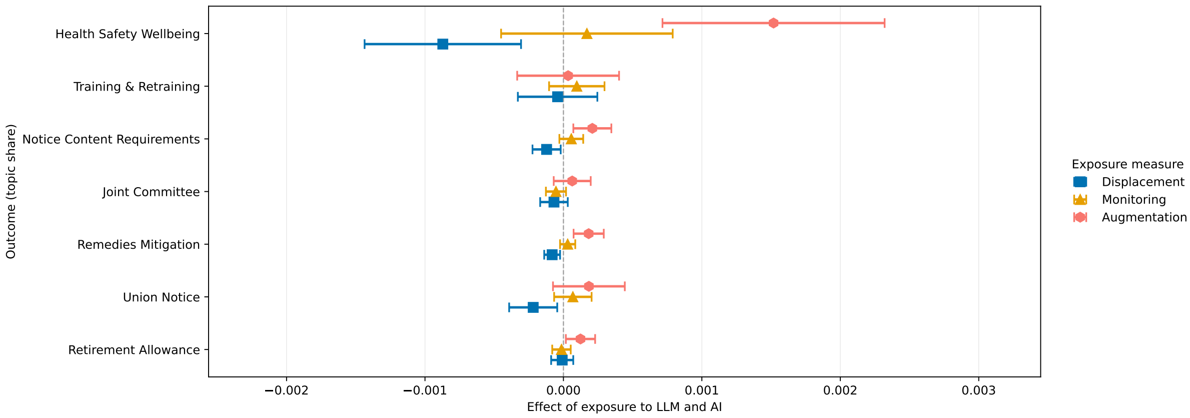



Figure 5: Exposure to AI and LLMs in Collective Wage Bargaining (2022-2025)

*Note*: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words devoted to each topic relative to the total document length (average length: 13,239 words). In this case, topics capture the inclusion of clauses related to health and well-being, training, notice requirements, union participation, and similar areas. The independent variables measure exposure to LLMs and AI, using an LLM-based classifier that categorizes technologies into three types: augmentation, displacement, and monitoring. Exposure is computed for each industry-occupation pair in the sample. All models control for the number of employees and include fixed effects for year and location. The sample of CBAs is limited to the years 2022-2025 (N = 788). Standard errors are clustered at the employer level. Each panel displays coefficient estimates with 95 percent confidence intervals.

Overall, augmentation is associated with training, worker protections, and joint governance; monitoring shifts bargaining toward notice and oversight; and displacement is associated with weaker proactive protections. The empirical implication is that unions are strongest where AI reorganizes work but leaves workers in place, and weakest where AI makes workers more easily substitutable.

## 5.7 CBAs Across the Globe

The Canadian results point to a common toolkit: early notice, information sharing, and training pathways. To examine how far these patterns generalize, and to illustrate concrete clause language, we present examples from other settings. For instance, a recent survey of European union officials and delegates directly involved in bargaining reports that about 20% of unions have a collective agreement addressing AI, while 42% are in discussions or negotiations (Brunnerová et al. 2024, 3). Where provisions exist, they most often cover training on new AI tools (75%), employee or union involvement when new technologies are introduced (62%), and the impact of AI or algorithmic management systems on working time and the right to disconnect (48%) (Brunnerová et al. 2024, 2). The recurring elements most commonly covered in CBAs are as follows. Broadly, these examples indicate that unions are bargaining for clear definitions of technological change, early notice and information sharing, structured implementation processes, limits on monitoring, and training provisions that keep new technology-related work within the bargaining unit.

**Defining the scope of technological change.** Agreements first clarify what constitutes "technological change," which anchors employer obligations toward employees. One contract states: "Technological change includes, but is not limited to, the use of machines (including, by way of example only, computers, robots, handheld devices, and tablets), automation software, systems, programs, applications, or other scientific advancements to replace or substitute for, improve, alter, increase or decrease, or evolve the type or manner of work performed by employees in the Employers workplace" (Bally's Las Vegas).[12] CBAs also add technology-specific definitions, especially for AI. As one agreement notes, "The parties acknowledge that 'Artificial Intelligence' and 'AI' have become catchall names that generally refer to the ability of a machine-based system to apply analysis and logic-based techniques to solve problems or perform tasks, and to improve as it analyzes more data" (IATSE).[13] Agreements further emphasize the importance of maintaining a human-in-the-loop role. For example, "The parties acknowledge the importance of human contributions in motion pictures and the need to address the potential impact of the use of AI systems on employment under the Basic Agreement, the Videotape Electronics

12. Bally's Las Vegas Manager, LLC and Local Joint Executive Board of Las Vegas 2019, 64

13. Alliance of Motion Picture and Television Producers and International Alliance of Theatrical Stage Employees, Moving Picture Technicians, Artists and Allied Crafts of the United States, its Territories and Canada 2024, 13

Supplemental Basic Agreement, and the West Coast Studio Local Agreements" (IATSE).[14]

**Baseline governance rights: notice, information, bargaining, and jurisdiction.** Consistent with the Canadian case, many agreements require advance notice so unions can assess job impacts and bargain over implementation. For example: "The State shall endeavor to notify the Union one hundred eighty (180) days, but no less than sixty (60) days, prior to implementation of automation or technological changes that will result in a significant impact on bargaining unit employees. Upon request of the Union within thirty (30) days of such notification, the State shall negotiate with the Union on the impact of such changes" (SEIU Local 1000).[15] Notice is paired with information rights that specify what the employer must provide, including the proposed implementation date, who is affected, how duties will change, whether the change replaces existing practice, the rationale, and the implementation plan (AFGE).[16] Similar rules appear in Norways 2018-2021 NHO-LO basic agreement, which requires companies to inform employees via shop stewards about planned control measures and, before acting, to explain the purpose, practical consequences, implementation steps, and expected duration (Brunnerová et al. 2024, 20).

**Algorithmic management (AM) and digital rights.** Telefónica, Spains leading telecommunications company, provides an example of an agreement addressing AM through a national accord on the right to disconnect, negotiated with the trade unions representing its employees (Brunnerová et al. 2024, 7). Spain also adopted Law 12/2021 on algorithmic management, which grants unions the right to request information about how AI is implemented and how it affects hiring and working conditions, recognizing AIs growing influence on human decision-making (Brunnerová et al. 2024, 7). In a separate case, an agreement between Spanish unions and JUST EAT in 2021 established a right to digital and work disconnection, stating that "the company is not to communicate with workers outside their working hours unless exceptional circumstances arise that justify such, and/or to communicate the weekly work schedule to the delivery group" (Brunnerová et al. 2024, 21). This safeguard is especially relevant amid reports of increasing after-hours work (e.g, Smith 2025).

14. Alliance of Motion Picture and Television Producers and International Alliance of Theatrical Stage Employees, Moving Picture Technicians, Artists and Allied Crafts of the United States, its Territories and Canada 2024, 13

15. State of California and Service Employees International Union (SEIU) Local 1000 2023–26.

16. National Science Foundation and American Federation of Government Employees (AFGE) Local 3403, AFLCIO 2022, 154.

**Electronic monitoring and surveillance.** Across countries, CBAs establish safeguards on data collection and use, addressing the "dual-use" problem whereby tools introduced for logistics, customer service, or safety purposes can later be repurposed for surveillance or discipline.[17] Many CBAs narrow permissible uses of monitoring technologies and reinforce due-process protections. For instance, one agreement states that "the surveillance system is not intended for use as a means to track employees time and attendance" (NAIL)[18], while another specifies that "security camera data will not be used for routine monitoring of bargaining-unit employees conduct, performance, behavior, or time and attendance" (AFGE)[19]. Similarly, the NTEU agreement clarifies that "the intent of the cameras is to maintain the safety and internal security of government property and not to monitor day-to-day employee performance or conduct."[20] Some agreements go further, explicitly prohibiting targeted surveillance: "No recording shall be used by any manager against any employee for the purpose of finding misconduct or issuing discipline The company will not randomly review audio, video, or other electronic monitoring data, nor review it for the purpose of discovering policy violations in the absence of an observation or incident" (ATU)[21]. In Italy, an agreement signed by the unions FILCAMS-CGIL and FISASCAT-CISL covering an application that checks drivers regulatory compliance and safety requires prior union approval and limits the tool strictly to its stated purposes (Brunnerová et al. 2024, 6).

**Bargaining-unit integrity and training pathways.** When technology creates new tasks or reshapes existing ones, CBAs aim to keep that work in the unit and to equip current workers for those roles. Examples include: "If a technological change creates new work that replaces, enhances or modifies bargaining unit work, bargaining unit employees will perform that new or modified work" (IBT)[22] and "The Employer shall not use technological changes for the sole purpose of converting jobs from bargaining unit status to non-bargaining unit status" (IAMAW).[23] Training and internal mobility rules then operationalize this aim: "present employees shall be given first consideration for any new or changed position... In the event

17. Examples of monitoring systems refer to tools like CCTV, Entry Control Video (ECV), and Intrusion Detection Systems (IDS).

18. Seymour Johnson Air Force Base, North Carolina and National Association of Independent Labor (NAIL) Local 7 2022, 102

19. American Federation of Government Employees (AFGE) Local 0446 and U.S. Department of Agriculture, Forest Service 2019, 66

20. National Park Service Headquarters and National Treasury Employees Union (NTEU) Chapter 296 2017, 166

21. First Transit, Inc., Mesa and Tempe Division and Amalgamated Transit Union (ATU) Local 1433 2016–21, 8

22. United Parcel Service, Inc. and International Brotherhood of Teamsters 2023–28, 18.

23. Adams County Circuit Clerk, Deputy Clerks and District No. 9, International Association of Machinists and Aerospace Workers (IAMAW), AFLCIO 2021–24, 11.

training is necessary... the employer will provide adequate training to all affected employees at the time the technology is implemented" (OPEIU).[24]

## 6 Conclusion

We have shown that digital technologies affect organized labor through a two-step process. First, they reshape the labor process by altering autonomy, pace, monitoring, and employment stability. Second, these grievances translate into collective organization only when workers remain in settings that preserve social contact, stable employment, and channels of voice. This framework helps explain why exposure to machine learning, embedded systems, remote monitoring, and smart mobility is associated with higher unionization, whereas exposure to food-ordering platforms and parts of logistics is not. Deteriorating work does not automatically produce organization; it does so only when the conditions for collective action remain intact.

The worker-level evidence is consistent with this argument. Across technologies, exposure is often associated with lower autonomy, weaker influence, and lower job satisfaction, especially under monitoring-intensive or platform-mediated forms of work. At the same time, employment stability varies sharply across technologies, and that variation helps explain differences in unionization. The political results point in a similar direction: exposed workers often express greater support for redistribution, but also show signs of alienation and disengagement. Where workplace grievances are not effectively converted into collective voice, they appear to spill over into weaker political attachment as well.

The bargaining evidence reinforces the same logic. Unions do not respond to all technologies in the same way. In our analysis of collective bargaining agreements, technologies that directly restructure workflow or intensify monitoring are associated with more training provisions, notice requirements, joint committees, and health and safety language. In the post-GenAI period, the contrast becomes especially sharp: augmentation is associated with stronger worker protections and joint governance, monitoring shifts bargaining toward oversight and disclosure, and replacement is associated with weaker proactive safeguards. Unions appear strongest where technology reorganizes work but leaves workers in place, and weakest where technology makes workers more replaceable.

These findings move beyond both robot-centered accounts of technological change and density-

24. Office and Professional Employees International Union (OPEIU) Local 537, AFLCIO and American Federation of Musicians Local 325 2019–24, 6.

centered accounts of labor power. Technological change does not uniformly weaken unions. Its consequences depend on how technologies reorganize work and on whether workers remain able to transform shared grievances into collective organization and bargaining. Automation, in this sense, is not only a labor demand shock but also a workplace-governance shock, reshaping how work is organized, monitored, and contested. More broadly, the politics of AI and digitalization will depend on whether workers retain the institutional capacity to respond collectively.

## References


Acemoglu, Daron, Philippe Aghion, and Giovanni L. Violante. 2001. Deunionization, technical change and inequality. *Carnegie-Rochester Conference Series on Public Policy* 55 (1): 229–264.

Acemoglu, Daron, and Pascual Restrepo. 2020. Robots and jobs: evidence from us labor markets. *Journal of Political Economy* 128 (6): 2188–2244.

Adams County Circuit Clerk, Deputy Clerks and District No. 9, International Association of Machinists and Aerospace Workers (IAMAW), AFLCIO. 2021–24. *Collective bargaining agreement between Adams County Circuit Clerk, Deputy Clerks and district no. 9, International Association of Machinists and Aerospace Workers, AFLCIO,* December 1, 2021–November 30, 2024.

Agnolin, Paolo. 2025. The candidate factory: technological change and political supply. *Unpublished manuscript.*

Agnolin, Paolo, Massimo Anelli, Italo Colantone, and Piero Stanig. 2025. *Robots Replacing Trade Unions: Novel Data and Evidence from Western Europe.* Technical report. IZA - Institute of Labor Economics.

Agnolin, Paolo, Italo Colantone, and Piero Stanig. 2025. In search of the causes of the globalization backlash: methodological considerations on post-treatment bias. *Comparative Political Studies* 58 (8): 1603–1635. eprint: https://doi.org/10.1177/00104140241271124.

Ahlquist, John. 2017. Labor unions, political representation, and economic inequality. *Annual Review of Political Science* 17:409–432.

Alliance of Motion Picture and Television Producers and International Alliance of Theatrical Stage Employees, Moving Picture Technicians, Artists and Allied Crafts of the United States, its Territories and Canada. 2024. *General memorandum of agreement for the producer–I.A.T.S.E. basic agreement and west coast studio local agreements,* August 1, 2024.

American Federation of Government Employees (AFGE) Local 0446 and U.S. Department of Agriculture, Forest Service. 2019. *Collective bargaining agreement between AFGE Local 0446 and the USDA Forest Service for the schenck and lyndon b. johnson job corps centers,* October 1, 2019.

Anelli, Massimo, Italo Colantone, and Piero Stanig. 2021. Individual vulnerability to industrial robot adoption increases support for the radical right. *Proceedings of the National Academy of Sciences* 118 (47).

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn. 2017. Revisiting the risk of automation. *Economics Letters* 159:157–160.

Arold, Benjamin W, Elliott Ash, W Bentley MacLeod, and Suresh Naidu. 2025. *The value of worker rights in collective bargaining.* Technical report. National Bureau of Economic Research.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics* 118 (4): 1279–1333.

Baccaro, Lucio, and Chris Howell. 2017. *Trajectories of neoliberal transformation: european industrial relations since the 1970s.* Cambridge University Press.

Balcazar, Carlos Felipe. 2022. Unions and robots: International competition, automation and the political power of organized labor.

Bally's Las Vegas Manager, LLC and Local Joint Executive Board of Las Vegas. 2019. *Collective bargaining agreement between Ballys Las Vegas Manager, LLC (on behalf of parball newco, llc) d/b/a Ballys Las Vegas and the Local Joint Executive Board of Las Vegas, 2018–2023.* Collective bargaining agreement. Clark County, Nevada, August 21, 2019.

Bankins, Sarah, Anna Carmella Ocampo, Mauricio Marrone, Simon Lloyd D. Restubog, and Sang Eun Woo. 2024. A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior* 45 (2): 159–182.

Becher, Michael, and Daniel Stegmueller. 2019. Cognitive ability, union membership, and voter turnout. *IAST Working Paper,* nos. 19-97.

———. 2021a. Reducing unequal representation: the impact of labor unions on legislative responsiveness in the u.s. congress. *Perspectives on Politics* 19 (1): 92–109.

———. 2021b. Reducing unequal representation: the impact of labor unions on legislative responsiveness in the us congress. *Perspectives on Politics* 19 (1): 92–109.

———. 2025. Machines against workers? the heterogeneous impact of robots on union strength.

Belloc, Filippo, Gabriel Burdin, and Fabio Landini. 2022. Robots, Digitalization, and Worker Voice. Rochester, NY.

Bicchi, Nicolas, Alexander Kuo, and Aina Gallego. 2024. Unpacking Technological Risks: Different Sources of Concern and Policy Preferences. *Political Studies,* 00323217241281575.

Boix, Carles, Valentina Gonzalez-Rostani, and Erica Owen. 2025. The Political Economy of Automation and Fragmented Production: Evidence from Mexico. *Available at SSRN.*

Borelli, Silvia, Antonio Loffredo, Claire Marzo, and Manfred Walser. 2025. *Sorry, we subcontracted you.* ETUI Report 2025.02. European Trade Union Institute (ETUI).

Borwein, Sophie, Bart Bonikowski, Peter John Loewen, Blake Lee-Whiting, and Beatrice Magistro. 2025. Perceived technological threat and vote choice: evidence from 15 European democracies. *West European Politics* 48 (3): 534–561.

Brunnerová, Simona, Daniela Ceccon, Barbora Holubová, Marta Kahancová, Katarína Lukáová, and Gabriele Medas. 2024. Collective bargaining practices on ai and algorithmic management in european services sectors. *Friedrich Ebert Stiftung,* 1–30.

Busemeyer, Marius R, Mia Gandenberger, Carlo Knotz, and Tobias Tober. 2023. Preferred policy responses to technological change: Survey evidence from OECD countries. *Socio-Economic Review* 21 (1): 593–615.

Busemeyer, Marius R., and Tobias Tober. 2023. Dealing with Technological Change: Social Policy Preferences and Institutional Context. *Comparative Political Studies* 56 (7): 968–999.

Cazes, Sandrine, Andrea Garnero, Sebast Martin, et al. 2019. *Negotiating our way up: collective bargaining in a changing world of work.*

Chaudoin, Stephen, and Michael-David Mangini. 2025. Robots, Foreigners, and Foreign Robots: Policy Responses to Automation and Trade. *The Journal of Politics.*

De La Rica, Sara, and Lucas Gortazar. 2016. Differences in Job De-Routinization in OECD Countries: Evidence from PIAAC. *SSRN Electronic Journal.*

De Stefano, Valerio, and Simon Taes. 2023. Algorithmic management and collective bargaining. *Transfer: European Review of Labour and Research* 29 (1): 21–36.

Doellgast, Virginia, Shruti Appalla, Dina Ginzburg, Jeonghun Kim, and Wen Li Thian. 2025. *Global case studies of social dialogue on ai and algorithmic management.* Working Paper 144. International Labour Organization.

Farber, Henry S, Daniel Herbst, Ilyana Kuziemko, and Suresh Naidu. 2021. Unions and inequality over the twentieth century: new evidence from survey data. *The Quarterly Journal of Economics* 136 (3): 1325–1385.

Ferguson, John-Paul. 2016. Racial Diversity and Union Organizing in the United States, 1999â2008. *ILR Review* 69 (1): 53–83.

First Transit, Inc., Mesa and Tempe Division and Amalgamated Transit Union (ATU) Local 1433. 2016–21. *Collective bargaining agreement between First Transit, Inc., Mesa and Tempe Division and Amalgamated Transit Union Local 1433,* July 1, 2016–June 30, 2021.

Freeman, Richard B, and James L Medoff. 1984. What do unions do? *Basic Book.*

Frey, Carl Benedikt, and Michael A. Osborne. 2017. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change* 114:254–280.

Frymer, Paul, and Jacob M Grumbach. 2021. Labor unions and white racial politics. *American Journal of Political Science* 65 (1): 225–240.

Gallego, Aina, Alexander Kuo, Dulce Manzano, and José Fernández-Albertos. 2022. Technological Risk and Policy Preferences. *Comparative Political Studies* 55 (1): 60–92.

Gingrich, Jane, Nicole Wu, and Baobao Zhang. 2026. Workplace governance and labor perceptions of technological risks and benefits. *Industrial and Corporate Change* 35 (1): 222–242.

Glavin, Paul, Alex Bierman, and Scott Schieman. 2024. Private Eyes, They See Your Every Move: Workplace Surveillance and Worker Well-Being. *Social Currents* 11 (4): 327–345.

Gonzalez-Rostani, Valentina. 2024a. Engaged robots, disengaged workers: Automation and political alienation. *Economics & Politics* 36 (3): 1703–1730.

———. 2024b. The Path from Automation to Right-Wing Populism.

———. 2026. Elections, Right-Wing Populism, and Political-Economic Polarization: The Role of Institutions and Political Outsiders. *The Journal of Politics* 88 (1): 125–144.

Gonzalez-Rostani, Valentina, and Tobias Tober. 2025. Navigating Uncertainty: How Experience Shapes Perception and Politics in the AI Era.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. Explaining job polarization: Routine-biased technological change and offshoring. *American economic review* 104 (8): 2509–26.

Hall, Peter A., and David Soskice. 2001. *Varieties of Capitalism: The Institutional Foundations of.* Research on Stakeholder Management.

Haslberger, Matthias, Jane Gingrich, and Jasmine Bhatia. 2024. Rage Against the Machine? Generative AI Use, Threat Perceptions, and Policy Preferences.

Hertel-Fernandez, Alexander. 2025. Civic organizations and the political participation of cross-pressured americans: the case of the labor movement. *American Political Science Review* 119 (3): 1173–1189.

Howe, John, Timothy Kariotis, Lev Bromberg, and Jack Fagan. 2026. Is the boss watching, and are unions doing anything about it? Workplace surveillance regulation in Australian Enterprise Agreements*. *Labour and Industry* 0 (0): 1–23.

Iversen, Torben. 1999. *Contested economic institutions: the politics of macroeconomics and wage bargaining in advanced democracies.* Cambridge; New York: Cambridge University Press.

Iversen, Torben, and David Soskice. 2015. Information, inequality, and mass polarization: ideology in advanced democracies. *Comparative Political Studies* 48 (13): 1781–1813.

Jäger, Simon, Suresh Naidu, and Benjamin Schoefer. 2025. Collective bargaining, unions, and the wage structure: an international perspective. Chap. 4, 6:229–372.

Kaplan, Ethan, and Suresh Naidu. 2025. Between government and market: the political economics of labor unions. *Annual Review of Economics* 17:367–396.

Kerrissey, Jasmine, and Evan Schofer. 2013. Union membership and political participation in the united states. *Social Forces* 91 (3): 895–928.

König, Cornelius J. 2025. Electronic Monitoring at Work.

Kostøl, Fredrik B., and Elin Svarstad. 2023. Trade Unions and the Process of Technological Change. *Labour Economics* 84:102386.

Kresge, Lisa. 2025. *Negotiating tech: an inventory of u.s. union contract provisions for the digital age.* Technical report. Center for Labor Research and Education, University of California, Berkeley.

Kurer, Thomas. 2020. The Declining Middle: Occupational Change, Social Status, and the Populist Right. *Comparative Political Studies,* 0010414020912283.

Kurer, Thomas, and Silja Häusermann. 2022. Automation Risk, Social Policy Preferences, and Political Participation. In *Digitalization and the Welfare State,* 139–156. Oxford University Press. ISBN: 978-0-19-284836-9 978-0-19-194365-2.

Leduc, Sylvain, and Zheng Liu. 2024. Automation, bargaining power, and labor market fluctuations. *American Economic Journal: Macroeconomics* 16 (4): 311–49.

Magistro, Beatrice, Sophie Borwein, R. Michael Alvarez, Bart Bonikowski, and Peter John Loewen. 2025. Attitudes toward artificial intelligence (AI) and globalization: Common microfoundations and political implications. *American Journal of Political Science* n/a (n/a).

Magistro, Beatrice, Peter Loewen, Bart Bonikowski, Sophie Borwein, and Blake Lee-Whiting. 2024. Attitudes toward automation and the demand for policies addressing job loss: the effects of information about trade-offs. *Political Science Research and Methods* 12 (4): 783–798.

Marsh, Elizabeth, Elvira Perez Vallejos, and Alexa Spence. 2022. The digital workplace and its dark side: An integrative review. *Computers in Human Behavior* 128:107118.

Milner, Helen V. 2021. Voting for Populism in Europe: Globalization, Technological Change, and the Extreme Right. *Comparative Political Studies* 54 (13): 2286–2320.

Montreuil, Véra-Line, and Roland Foucher. 2023. Technological changes in the era of digitalization: what do collective agreements tell us? *Industrial Relations Journal* 54 (1): 20–39.

Naidu, Suresh. 2022. Is There Any Future for a US Labor Movement? *Journal of Economic Perspectives* 36 (4): 3–28.

National Park Service Headquarters and National Treasury Employees Union (NTEU) Chapter 296. 2017. *Collective bargaining agreement between National Park Service Headquarters and NTEU Chapter 296,* March 23, 2017.

National Science Foundation and American Federation of Government Employees (AFGE) Local 3403, AFLCIO. 2022. *Collective bargaining agreement between the national science foundation and local 3403, american federation of government employees, aflcio,* November 17, 2022.

O'Brady, Sean, and Virginia Doellgast. 2021. Collective Voice and Worker Well-being: Union Influence on Performance Monitoring and Emotional Exhaustion in Call Centers. *Industrial Relations A Journal of Economy and Society* 60.

Office and Professional Employees International Union (OPEIU) Local 537, AFLCIO and American Federation of Musicians Local 325. 2019–24. *Agreement between OPEIU Local 537, AFLCIO and American Federation of Musicians Local 325,* March 1, 2019–February 29, 2024.

Pontusson, Jonas, and Peter Swenson. 1996. Labor markets, production strategies, and wage bargaining institutions: the swedish employer offensive in comparative perspective. *Comparative Political Studies* 29 (2): 223–250.

Prytkova, Ekaterina, Fabien Petit, Deyu Li, Sugat Chaturvedi, and Tommaso Ciarli. 2025. The employment impact of emerging digital technologies.

Rainone, Silvia. 2025. The collective rights dimension of the platform work directive: assessing regulatory effectiveness in the digital labour context. *European Labour Law Journal,* 20319525251375024.

Rosenfeld, Jake. 2019. Us labor studies in the twenty-first century: understanding laborism without labor. *Annual Review of Sociology* 45 (Volume 45, 2019): 449–465.

Seymour Johnson Air Force Base, North Carolina and National Association of Independent Labor (NAIL) Local 7. 2022. *Negotiated agreement between Seymour Johnson Air Force Base, North Carolina and local 7, National Association of Independent Labor,* October 25, 2022.

Smith, Ray A. 2025. More of us are putting in extra hours after the workday. *The Wall Street Journal* (June 17, 2025).

State of California and Service Employees International Union (SEIU) Local 1000. 2023–26. *Memorandum of understanding (mou) for bargaining units 1, 3, 4, 11, 14, 15, 17, 20, and 21,* July 1, 2023–June 30, 2026.

Thewissen, Stefan, and David Rueda. 2019. Automation and the Welfare State: Technological Change as a Determinant of Redistribution Preferences. *Comparative Political Studies* 52 (2): 171–208.

Traxler, Franz, Sabine Blaschke, and Bernhard Kittel. 2001. *National labour relations in internationalized markets: a comparative study of institutions, change and performance.* Oxford University Press.

Umblijs, Janis, Pål Schøne, and Henning Finseraas. 2025. Automation and worker organisation. *Applied Economics Letters* 32 (20): 3027–3031.

United Parcel Service, Inc. and International Brotherhood of Teamsters. 2023–28. *National master United Parcel Service agreement,* August 1, 2023–July 31, 2028.

Visser, Jelle. 2016. What happened to collective bargaining during the great recession? *IZA Journal of Labor Policy* 5 (1): 9.

Yan, Alan. 2025. The minimal effects of union membership on political behavior. *Quarterly Journal of Political Science,* forthcoming.

# A Appendix

## Contents

## A.1 Descriptive ESS Variables

Table A.1: Description of ESS Variables

| **Variable** | **Description** | **Coding** | **ESS** |
|---|---|---|---|
| Union member | Member of trade union or similar organisation | 0 = No (or yes previously), 1 = Yes | 6–11 |
| Influence on decisions | Allowed to influence policy decisions about activities of organisation | 10-point scale: 1 = no influence, 10 = complete control | 6–11 |
| Decide daily work | Allowed to decide how daily work is organised | 10-point scale: 1 = no influence, 10 = complete control | 6–11 |
| Satisfaction job | How satisfied with job | 10-point scale: 1 = Extremely dissatisfied, 10 = Extremely satisfied | 6 |
| Satisfaction life | How satisfied with life | 10-point scale: 1 = Extremely dissatisfied, 10 = Extremely satisfied | 6–11 |
| Limited contract | Employment contract: unlimited or limited | 0 = unlimited, 1 = limited | 6–11 |
| Interaction (in person) | Speak with colleagues in person, how often | 7-point scale: Never, Less often, Once a month, Several times a month, Several times a week, Once a day, Several times a day | 10 |
| Interaction (phone) | Speak with colleagues about work using a phone, how often | 7-point scale: Never, Less often, Once a month, Several times a month, Several times a week, Once a day, Several times a day | 10 |
| Income | Household's total net income, all sources | 10 income deciles | 6–11 |
| Left-Right | Placement on left-right scale | 10-point scale: Left to Right | 6–11 |
| Redistribution | Government should reduce differences in income levels | 5-point scale: Disagree strongly, Disagree, Neither agree nor disagree, Agree, Agree strongly | 6–11 |
| Voted | Voted last national election | 0 = Not voted, 1 = Voted | 6–11 |
| Interest politics | How interested in politics | 4-point scale: Not at all interested, Hardly interested, Quite interested, Very interested | 6–11 |
| Satisfaction dem. | How satisfied with the way democracy works in country | 10-point scale: 1 = Extremely dissatisfied, 10 = Extremely satisfied | 6–11 |

## A.2 Types of Technologies and descriptives

### A.2.1 Types of Technology

Table A.2: Types of Technology

| **Type of Technology** | **Description** |
|---|---|
| Machine Learning & Neural Networks | Machine learning training techniques, model architectures, and data processing for computer vision applications. |
| Embedded Systems | - Smart Agriculture & Water Management: IoT technologies for intelligent and remote management in agriculture and water/sewage systems.<br>- Internet of Things (IoT): Systems and devices interconnected via IoT for data collection, remote control, and real-time monitoring in applications including agriculture, home automation, and environmental monitoring.<br>- Predictive Energy Management and Distribution: Network, data management, and AI technologies for monitoring, distribution, and efficient use of electrical power, including renewables, and for consumption prediction in intelligent power management.<br>- Remote Monitoring & Control Systems: Real-time remote monitoring and management technologies for factories, building management, warehouses, intelligent homes, disaster management, and network security.<br>- Industrial Automation & Robot Control: Industrial process automation including robots, programmable logic controllers, and related control apparatuses such as remote control and fault diagnosis.<br>- Smart Home & Intelligent Household Control: IoT technologies for intelligent control of homes and buildings, including household appliances, home environments, and smart home integrations, often using wireless communication and monitoring. |
| Remote Monitoring & Control Systems | Real-time remote monitoring and management technologies for factories, building management, warehouses, intelligent homes, disaster management, and network security. |
| Smart Mobility | - Intelligent Logistics: Monitoring, remote control, data acquisition, and mobile robot technologies for logistics and delivery, including supply chain management, warehouse operations, package tracking, and courier services.<br>- Autonomous Vehicles & UAVs: Developments in UAVs, drones, and autonomous driving technologies, emphasizing vehicle control, navigation, and sensor integration.<br>- Parking & Vehicle Space Management: Networking technologies for parking management, including systems for monitoring available spaces and intelligent parking solutions.<br>- Vehicle Telematics & Electric Vehicle Management: Intra-vehicle information management for electric vehicles, including real-time monitoring, traffic information, and diagnostics.<br>- Passenger Transportation: Technologies for ride-sharing, taxi hailing, and public transportation reservations using real-time information, electronic ticketing, and route optimization. |
| Intelligent Logistics | Monitoring, remote control, data acquisition, and mobile robot technologies for logistics and delivery applications, including supply chain management, warehouse operations, package tracking, and courier services. |
| Food Ordering & Vending Systems | Wireless infrastructures, encryption, monitoring, and remote control technologies for food order management, such as automatic vending, self-service ordering, meal preparation, and delivery. |

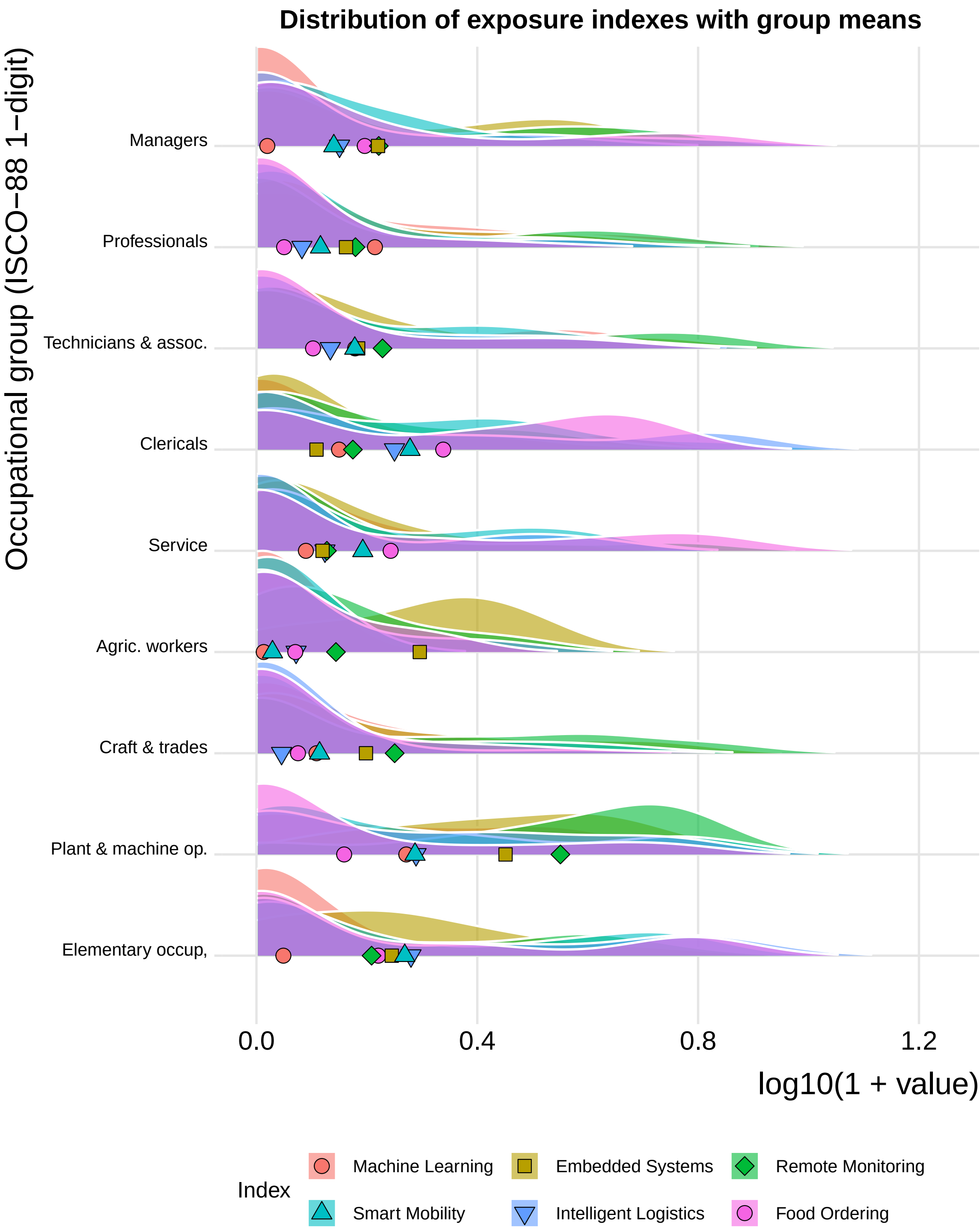
*Note:* Descriptions are sourced from Prytkova et al. 2025.

### A.2.2 Exposure to types of technology by occupation

Table A.3: Top five most exposed occupations to each technology.

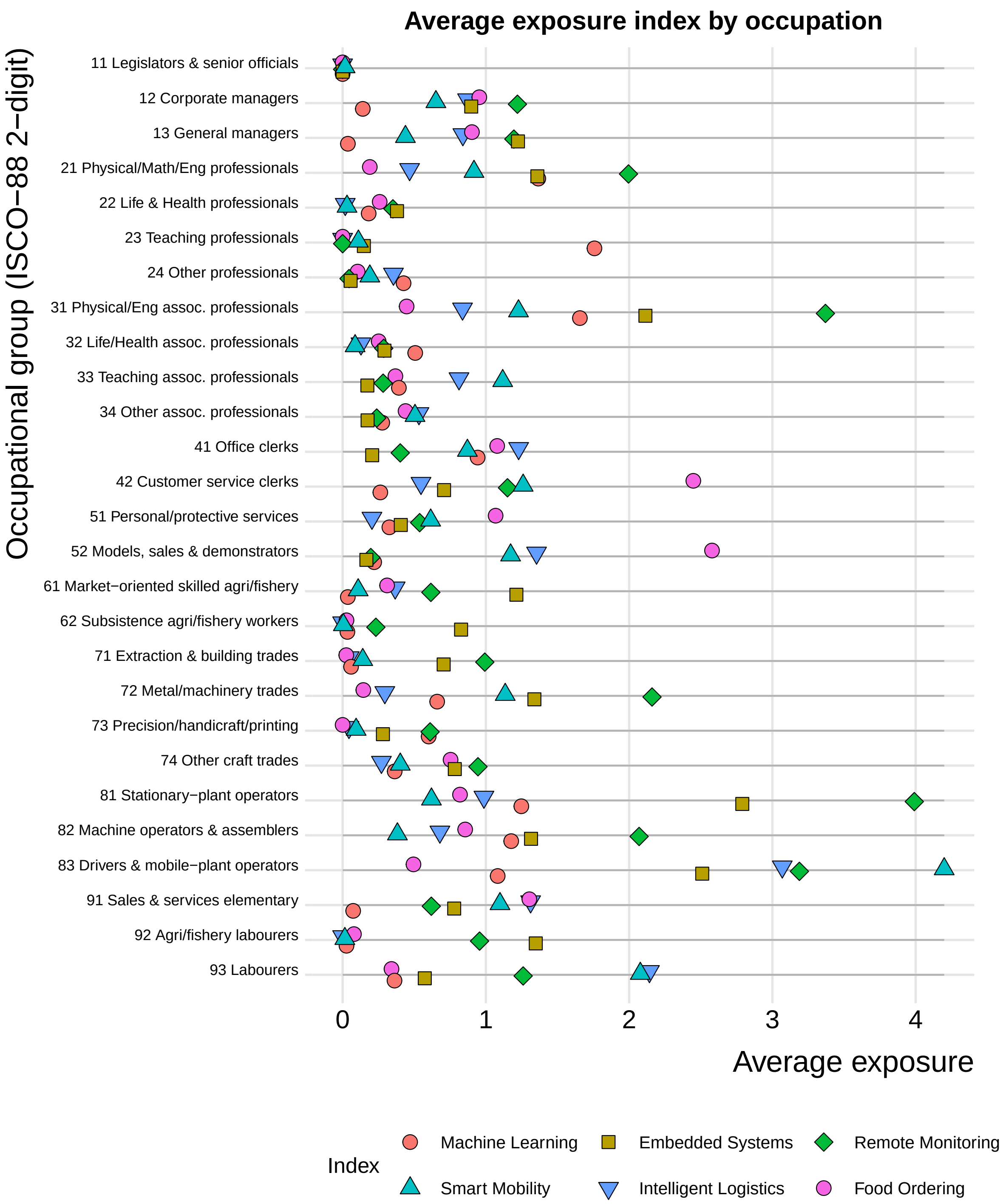
| **Technology** | **ISCO-08 Occupation** | **4-digit code** |
|---|---|---|
| **Machine learning** | Photographic products machine operators | 8132 |
| | Electronics engineers | 2152 |
| | Information technology trainers | 2356 |
| | Telecommunications engineers | 2153 |
| | Chemical and photographic products plant and machine operators | 8130 |
| **Embedded systems** | Chemical processing plant controllers | 3133 |
| | Process control technicians | 3130 |
| | Power production plant operators | 3131 |
| | Computer network professionals | 2523 |
| | Meter readers and vending-machine collectors | 9623 |
| **Remote monitoring** | Chemical processing plant controllers | 3133 |
| | ICT installers and servicers | 7422 |
| | Computer network professionals | 2523 |
| | Computer network and systems technicians | 3513 |
| | Electronics and telecommunications installers and repairers | 7420 |
| **Smart mobility** | Car, taxi and van drivers | 8322 |
| | Transport clerks | 4323 |
| | Car, van and motorcycle drivers | 8320 |
| | Material-recording and transport clerks | 4320 |
| | Town and traffic planners | 2164 |
| **Intelligent logistics** | Messengers, package deliverers and luggage porters | 9621 |
| | Freight handlers | 9333 |
| | Supply, distribution and related managers | 1324 |
| | Transport clerks | 4323 |
| | Mail carriers and sorting clerks | 4412 |
| **Food ordering** | Food service counter attendants | 5246 |
| | Fast food preparers | 9411 |
| | Restaurant managers | 1412 |
| | Food preparation assistants | 9410 |
| | Food preparation assistants | 9400 |

Figure A.1: Exposure to Types of Technology by Occupational Group




*Note:* The figure shows the distribution of exposure to the six technological types across ISCO-08 4-digit occupations. For each ISCO-88 1-digit major occupational group, kernel density ridges summarise how exposure values are distributed. Values are trimmed at 0 given that 0 is the minimum exposure. Exposure is expressed as $\log_{10}(1 + \text{value})$ to reduce skewness and improve readability. The colored markers overlaid on each ridge indicate the average exposure of the occupations within that major group for each technology.

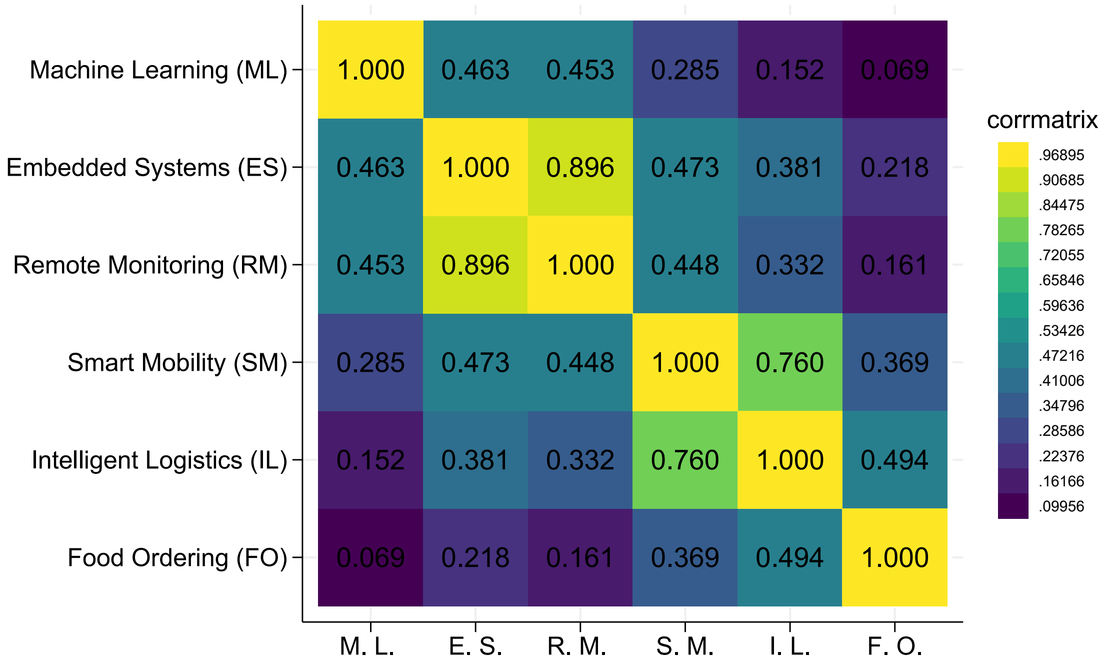
Figure A.2: Average Exposure to Types of Technology by Occupation




*Note:* The figure reports the average exposure to the various technological types across ISCO-88 2-digit occupational groups. For each group, the exposure value corresponds to the mean of the underlying ISCO-08 4-digit occupations classified within that category. Coloured markers denote the average exposure for each technology.

### A.2.3 Correlation between Exposure Indexes

Figure A.3: Correlation Matrix of Exposure Indexes



## A.3 Additional Results: The Impact of Emerging Digital Technologies on Working Conditions and Unionization

Table A.4: The Impact of Technology on Unionization (unadjusted measure)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var.: | | | Union member | | | |
| Technology exposure: $\theta$ | 0.007*** | 0.010*** | 0.013*** | 0.004** | -0.000 | -0.006*** |
| | [0.001] | [0.001] | [0.002] | [0.001] | [0.001] | [0.001] |
| Technology type | Machine Learning | Embedded Systems | Remote Monitoring | Smart Mobility | Intelligent Logistics | Food Ordering |
| Controls | X | X | X | X | X | X |
| Country-Year FE | X | X | X | X | X | X |
| Region FE | X | X | X | X | X | X |
| Industry FE | X | X | X | X | X | X |
| Observations | 129,129 | 129,129 | 129,129 | 129,129 | 129,129 | 129,129 |
| R-squared | 0.250 | 0.250 | 0.250 | 0.250 | 0.250 | 0.250 |

Standard errors are clustered at the country-year level and are reported in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table A.5: The Impact of Technology on Unionization (robust to industry shocks)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var.: | | | Union member | | | |
| Technology exposure | 0.006*** | 0.009*** | 0.011*** | 0.004*** | 0.000 | -0.005*** |
| | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] |
| Technology type | Machine Learning | Embedded Systems | Remote Monitoring | Smart Mobility | Intelligent Logistics | Food Ordering |
| Controls | X | X | X | X | X | X |
| Country-NACE-Year FE | X | X | X | X | X | X |
| Region FE | X | X | X | X | X | X |
| Observations | 128,698 | 128,698 | 128,698 | 128,698 | 128,698 | 128,698 |
| R-squared | 0.307 | 0.308 | 0.308 | 0.307 | 0.307 | 0.307 |

Standard errors are clustered at the country-year level and are reported in brackets
*** p<0.01, ** p<0.05, * p<0.1

## A.4 Canadian Labor Relations and Technological Change Background

### A.4.1 Collective Bargaining Structure in Canada

Canadian collective bargaining is characterized by a decentralized, enterprise-level system of industrial relations. The majority of labor relations fall under provincial jurisdiction, with each province (and territory) administering its own labor relations legislation and board. In practice, this means rules and procedures can vary across Canadas sub-national units, although all adhere to the general Wagner Act model of union recognition and collective bargaining rights. Bargaining typically occurs at the level of the individual employer or bargaining unit, rather than through national or sector-wide agreements. Unlike many European countries, Canada has no legal provision for extending a single collective agreement to an entire industry, and

Table A.6: The Impact of Technology and Limited Contract on Unionization

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var.: | Union member | | | | | |
| Technology exposure | 0.007*** | 0.013*** | 0.015*** | 0.006*** | 0.003** | -0.003 |
| | [0.002] | [0.002] | [0.002] | [0.002] | [0.002] | [0.002] |
| Limited Contract | -0.049*** | -0.050*** | -0.049*** | -0.049*** | -0.049*** | -0.049*** |
| | [0.005] | [0.005] | [0.005] | [0.005] | [0.005] | [0.005] |
| Tech exposure X Lim. Contract | -0.004 | -0.008** | -0.007** | -0.006* | -0.007*** | -0.004 |
| | [0.003] | [0.003] | [0.003] | [0.003] | [0.003] | [0.003] |
| Technology type | Machine Learning | Embedded Systems | Remote Monitoring | Smart Mobility | Intelligent Logistics | Food Ordering |
| Controls | X | X | X | X | X | X |
| Country-Year FE | X | X | X | X | X | X |
| Region FE | X | X | X | X | X | X |
| Industry FE | X | X | X | X | X | X |
| Observations | 103,347 | 103,347 | 103,347 | 103,347 | 103,347 | 103,347 |
| R-squared | 0.262 | 0.263 | 0.263 | 0.262 | 0.262 | 0.262 |

Standard errors are clustered at the country-year level and are reported in brackets
*** p<0.01, ** p<0.05, * p<0.1

multi-employer or sectoral contracts are the exception rather than the norm. One consequence of this structure is that outcomes and union strategies may differ by sector and region, making Canada an insightful laboratory of diverse industrial relations practices within one country.

### A.4.2 Union Density and Coverage Rates

Canadas unionization rate is relatively high for a developed economy without national-level bargaining, though it has declined from its peak in the 1980s. As of 2023, just over 30% of Canadian employees (approximately 5.3 million workers) were covered by a collective agreement.[25] This overall coverage rate has fallen from about 37% in 1981 to 30.4% in 2023, reflecting changes in the economy and labor laws over time. Crucially, union density in Canada is highly bifurcated by sector. The public sector is heavily unionized, with around 76-77% of public-sector employees covered by collective agreements, a rate nearly five times that of the private sector. In contrast, the private-sector union coverage has dropped to roughly 15.5% in recent years. This gap has widened over time: private unionization declined sharply after the 1990s (e.g. manufacturing unions suffered losses due to industrial restructuring), even as public-sector unions maintained or grew their presence.

### A.4.3 Recent Developments in AI and Digital Technologies in Canadian Workplaces

In recent years, Canada has experienced a rapid uptick in the adoption of AI and digital technologies across industries, prompting responses from policymakers and labor organizations. According to the latest Statistics Canada data, AI use by businesses has been growing quickly. In the second quarter of 2025, about 12.2% of Canadian businesses reported using AI in their operations (for producing goods or delivering services), double the share that had adopted AI just one year earlier (6.1% in Q2 2024).[26] These applications range from data analytics and chatbots to machine-learning-driven process automation. Certain sectors are leading the way: information and cultural industries, professional and technical services, and finance have the

25. https://www.statcan.gc.ca/o1/en/plus/7416-state-unions-canada.
26. https://www150.statcan.gc.ca/n1/pub/11-621-m/11-621-m2025008-eng.htm.

highest AI uptake, whereas industries like agriculture and hospitality report minimal AI use so far. Parallel research has estimated that three in five Canadian workers are employed in occupations with a high potential exposure to AI technologies, underscoring the broad relevance of AI to the workforce.

Table A.7: Use of AI among businesses in producing goods or delivering services over the last 12 months, second quarter of 2024 and 2025

| | **2nd quarter of 2025** | **2nd quarter of 2024** |
|---|---|---|
| AI used in producing goods or delivering services | 12.2 | 6.1 |
| Text analytics using AI | 35.7 | 27.0 |
| Data analytics using AI | 26.4 | 25.0 |
| Virtual agents or chat bots | 24.8 | 26.5 |
| Natural language processing | 23.1 | 28.9 |
| Marketing automation using AI | 23.1 | 15.2 |
| Speech or voice recognition using AI | 20.0 | 18.1 |
| Large language models | 19.1 | 21.9 |
| Machine learning | 18.6 | 20.1 |
| Recommendation systems using AI | 14.0 | 12.3 |
| Image or pattern recognition | 11.4 | 21.8 |
| Deep learning | 6.6 | 1.9 |
| Decision making systems based on AI | 5.7 | 6.1 |
| Robotics process automation | 3.8 | 2.6 |
| Augmented reality | 3.2 | 2.6 |
| Biometrics | 3.2 | 1.0 |
| Machine or computer vision | 3.1 | 4.7 |
| Neural networks | 2.5 | 4.4 |
| Other type | 6.1 | 6.7 |

*Notes:* The results in this table are based on the survey that was in collection from April 1 to May 5, 2025, and from April 2 to May 6, 2024. Respondents were asked what the business or organization experienced in the last 12-month period. As a result, those 12 months could range from April 1, 2024, to May 5, 2025, and from April 2, 2023, to May 6, 2024, depending on when the business responded.
*Source:* Canadian Survey on Business Conditions, second quarter of 2025 (Table 33-10-1004-01) and second quarter of 2024 (Table 33-10-0825-01).

Against this backdrop, unions and labor stakeholders in Canada have become increasingly engaged with the implications of AI and digitalization. Major unions have started to proactively address AI in collective bargaining and policy forums. For example, the Canadian Union of Public Employees (CUPE), Canadas largest public-sector union, released guidance in 2025 for bargaining strong collective agreements for the digital age.[27] This guide emphasizes that there is no single AI clause - instead, unions must review and update many parts of their agreements to meet the challenges of AI. It outlines how contract provisions can ensure consultation and negotiation before new tech is introduced, protect workers data and privacy, guard against discriminatory or unsafe technology, and secure jobs and wages as work is transformed. Likewise, Unifor (the countrys largest private-sector union) has highlighted its efforts in bargaining over new technology.[28] Unifor reports that it has negotiated contract language to give workers a say in technology implementation - guaranteeing advance notice of automation, the right for workers to participate in deploying new systems, and just transition supports for those displaced. These negotiated provisions aim to ensure that technological changes are made with workers

27. https://cupe.ca/sites/default/files/bargaining_ca_digital_age_en.pdf.
28. https://www.unifor.org/sites/default/files/legacy/documents/document/1173-future_of_work_eng_no_bleed.pdf.

rather than to workers, reflecting a strategy of adaptation and influence instead of resistance. Canadian union federations and professional associations are also weighing in. The Canadian Labour Congress (CLC) and various sectoral unions have been advocating for a national strategy on AI that includes worker protections. For instance, unions in knowledge-based sectors (like university faculty associations under CAUT, or federal public service professionals under PIPSC) have called for frameworks to manage AIs effects on jobs, emphasizing retraining and skills development, ethical use of AI, and job protection as key priorities.[29]

On the policy side, the Canadian government and research institutes have begun addressing the future of work in the AI era. Federal initiatives, like the Future Skills Centre,[30] have funded research on AI-related skill needs, and think tanks have proposed strategies for inclusive AI adoption. A notable theme in recent policy discourse is the call for worker engagement in AI rollout. Analysts argue that Canada should avoid a purely technocratic implementation of AI and instead involve employees and their unions in designing how AI is integrated into workplaces. A Macdonald-Laurier Institute report (2023)[31] echoes a Brookings Institution finding that enhancing worker voice through unions or other means during AI adoption leads to better outcomes, ensuring that productivity gains translate into shared benefits:

> Policy should encourage companies to bring workers (and their unions, where applicable) into the AI design and implementation process. This could be achieved through formal structures - for example, work councils or joint management-labour committees focused on technology - or through requirements for consultation when government funding is involved.

For example, recent collective bargaining in sectors like warehousing and transportation has touched on algorithmic scheduling and monitoring - unions have pushed back against unilateral use of AI-driven performance management tools, citing privacy and fairness concerns. In 2023, a high-profile strike in the federal public service (PSAC strike) prominently featured remote work and the handling of new digital work arrangements as key issues, illustrating how technology is becoming a core subject of labor relations.

## A.5 Data CBAs

29. https://www.caut.ca/bulletin/commentary-is-your-union-strategizing-about-ai-and-automation/.
30. https://fsc-ccf.ca/wp-content/uploads/2025/09/canadas-workforce-in-transition_sept2025.pdf.
31. https://macdonaldlaurier.ca/unleashing-ai-canadas-blueprint-for-productivity-innovation-and-workforce-integration/.

Table A.8: Total Count for CBAs by NAICS2 (1993–2025)

| **NAICS-2 Digit** | **Count** |
|---|---:|
| 11 | 141 |
| 21 | 484 |
| 22 | 687 |
| 23 | 1,845 |
| 33 | 7,191 |
| 41 | 423 |
| 45 | 821 |
| 48 | 7,174 |
| 51 | 2,125 |
| 52 | 295 |
| 53 | 50 |
| 54 | 367 |
| 56 | 630 |
| 61 | 7,296 |
| 62 | 5,117 |
| 71 | 456 |
| 72 | 741 |
| 81 | 208 |
| 91 | 4,721 |
| **Total** | **40,742** |

### A.5.1 Descriptives CBAs

Figure A.4 plots the monthly count of agreements. The series declines over time. Counts are high in the mid-1990s (several months above 500), trend downward through the 2000s and 2010s, and fall below 100 per month by the late 2010s, with low flows in 2024-2025. Much of the decline occurs in manufacturing (NAICS 31-33). Because contract length and bargaining-unit consolidation can change, we interpret the series as agreement *flow* in our corpus, not as coverage or bargaining intensity.

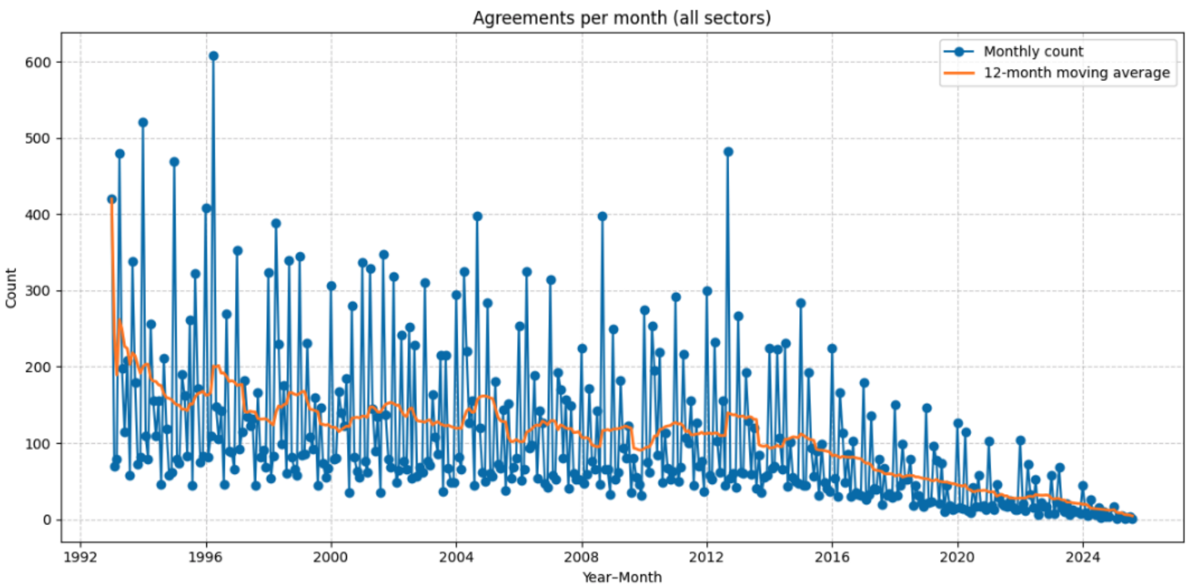



Figure A.4: Monthly Canadian collective bargaining agreements, 1993–2025

Table A.9: Total # of Unique Elements:

| metric | value |
|---|---|
| CBA | 40772 |
| Employers | 9611 |
| Unions | 597 |
| Industries 6 digits | 673 |
| Jurisdictions | 21 |
| Location | 854 |
| Years | 33 |

Figure A.5: Number of CBA by Industry

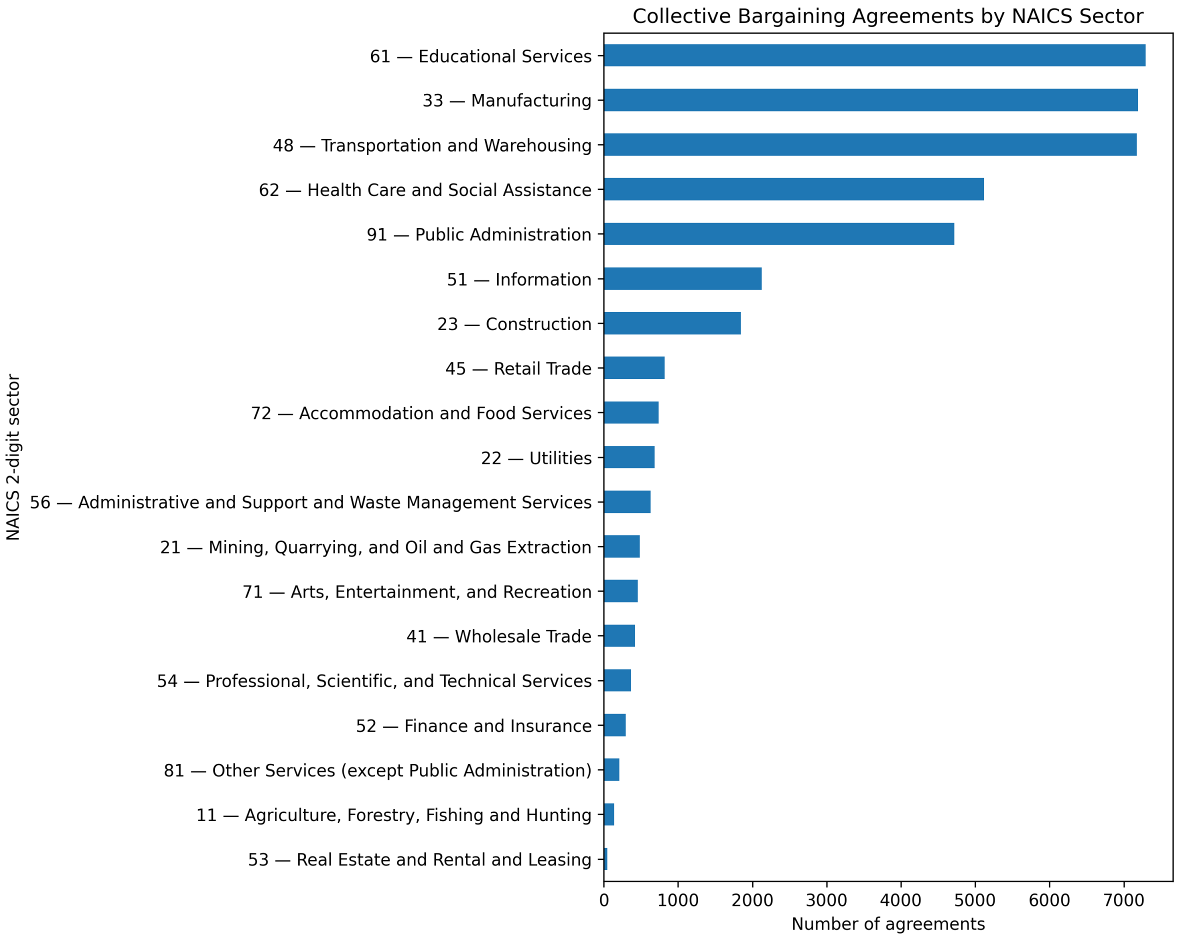


Figure A.6: Number of CBA by Jurisdiction

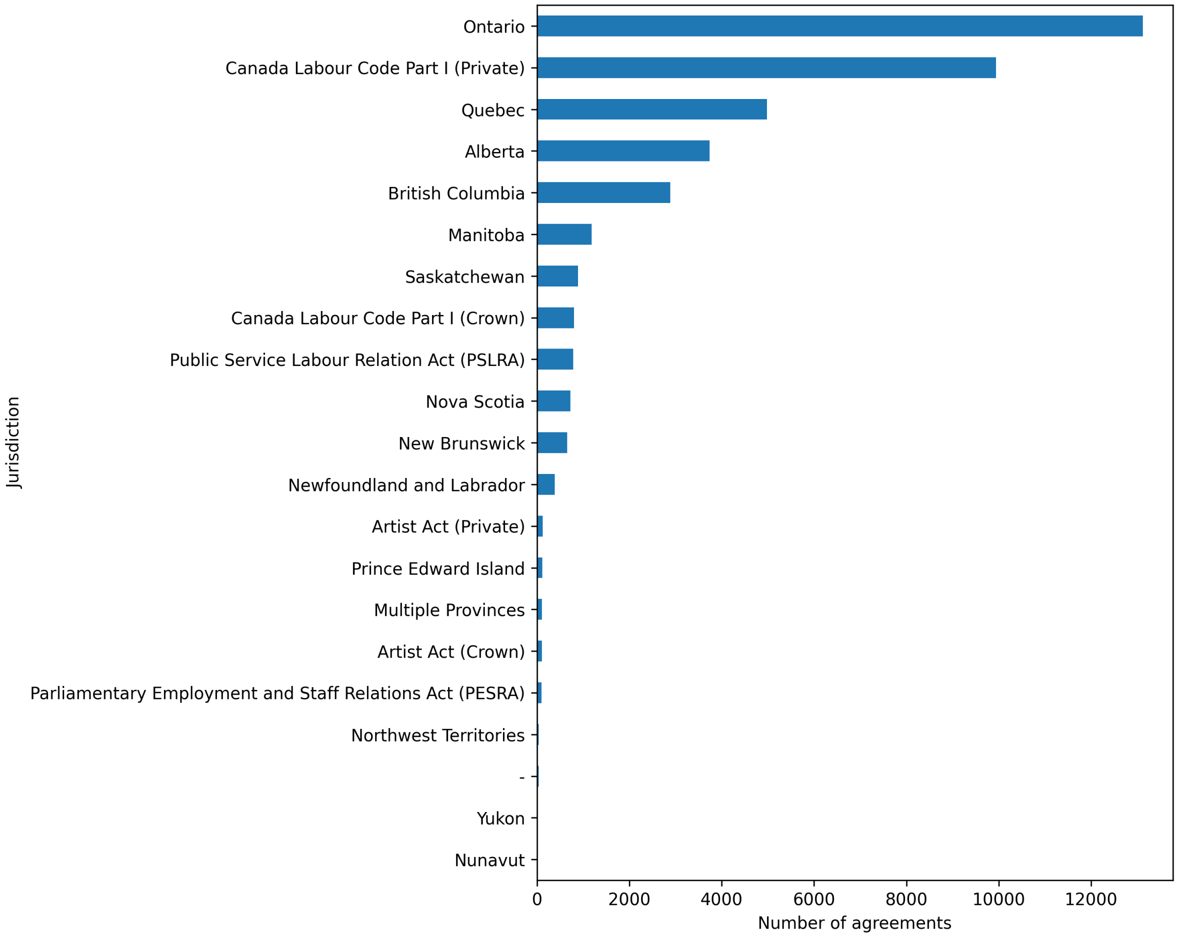
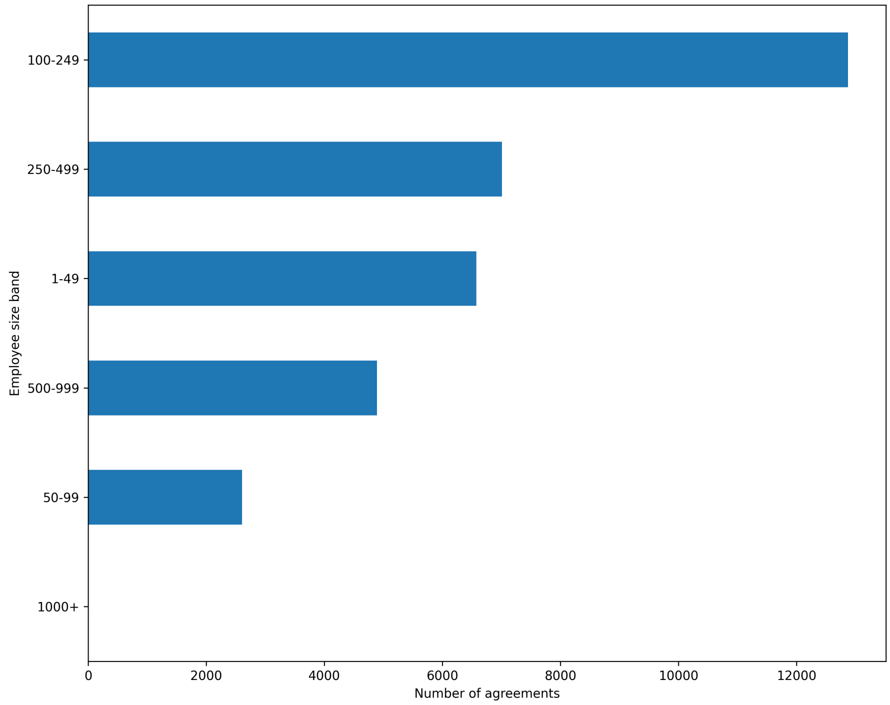


Figure A.7: Number of CBA by Employer Size




## A.6 Measuring Topics in CBAs

The dependent variables used in the analysis are constructed with a dictionary-based text-as-data approach. For each agreement, the text is lowercased, tokenized, and English and French stopwords are removed. For each provision category, we define a bilingual dictionary consisting of single-word and ordered multi-word expressions. For a given contract and category, the dictionary count is the number of occurrences of any of these expressions in the text (multi-word expressions must appear in the specified order). The final measure is a share: the dictionary count divided by the total number of non-stop words in the agreement. In the main text we report results for the following provision categories; below we list the English components of each dictionary (parallel French terms are also included in the implementation but omitted here for brevity).

**Health Safety Wellbeing** *work intensification*, *workload*, *psychosocial risks*, *mental health*, *right disconnect*, *remote work*, *privacy*, *working conditions*, *conditions of work*, *hours*, *shift*, *overtime*, *night shift*, *telework*, *hybrid*, *flexible schedule*, *breaks*, *rest period*, *paid break*, *heat stress*, *cold exposure*, *noise*, *vibration*, *dust*, *fumes*, *chemical exposure*, *ppe*, *personal protective equipment*, *hearing protection*, *respirator*, *gloves*, *safety boots*, *ergonomic*, *musculoskeletal*, *repetitive motion*, *manual handling*, *lifting*, *conveyor*, *assembly line*, *line speed*, *machine guarding*, *lockout tagout*, *loto*, *safeguard*, *incident reporting*, *near miss*, *first aid*, *joint health and safety committee*, *jhsc*.

**Training & Retraining** *training*, *retraining*, *upskilling*, *reskilling*, *instruction*, *orientation*, *education*, *no loss pay*, *during working hours*, *at employer expense*, *training plan*, *onboarding*, *apprenticeship*, *journeyperson*, *red seal*, *trade certification*, *ticket*, *license*, *licence*, *skills*, *competence*, *competency*, *competencies*, *skill upgrade*, *professional development*, *in-house training*, *on the job training*, *ojt*, *safety training*, *lockout training*, *forklift training*, *first aid training*, *whmis*, *hazcom*, *standard operating procedure*, *sop*, *work instruction*.

**Notice Content Requirements** *notice state nature change*, *effective date change*, *anticipated impacts*, *employees affected*, *classifications affected*, *locations affected*, *training plan*, *timelines*, *mitigation measures.*

**Joint Committee** *union management committee*, *joint committee*, *technological change committee*, *bilateral committee.*

**Rights Active** *receive*, *gain*, *earn.*

**Rights Passive** *entitle*, *give*, *offer*, *reimburse*, *pay*, *grant*, *provide*, *compensate*, *guarantee*, *hire*, *train*, *supply*, *protect*, *allow*, *cover*, *inform*, *notify*, *select*, *award.*

**Working Conditions Protection** *no reduction pay*, *no loss wages*, *no reduction hours*, *no loss benefits*, *classification protection*, *wage protection*, *maintain employment status.*

**Remedies Mitigation** *mitigation measures*, *transition plan*, *adjustment plan*, *impact review*, *employment security plan*, *job security plan*, *avoid layoff*, *minimize adverse effects*, *placement services.*

**Union Notice** *advance notice*, *written notice*, *notice union*, *effective date*, *number employees affected*, *classifications affected.*

**Displacement Rights Bumping** *displacement*, *bumping*, *redeployment*, *seniority rights*, *layoff avoidance*, *surplus employee.*

**Exceptions Limits** *de minimis changes*, *minor modifications*, *routine maintenance*, *like for like replacement*, *pilot project*, *trial basis*, *emergency change.*

**Agent Union** *union*, *unions*, *representative*, *representatives*, *steward*, *stewards*, *local.*

**Agent Worker** *employee*, *employees*, *worker*, *workers*, *nurse*, *nurses*, *teacher*, *teachers*, *member*, *members*, *operator*, *operators*, *driver*, *drivers*, *mechanic*, *mechanics*, *clerk*, *clerks*, *labourer*, *laborer*, *labourers*, *laborers*, *steward*, *stewards.*

**Agent Firm** *employer*, *employers*, *company*, *companies*, *board*, *management*, *firm*, *firms.*

**Retirement Allowance** *early retirement*, *retirement allowance*, *voluntary retirement*, *severance pay*, *bridging retirement.*

In all cases, the dependent variable measures reported in the paper are defined as the share of non-stop words in the agreement that belong to the corresponding dictionary.

Table A.10: Descriptive Statistics of Collective Bargaining Agreement Topics

| Topics | mean | sd | min | max |
|---|---|---|---|---|
| Health Safety Wellbeing | 0.010 | 0.007 | 0.000 | 0.075 |
| Training & Retraining | 0.005 | 0.003 | 0.000 | 0.062 |
| Notice Content Requirements | 0.002 | 0.001 | 0.000 | 0.015 |
| Joint Committee | 0.001 | 0.001 | 0.000 | 0.018 |
| Rights Active | 0.001 | 0.001 | 0.000 | 0.019 |
| Rights Passive | 0.009 | 0.006 | 0.000 | 0.065 |
| Working Conditions Protection | 0.001 | 0.001 | 0.000 | 0.029 |
| Remedies Mitigation | 0.001 | 0.001 | 0.000 | 0.013 |
| Union Notice | 0.004 | 0.003 | 0.000 | 0.022 |
| Displacement Rights Bumping | 0.001 | 0.001 | 0.000 | 0.009 |
| Exceptions Limits | 0.000 | 0.000 | 0.000 | 0.004 |
| Agent Union | 0.010 | 0.011 | 0.000 | 0.182 |
| Agent Worker | 0.029 | 0.018 | 0.000 | 0.154 |
| Agent Firm | 0.013 | 0.010 | 0.000 | 0.100 |
| Retirement Allowance | 0.001 | 0.001 | 0.000 | 0.017 |

## A.7 Measuring Exposure to AI

### A.7.1 Definition

**Unit of observation** A unique *industry-occupation* pair.

**Output schema (one CSV row; 15 fields, exact order)**

```
Industry,Occupation,E0,E1,E2,E3,AI_capability,AI_capability_certainty,
Replacement,Replacement_certainty,Augmentation,Augmentation_certainty,
Monitoring,Monitoring_certainty,Rationale
```

**Meaning of fields**

- `Industry`, `Occupation`: strings containing codes and labels.
- `E0`–`E3`: binary flags (0/1). These are not mutually exclusive. Mark 1 if a non-trivial share of core tasks fits the category; else 0.
  - `E0`: no exposure to LLMs.
  - `E1`: direct exposure; an LLM alone can reduce task time by ≥50% with no quality loss.
  - `E2`: exposure via LLM-powered software; ≥50% time saving when software is added on top of an LLM.
  - `E3`: exposure with image capabilities; ≥50% time saving when an LLM is paired with systems that read/create/interpret images.
- `AI_capability`, `Replacement`, `Augmentation`, `Monitoring`: 1–10 scores.
- `AI_capability_certainty`, `Replacement_certainty`, `Augmentation_certainty`, `Monitoring_certain`
  1–10 certainties aligned to each score.
- `Rationale`: short free-text justification (1–2 sentences). *Do not use commas; use semi-colons.*

**Derived components (certainty-weighted)** Let $s_j$ be the 1–10 score and $c_j$ the 1–10 certainty for $j \in \{\text{Aug}, \text{Mon}, \text{Cap}, \text{Rep}\}$. Define:

$$\text{augmentation\_ex} = s_{\text{Aug}} \cdot \frac{c_{\text{Aug}}}{10}, \quad \text{monitoring\_ex} = s_{\text{Mon}} \cdot \frac{c_{\text{Mon}}}{10},$$

$$\text{ai\_capability\_ex} = s_{\text{Cap}} \cdot \frac{c_{\text{Cap}}}{10}, \quad \text{replacement\_ex} = s_{\text{Rep}} \cdot \frac{c_{\text{Rep}}}{10}.$$

**Indices**

$$\text{ai\_exposure\_index} = \text{mean}\,\{\text{augmentation\_ex, monitoring\_ex, ai\_capability\_ex, replacement\_ex}\}$$

$$\text{ai\_exposure\_negative} = \text{mean}\,\{\text{monitoring\_ex, ai\_capability\_ex, replacement\_ex}\}$$

For the category flags, apply weights `E1` $= 1$, `E2` $= 0.5$, `E0` $= 0$, `E3` $= 0$:

$$\text{E\_exposure\_index} = 1 \cdot E1 + 0.5 \cdot E2 + 0 \cdot E0 + 0 \cdot E3.$$

Normalize when any flag is 1:

$$\text{E\_exposure\_index\_0\_1} = \frac{\text{E\_exposure\_index}}{E0 + E1 + E2 + E3}, \qquad \text{E\_exposure\_index\_0\_10} = 10 \cdot \text{E\_exposure\_index\_0\_}$$

For sensitivity, keep raw (unweighted-by-certainty) versions:
`ai_exposure_index_raw`, `ai_exposure_negative_raw`.

### A.7.2 Implementation

**Data inputs** De-duplicated industry-occupation pairs; optional admin records to enrich with scores.

**OpenAI model and call** Model: `gpt-4o-mini`. Low temperature (0.1) to reduce variance. Keys are read from the environment.

```
from openai import OpenAI
import os
client = OpenAI(api_key=os.environ["OPENAI_API_KEY"])

resp = client.responses.create(
    model="gpt-4o-mini",
    input=prompt_string,
    temperature=0
)
text = resp.output_text
```

**Prompt (exact string from the notebook)** The scoring prompt was stored as `FEW_SHOT_PROMPT`. Below is the verbatim content (ellipses appear in the notebook examples):

```
You are an expert in labor economics and AI task analysis.
I will give you an industry (NAICS code + description) and an occupation
(NOC code + description).

Task:
1) Classify the core tasks into exposure categories. Indicate each category with 0/1:
   - E0: No exposure to LLMs.
```

```
   - E1: Direct exposure to LLMs; an LLM alone can reduce task time by 50% without
   quality loss.
   - E2: Exposure via LLM-powered applications; cuts time by 50% when software
   is added on top of an LLM.
   - E3: Exposure with image capabilities; cuts time by 50% whe... LLM is
   combined with systems that read/create/interpret images.
   Rule for 1 vs 0: mark 1 if a non-trivial portion of core tasks falls in that
   category; else 0. Never leave blanks.

2) Provide four 1-10 scores + a 1-10 certainty for each:
   - AI_capability (automation potential)
   - Replacement (displacement likelihood)
   - Augmentation (complementarity likelihood)
...

Output:
722511 - Full-service restaurants,65200 - Food and beverage serv...
and POS enable monitoring; Replacement low; Augmentation modest

Input:
Industry: 622110 - General medical and surgical hospitals
Occupation: 31301 - Registered nurses

Output:
622110 - General medical and surgical hospitals,31301 - Register...
Replacement low; Augmentation high; Monitoring very high via EHR

--- End of examples ---

Now produce one CSV row for the following pair.
```

### Output hygiene and validation

1. Sanitize to a single line: strip code fences/backticks, collapse newlines.
2. Enforce 15 fields: if extra commas appear, overflow text is glued into `Rationale`.
3. Coerce `E0`–`E3` to {0,1}, accepting variants like `true`/`True` as 1.
4. Replace any commas in `Rationale` with semicolons so the CSV stays parseable.
5. Retry on transient errors up to 5 times with exponential backoff and small jitter.

### Two-pass match back to the user data

1. *Exact code join*: extract numeric prefixes via regex, e.g., `industry_code = ^(\d+)`, `occupation_code = ^(\d+)`. Join on the code pair.
2. *Fuzzy rescue*: build `pair_text = Industry || Occupation`. Use RapidFuzz `token_set_ratio` and accept only if similarity $\geq 80$. Record `match_type` $\in$ {`perfect_code`, `imperfect_pair`, `unmatched`} and `match_score`.

### Feature engineering

- Cast `E0`–`E3` to numeric.

- Compute certainty-weighted components and indices defined in Section A1.
- Keep raw counterparts for sensitivity checks.
- Optional roll-ups: derive `naics2` from the first two digits of `industry_code` and summarize by sector.

**Reproducibility and security** Fix seeds when sampling; keep `temperature=0.1`; save the exact prompt used; avoid hard-coded keys; version the prompt, scored CSV, and post-processing scripts; pin library versions (`pandas`, `rapidfuzz`, `openai`).

**Practical interpretation** `ai_exposure_index` blends capability, replacement risk, augmentation, and monitoring, each scaled by certainty. `ai_exposure_negative` removes augmentation for a risk-tilted view. `E_*` indices summarize the binary exposure flags.

### Variable map (as used in code)

- Inputs: `Industry`, `Occupation`
- Flags: `E0`, `E1`, `E2`, `E3`
- Scores: `AI_capability`, `Replacement`, `Augmentation`, `Monitoring`
- Certainties: `AI_capability_certainty`, `Replacement_certainty`, `Augmentation_certainty`, `Monitoring_certainty`
- Weighted components: `ai_capability_ex`, `replacement_ex`, `augmentation_ex`, `monitoring_ex`
- Indices: `ai_exposure_index`, `ai_exposure_index_raw`,

  `ai_exposure_negative`, `ai_exposure_negative_raw`, `E_exposure_index`, `E_exposure_index_0_1`, `E_exposure_index_0_10`

### A.7.3 Descriptives Measuring AI exposure

In this section you will find descriptives about our main measure of exposure to AI and LLM.

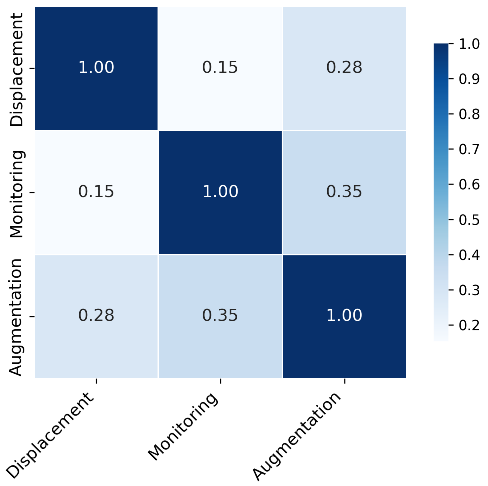
- Figure A.8 displays the pairwise correlations among the three AIexposure measures used in the analysis: displacement, monitoring, and augmentation. The matrix shows that the measures are positively related but not strongly collinear, indicating that each captures a distinct dimension of AI-related task transformation. Displacement correlates moderately with augmentation and weakly with monitoring, while monitoring and augmentation show a slightly stronger association. These patterns support treating the three indices as complementary rather than interchangeable measures of AI exposure in collective bargaining agreements.

- Figure A.9 shows the distribution of the three AI-exposure measures across all collective bargaining agreements in the dataset. Displacement exposure is concentrated at relatively low values, reflecting limited substitutability of human labor for most covered occupations. In contrast, monitoring and augmentation exhibit wider variation, with clear clusters at moderate and higher levels of exposure. These distributions highlight meaningful heterogeneity across agreements and sectors, underscoring that different AI-related task transformations vary in relevance and intensity across occupations.

- Figure A.10 reports average exposure levels by NAICS 2-digit industry for the three AI-related measures. Displacement exposure varies comparatively little across sectors, with most industries clustered at low to moderate values. Monitoring and augmentation show wider dispersion, with professional services, finance, transportation, and information exhibiting some of the highest levels, while sectors such as agriculture, mining, and administrative support show lower exposure. These patterns indicate that the relevance of different AI task transformations is uneven across industries, reflecting variation in occupational mixes and workplace processes.

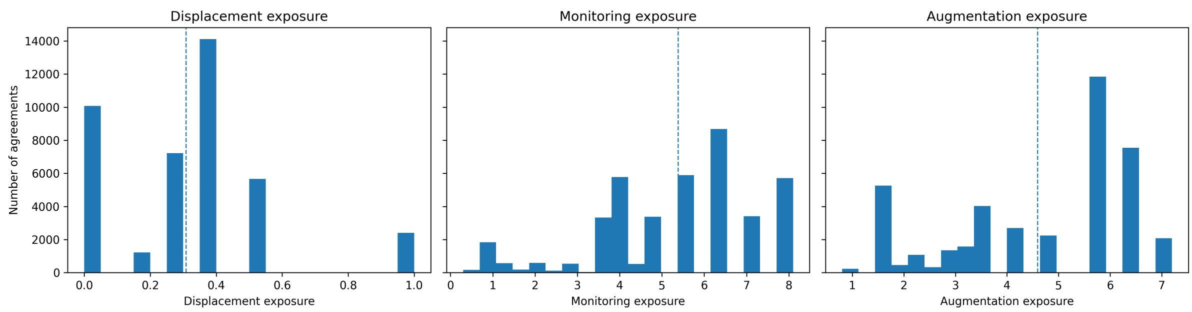
- Tables A.10 to A.14 summarize patterns of AI exposure across major dimensions of the collective bargaining agreement dataset. Table A.14 reports average exposure scores for agreements signed by the twenty largest unions, showing substantial variation in displacement, monitoring, and augmentation across organizations. Table A.13 presents average exposure by jurisdiction, reflecting differences across states and federal categories. Table A.11 shows exposure levels by NAICS sector, while Table A.12 breaks out the same measures by employer size. Together, these tables highlight meaningful heterogeneity in AI-related task exposure across unions, industries, jurisdictions, and firm sizes, underscoring the diverse contexts in which collective bargaining agreements operate.

Figure A.8: Correlation Matrix of Exposure Measures in CBA using LLMs



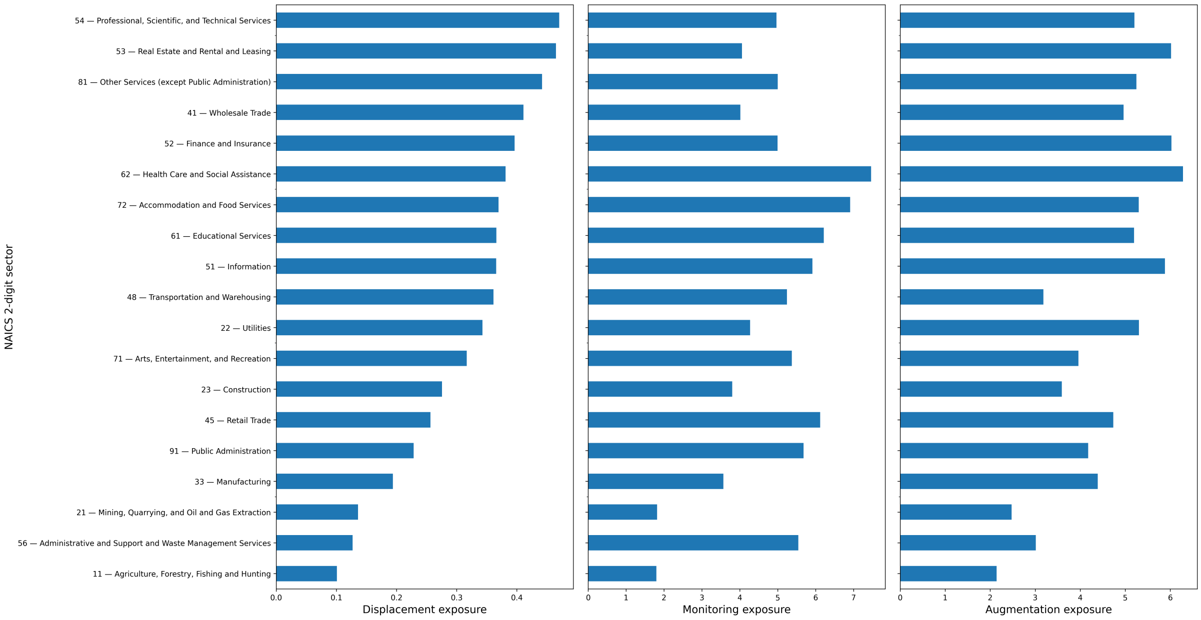

*Note*: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Figure A.9: Frequency of Exposure in CBA




*Note*: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Figure A.10: Frequency of Exposure in CBA by Industry




*Note*: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Table A.11: Collective Bargaining Agreements by NAICS Sector

| Industry | NAICS | CBAs | Share (%) | Displacement av | Displacement sd | Monitoring av | Monitoring sd | Augmentation av | Augmentation sd | Employees av | Employees sd |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Educational Services | 61 | 7296 | 17.9 | 0.37 | 0.13 | 6.21 | 1.46 | 5.2 | 1.39 | 362.87 | 237.21 |
| Manufacturing | 33 | 7191 | 17.6 | 0.19 | 0.18 | 3.57 | 1.6 | 4.39 | 1.64 | 244.85 | 186.47 |
| Transportation and Warehousing | 48 | 7174 | 17.6 | 0.36 | 0.37 | 5.24 | 1.69 | 3.18 | 1.79 | 106.11 | 159.13 |
| Health Care and Social Assistance | 62 | 5117 | 12.6 | 0.38 | 0.06 | 7.46 | 1.01 | 6.29 | 0.93 | 259.25 | 200.01 |
| Public Administration | 91 | 4721 | 11.6 | 0.23 | 0.25 | 5.68 | 0.93 | 4.18 | 1.44 | 243.71 | 230.76 |
| Information | 51 | 2125 | 5.2 | 0.37 | 0.09 | 5.91 | 1.47 | 5.88 | 0.83 | 146.75 | 184.76 |
| Construction | 23 | 1845 | 4.5 | 0.28 | 0.39 | 3.8 | 1.91 | 3.59 | 1.15 | 328.13 | 239.31 |
| Retail Trade | 45 | 821 | 2 | 0.26 | 0.14 | 6.12 | 0.87 | 4.74 | 0.84 | 300.64 | 244.17 |
| Accommodation and Food Services | 72 | 741 | 1.8 | 0.37 | 0.08 | 6.91 | 0.72 | 5.3 | 0.85 | 272.79 | 181.6 |
| Utilities | 22 | 687 | 1.7 | 0.34 | 0.19 | 4.27 | 0.94 | 5.3 | 1.18 | 371.06 | 264.47 |
| Administrative and Support and Waste Management Services | 56 | 630 | 1.5 | 0.13 | 0.23 | 5.54 | 1.5 | 3.01 | 1.66 | 184.12 | 213.8 |
| Mining, Quarrying, and Oil and Gas Extraction | 21 | 484 | 1.2 | 0.14 | 0.29 | 1.82 | 1.6 | 2.48 | 1.48 | 312.99 | 226.9 |
| Arts, Entertainment, and Recreation | 71 | 456 | 1.1 | 0.32 | 0.24 | 5.37 | 1.14 | 3.96 | 1.38 | 229.14 | 207.04 |
| Wholesale Trade | 41 | 423 | 1 | 0.41 | 0.2 | 4.02 | 1.35 | 4.96 | 1.55 | 210.24 | 192.59 |
| Professional, Scientific, and Technical Services | 54 | 367 | 0.9 | 0.47 | 0.23 | 4.97 | 1.02 | 5.2 | 1.81 | 205.8 | 202.27 |
| Finance and Insurance | 52 | 295 | 0.7 | 0.4 | 0.09 | 5 | 1.15 | 6.03 | 0.69 | 187.37 | 229.12 |
| Other Services (except Public Administration) | 81 | 208 | 0.5 | 0.44 | 0.22 | 5 | 0.88 | 5.25 | 1.3 | 214.39 | 170.21 |
| Agriculture, Forestry, Fishing and Hunting | 11 | 141 | 0.3 | 0.1 | 0.24 | 1.8 | 2 | 2.15 | 1.57 | 156.62 | 146.6 |
| Real Estate and Rental and Leasing | 53 | 50 | 0.1 | 0.47 | 0.22 | 4.06 | 0.48 | 6.02 | 0.89 | 218.52 | 269.84 |

*Note*: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Table A.12: Collective Bargaining Agreements by Employer Size

| Size band | CBAs | Share (%) | Displacement av | Displacement sd | Monitoring av | Monitoring sd | Augmentation av | Augmentation sd | Employees av | Employees sd |
|---|---|---|---|---|---|---|---|---|---|---|
| 1-49 | 6574 | 16.1 | 0.335 | 0.303 | 5.148 | 1.767 | 4.015 | 1.86 | 20.275 | 12.763 |
| 50-99 | 2605 | 6.4 | 0.33 | 0.331 | 5.336 | 1.782 | 3.878 | 1.917 | 69.672 | 14.201 |
| 100-249 | 12870 | 31.6 | 0.282 | 0.229 | 5.243 | 1.946 | 4.551 | 1.652 | 157.511 | 41.8 |
| 250-499 | 7011 | 17.2 | 0.293 | 0.221 | 5.276 | 1.978 | 4.647 | 1.66 | 344.627 | 70.554 |
| 500-999 | 4894 | 12 | 0.307 | 0.223 | 5.295 | 1.882 | 4.71 | 1.648 | 683.357 | 137.421 |

*Note*: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Table A.13: Collective Bargaining Agreements by Jurisdiction

| Jurisdiction | CBAs | Share (%) | Displacement av | Displacement sd | Monitoring av | Monitoring sd | Augmentation av | Augmentation sd | Employees av | Employees sd |
|---|---|---|---|---|---|---|---|---|---|---|
| - | 38 | 0.1 | 0.359 | 0.24 | 5.584 | 1.527 | 4.842 | 1.945 | 384.111 | 319.063 |
| Alberta | 3740 | 9.2 | 0.334 | 0.242 | 5.543 | 2.063 | 4.793 | 1.526 | 298.485 | 211.209 |
| Artist Act (Crown) | 109 | 0.3 | 0.369 | 0.122 | 6.15 | 1.381 | 5.77 | 1.181 | 74.5 | 13.472 |
| Artist Act (Private) | 127 | 0.3 | 0.418 | 0.144 | 5.637 | 1.333 | 5.429 | 1.205 | 256 | 214.745 |
| British Columbia | 2887 | 7.1 | 0.272 | 0.235 | 5.096 | 1.792 | 4.405 | 1.635 | 327.854 | 218.511 |
| Canada Labour Code Part I (Crown) | 804 | 2 | 0.312 | 0.211 | 5.029 | 1.526 | 4.415 | 1.654 | 157.545 | 205.393 |
| Canada Labour Code Part I (Private) | 9945 | 24.4 | 0.323 | 0.32 | 5.258 | 1.79 | 3.83 | 1.931 | 86.049 | 137.887 |
| Manitoba | 1186 | 2.9 | 0.345 | 0.226 | 5.93 | 1.932 | 4.97 | 1.442 | 331.057 | 241.657 |
| Multiple Provinces | 109 | 0.3 | 0.327 | 0.341 | 4.558 | 1.904 | 3.969 | 1.755 | 299.967 | 232.409 |
| New Brunswick | 654 | 1.6 | 0.229 | 0.237 | 4.493 | 2.223 | 4.163 | 1.69 | 302.158 | 203.523 |
| Newfoundland and Labrador | 387 | 0.9 | 0.269 | 0.191 | 4.976 | 2.227 | 4.484 | 1.818 | 346.786 | 244.616 |
| Northwest Territories | 39 | 0.1 | 0.343 | 0.2 | 5.708 | 2.617 | 5.044 | 1.671 | 242.704 | 210.81 |
| Nova Scotia | 721 | 1.8 | 0.306 | 0.217 | 5.423 | 2.157 | 4.762 | 1.633 | 362.25 | 239.602 |
| Nunavut | 18 | 0 | 0.667 | 0.243 | 5.3 | 2.173 | 4.433 | 1.698 | 419.417 | 265.957 |
| Ontario | 13116 | 32.2 | 0.294 | 0.188 | 5.749 | 1.944 | 5.021 | 1.686 | 306.518 | 218.798 |
| Parliamentary Employment and Staff Relations Act (PESRA) | 100 | 0.2 | 0.291 | 0.198 | 5.377 | 1.206 | 5.266 | 1.209 | 111.46 | 93.219 |
| Prince Edward Island | 116 | 0.3 | 0.317 | 0.141 | 6.715 | 1.5 | 5.116 | 1.461 | 434.013 | 272.235 |
| Public Service Labour Relation Act (PSLRA) | 784 | 1.9 | 0.534 | 0.277 | 5.191 | 1.08 | 5.326 | 1.425 | 199.968 | 225.928 |
| Quebec | 4978 | 12.2 | 0.278 | 0.2 | 4.678 | 1.823 | 4.717 | 1.584 | 274.081 | 203.534 |
| Saskatchewan | 892 | 2.2 | 0.325 | 0.223 | 5.998 | 2.06 | 4.738 | 1.581 | 326.858 | 225.079 |
| Yukon | 22 | 0.1 | 0.5 | 0 | 6.85 | 1.279 | 4.9 | 0.716 | 702.273 | 117.587 |

*Note*: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Table A.14: Collective Bargaining Agreements by Top 20 Unions

| Union | CBAs | Share (%) | Displacement av | Displacement sd | Monitoring av | Monitoring sd | Augmentation av | Augmentation sd | Employees av | Employees sd |
|---|---|---|---|---|---|---|---|---|---|---|
| Unifor, Independent-national | 958 | 2.3 | 0.301 | 0.259 | 5.103 | 1.978 | 4.394 | 1.871 | 215.4 | 219.471 |
| Alberta Teachers' Association, Independent-national | 632 | 1.6 | 0.5 | 0 | 8.084 | 0.198 | 5.595 | 0.063 | 321.619 | 178.921 |
| Canadian Merchant Service Guild, Independent-national | 448 | 1.1 | 0.735 | 0.279 | 3.625 | 1.582 | 3.686 | 1.139 | 40.924 | 114.726 |
| Christian Labour Association of Canada, Independent-national | 394 | 1 | 0.33 | 0.392 | 5.107 | 1.914 | 3.845 | 1.626 | 214.332 | 212.559 |
| Alberta Union of Provincial Employees, Independent-national | 356 | 0.9 | 0.381 | 0.148 | 5.844 | 1.607 | 5.444 | 1.366 | 297.622 | 211.669 |
| Manitoba Teachers' Society, Independent-national | 329 | 0.8 | 0.491 | 0.04 | 7.921 | 0.692 | 5.581 | 0.501 | 285.408 | 220.976 |
| Saskatchewan Teachers' Federation, Independent-national | 246 | 0.6 | 0.499 | 0.008 | 8.093 | 0.108 | 5.6 | 0 | 284.292 | 225.768 |
| Ontario Secondary School Teachers' Federation, Independent-national | 167 | 0.4 | 0.328 | 0.068 | 6.772 | 0.718 | 4.719 | 1.501 | 198.013 | 188.756 |
| Association des enseignantes et des enseignants franco-ontariens, Independent-national | 124 | 0.3 | 0.387 | 0.101 | 7.135 | 0.923 | 5.081 | 1.548 | 383.595 | 215.005 |
| Federation of Women Teachers' Associations of Ontario, Independent-national | 106 | 0.3 | 0.375 | 0 | 5.6 | 0 | 7.2 | 0 | 497.707 | 245.045 |
| Nova Scotia Teachers Union, Independent-national | 95 | 0.2 | 0.5 | 0 | 7.689 | 1.203 | 5.642 | 0.18 | 403.778 | 230.332 |
| Ontario Public School Teachers' Federation, Independent-national | 76 | 0.2 | 0.301 | 0.062 | 6.591 | 0.796 | 4.584 | 2.166 | 317.621 | 194.165 |
| Ontario English Catholic Teachers' Association, Independent-national | 69 | 0.2 | 0.408 | 0.079 | 6.865 | 1.047 | 5.78 | 1.236 | 318.661 | 218.014 |
| Fédération des syndicats du secteur aluminium, Independent-national | 65 | 0.2 | 0.323 | 0.174 | 4.754 | 1.778 | 4.403 | 1.678 | 249.035 | 197.873 |
| Elementary Teachers' Federation of Ontario, Independent-national | 59 | 0.1 | 0.32 | 0.063 | 6.305 | 0.801 | 5.261 | 2.203 | 446.389 | 204.453 |
| Research Council Employees' Association, Independent-national | 56 | 0.1 | 0.467 | 0.256 | 4.361 | 0.679 | 5.368 | 1.846 | 231.694 | 213.658 |
| L'Association des employés de Malo Transport (1971) inc., Independent-local | 43 | 0.1 | 0.116 | 0.126 | 3.609 | 2.15 | 3.74 | 1.649 | 229.051 | 171.581 |
| Ontario Professional Fire Fighters Association, Independent-national | 40 | 0.1 | 0.044 | 0.096 | 6.4 | 0 | 2.345 | 0.539 | 236.55 | 173.676 |
| Toronto Police Association, Independent-local | 40 | 0.1 | 0.412 | 0.058 | 5.89 | 1.191 | 5.6 | 0 | 323.846 | 358.297 |
| Syndicat de professionnelles et professionnels du Gouvernement du Québec, Independent-national | 32 | 0.1 | 0.355 | 0.072 | 4.625 | 0.773 | 5.45 | 1.675 | 354.143 | 222.024 |

*Note*: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

### A.7.4 Implementing AI Measure on ISCO 08

In addition to the industry–occupation measures described earlier, we extended the approach to the international ISCO-08 classification at the four-digit unit-group level. For each occupation, the model received the full ISCO entry exactly as published, including the ISCO level, the ISCO 08 code, the occupation title, definition, tasks (usually presented as a lettered list), examples of roles included in that unit group, and any accompanying notes. The model was instructed to use only that information to generate the same set of AI exposure indicators and certainty scores, following the exact instructions already described in the previous subsection.

To illustrate the type of input the model processed, consider the ISCO entry for *Legislators*, which includes structured information such as the code, definition, and detailed task list:

> Level 4, ISCO 08 Code 1111, Title Legislators, Definition: Legislators determine, formulate, and direct policies of national, state, regional or local governments and international governmental agencies, and make, ratify, amend or repeal laws, public rules and regulations. They include elected and non-elected members of parliaments, councils and governments., Tasks: Tasks include – (a) presiding over or participating in the proceedings of legislative bodies and administrative councils of national, state, regional or local governments or legislative assemblies; (b) determining, formulating and directing policies of national, state, regional or local governments; (c) making, ratifying, amending or repealing laws, public rules and regulations within a statutory or constitutional framework; (d) serving on government administrative boards or official committees; (e) investigating matters of concern to the public and promoting the interests of the constituencies which they represent; (f) attending community functions and meetings to provide service to the community, understand public opinion and provide information on government plans; (g) negotiating with other legislators and representatives of interest groups in order to reconcile differing interests, and to create policies and agreements; (h) as members of the government, directing senior administrators and officials of government departments and agencies in the interpretation and implementation of government policies., Occupations: Examples of the occupations classified here: – City councillor – Government minister – Mayor – Member of parliament – President (government) – Secretary of State – Senator – State governor, Notes:

Entries such as this were processed one-by-one by the model. For each occupation, it returned a single comma-separated row containing the occupation identifier, the exposure categories, the exposure and certainty scores, and a brief rationale, following the same instructions used for CBAs' analysis. These outputs were then compiled and merged with the ISCO structure to create the final dataset of AI exposure scores at the four-digit occupation level.

### A.7.5 Descriptives AI Measure on ISCO 08

Table A.15: Top 10 ISCO-08 Level 4 Occupations by Augmentation Exposure

| ISCO 08 Code | Title EN | Augmentation |
|---|---|---|
| 2166 | Graphic and Multimedia Designers | 8.1 |
| 4132 | Data Entry Clerks | 8.1 |
| 2642 | Journalists | 8.1 |
| 2413 | Financial Analysts | 8.1 |
| 2511 | Systems Analysts | 8.1 |
| 2431 | Advertising and Marketing Professionals | 8.1 |
| 2310 | University and Higher Education Teachers | 8.1 |
| 2513 | Web and Multimedia Developers | 8.1 |
| 2641 | Authors and Related Writers | 8.1 |
| 4120 | Secretaries (general) | 8.1 |

Table A.16: Top 10 ISCO-08 Level 4 Occupations by Monitoring Exposure

| ISCO 08 Code | Title EN | Monitoring |
|---|---|---|
| 1114 | Senior Officials of Special-interest Organizations | 8.1 |
| 3212 | Medical and Pathology Laboratory Technicians | 8.1 |
| 3251 | Dental Assistants and Therapists | 8.1 |
| 4131 | Typists and Word Processing Operators | 8.1 |
| 2267 | Optometrists and Ophthalmic Opticians | 8.1 |
| 4321 | Stock Clerks | 8.1 |
| 4313 | Payroll Clerks | 8.1 |
| 4414 | Scribes and Related Workers | 8.1 |
| 4416 | Personnel Clerks | 8.1 |
| 5329 | Personal Care Workers in Health Services Not Elsewhere Classified | 8.1 |

Table A.17: Top 10 ISCO-08 Level 4 Occupations by AI Capability Exposure

| ISCO 08 Code | Title EN | AI Capability |
|---|---|---|
| 4131 | Typists and Word Processing Operators | 8.1 |
| 2512 | Software Developers | 7.2 |
| 2631 | Economists | 7.2 |
| 2641 | Authors and Related Writers | 7.2 |
| 2514 | Applications Programmers | 7.2 |
| 2431 | Advertising and Marketing Professionals | 6.4 |
| 2513 | Web and Multimedia Developers | 6.4 |
| 2511 | Systems Analysts | 6.4 |
| 2413 | Financial Analysts | 6.4 |
| 2642 | Journalists | 6.4 |

## A.8 Additional Results CBAs

Figure A.11 turns to who is named in the agreements. Exposure to *smart mobility* increases references to unions and workers while reducing references to firms, pointing to a more collective framing of implementation. *Food ordering* modestly raises worker-oriented language. Meanwhile, exposure to *Embedded systems* technologies tend to reduce mentions of workers and unions and

Table A.18: Top 10 ISCO-08 Level 4 Occupations by Replacement Exposure

| ISCO 08 Code | Title EN | Replacement |
|---|---|---|
| 2131 | Biologists, Botanists, Zoologists and Related Professionals | 5.6 |
| 2120 | Mathematicians, Actuaries and Statisticians | 4.0 |
| 2643 | Translators, Interpreters and Other Linguists | 4.0 |
| 4312 | Statistical, Finance and Insurance Clerks | 4.0 |
| 5223 | Shop Sales Assistants | 3.5 |
| 5244 | Contact Centre Salespersons | 3.5 |
| 5230 | Cashiers and Ticket Clerks | 3.5 |
| 3311 | Securities and Finance Dealers and Brokers | 3.5 |
| 3513 | Computer Network and Systems Technicians | 3.5 |
| 3512 | Information and Communications Technology User Support Technicians | 3.5 |

Table A.19: Top 10 ISCO-08 Level 4 Occupations by Displacement Exposure

| ISCO 08 Code | Title EN | Displacem |
|---|---|---|
| 8312 | Railway Brake, Signal and Switch Operators | |
| 8122 | Metal Finishing, Plating and Coating Machine Operators | |
| 9621 | Messengers, Package Deliverers and Luggage Porters | |
| 7512 | Bakers, Pastry-cooks and Confectionery Makers | |
| 8159 | Textile, Fur and Leather Products Machine Operators Not Elsewhere Classified | |
| 8151 | Fibre Preparing, Spinning and Winding Machine Operators | |
| 7511 | Butchers, Fishmongers and Related Food Preparers | |
| 8183 | Packing, Bottling and Labelling Machine Operators | |
| 8322 | Car, Taxi and Van Drivers | |
| 7114 | Concrete Placers, Concrete Finishers and Related Workers | |

shift focus toward firms.

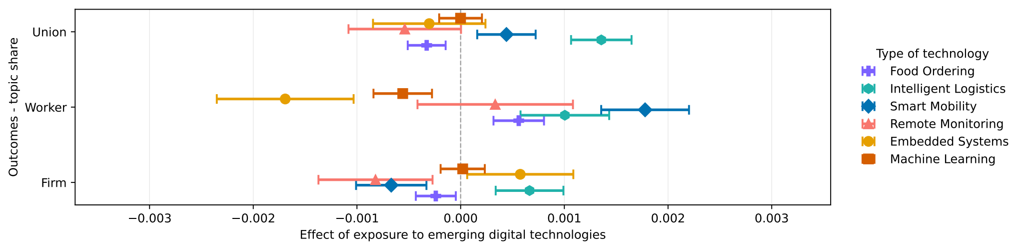



Figure A.11: Exposure to Emerging Digital Technologies and CBAs (1993-2025)
*Note*: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words devoted to each topic relative to the total document length (average length: 13,239 words). In this case, topics refer to the actor emphasized in the agreement-whether it is the worker, the union, or the firm. The independent variables capture exposure to emerging technologies, measured using related patent data at the four-digit NAICS level. All models control for the number of employees and include fixed effects for year and location. The sample of CBAs covers all agreements signed between 1993 and 2025 (N = 40,742). Standard errors are clustered at the employer level. Each panel displays coefficient estimates with 95% confidence intervals.

Actor language exhibits a similar pattern (Figure A.12). Under *augmentation*, references to the *worker* become more frequent, and mentions of the *firm* also rise. With *monitoring*, both actors appear more often, reflecting shared oversight and newly formalized responsibilities. By contrast, under *replacement*, mentions of the *worker* and the *union* decline. In short, when AI is framed as augmenting rather than substituting labor, unions appear to emphasize coordinated responses that involve both workers and firms.

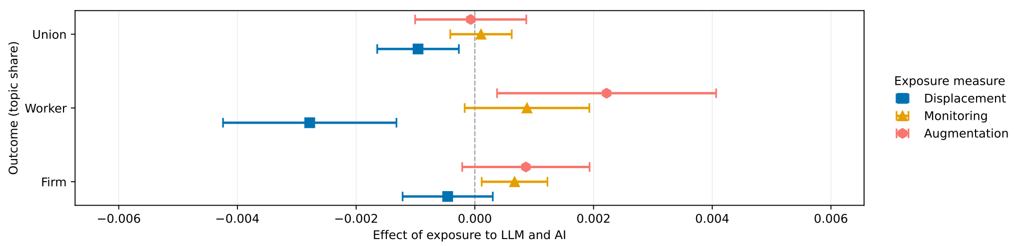
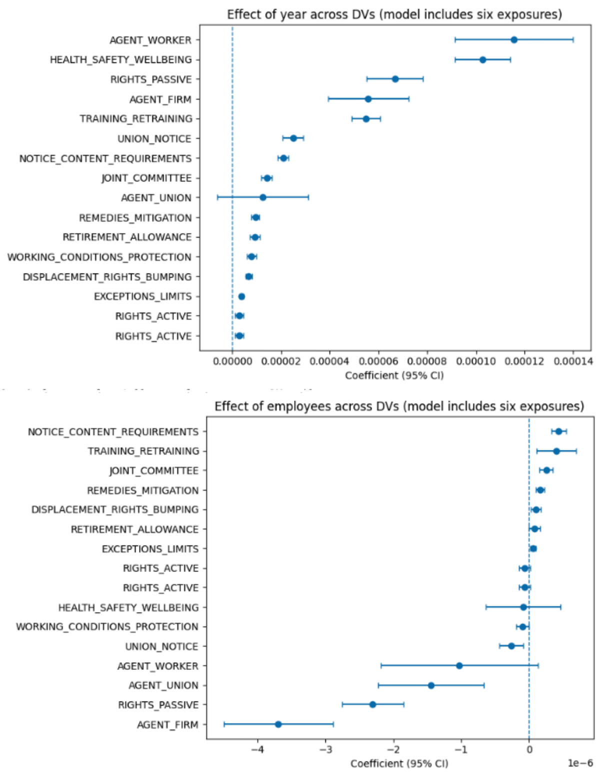



Figure A.12: Predominant Actors Mentioned in AI- and LLM-Exposed Agreements (2022-2025)
*Note*: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words devoted to each topic relative to the total document length (average length: 13,239 words). In this case, topics refer to the actor emphasized in the agreement-whether it is the worker, the union, or the firm. The independent variables measure exposure to LLMs and AI, using an LLM-based classifier that categorizes technologies into three types: augmentation, displacement, and monitoring. Exposure is computed for each industry-occupation pair in the sample. All models control for the number of employees and include fixed effects for year and location. The sample of CBAs is limited to the years 2022-2025 (N = 788). Standard errors are clustered at the employer level. Each panel displays coefficient estimates with 95% confidence intervals.

Figure A.13: Exposure to Emerging Digital Technologies and CBAs




*Note*: Each panel reports coefficient estimates with 95% confidence intervals.