Machines Against Workers? The Heterogeneous Impact of Robots on Union Strength*

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Comments welcome

Abstract

Does the increasing automation of the workplace weaken labor unions? The dominant hypothesis in current political economy research is that automation weakens unions and, as a result, undermines worker voice in democratic politics. However, the standard economic theory of automation does not consider unions, and recent political science studies focus on estimating average effects. We argue that the relationship between automation and organized labor is heterogeneous. We integrate task-based automation into a model of strategic worker mobilization and collective bargaining. Our new model suggests that automation can disempower but also empower unions. Empirically, we use quantile instrumental variable regression and find that the impact of robotization on unionization significantly varies across regional labor markets in the US. Consistent with the theoretical perspective, this heterogeneity is mostly due to unobserved characteristics. Our results suggest that research on the political economy impacts of automation should pay more attention to strategic worker mobilization.

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1 Introduction

Does the increasing automation of the workplace undermine the capacity of workers to organize in labor unions? The answer to this question is relevant for scholars of the workplace and scholars of democratic politics. In the workplace, unions shape wages, working conditions, and wage inequality (Doellgast 2022; Farber et al. 2021; Pontusson, Rueda, and Way 2002). In democratic politics, unions have been linked to preference formation, elections, policymaking, and political equality (Ahlquist 2017; Becher and Stegmueller 2021; Flavin 2018; Hartney and Kogan 2025; Hertel-Fernandez 2025; Kim and Margalit 2017; Leighley and Nagler 2007; Schlozman 2015; but see Rosenfeld 2014; Yan 2025). Crucially, the strength of unions is not set in stone. It has varied widely over time and across space, within and across countries (Naidu 2022; Wallerstein and Western 2000). Technological change may contribute to union decline, foster a revival, or not matter.

The adoption of industrial robots is a leading example of automation technology that substitutes tasks performed by labor with tasks performed by machines. Since the 1990s, the number of robots at work has increased at least four-fold. A booming literature in the social sciences is dedicated to untangling the economic (Acemoglu and Restrepo 2020; Graetz and Michaels 2018) and political consequences of robotization (Anelli, Colantone, and Stanig 2021; Chaudoin and Mangini 2026; Frey, Berger, and Chen 2018; Schöll and Kurer 2024). More recently, the adoption of artificial intelligence (AI) in the workplace and the rise of industrial AI has spurred further debate about the functioning of democratic capitalism (Boix 2019; Gallego and Kurer 2022; Magistro et al. 2026; McElheran, Brynjolfsson, and Kroff 2025; Tan and Thelen 2026).

While scholars have paid less attention to how automation affects labor unions, the dominant view in the nascent literature is that automation is bad for unions. We develop and test the political economy theory that automation can empower as well as disempower unions. It implies that the effects of automation exposure on union strength should be heterogeneous. Using a quantile instrumental variable research design that leverages plausibly exogenous variation in automation exposure, we find that the impact of robotization on unionization significantly varies across regional labor markets in the United States. Our findings underline the importance of strategic worker mobilization and bargaining for understanding the effects of automation on the functioning of democratic capitalism.

Economists have developed an innovative task-based theory for analyzing the impact of technological change on labor demand (Acemoglu and Autor 2011; Acemoglu and Restrepo 2020). In contrast to older models of technological change, it captures that automation enables some tasks previously performed by workers to be performed by more or less intelligent machines. While the task-based approach has revolutionized the study of automation and its economic and political consequences, the standard model has little to say about the impact of automation on labor unions. The (unrealistic) assumption of perfectly competitive markets implies that there is little scope for worker mobilization and collective bargaining over working conditions.

Several recent studies have empirically explored the impact of automation on unions, and theoretical work has started to integrate bargaining into the task-based framework, albeit without directly studying union strength. Research in political science finds that higher exposure of local labor markets to robots weakens unions in the US (Balcázar 2023) and Western Europe (Agnolin et al. 2025). The latter provides evidence for a compositional effect, whereby robotization shifts employment from more to less unionized industries. Moreover, routine-biased technological change is negatively associated with union density across countries (Meyer 2019).[1] One recent theory extends the task model of automation to allow for exogenous wage wedges, showing that firms target automation (inefficiently) to high-rent tasks (Acemoglu and Restrepo 2026). To the degree that rents are due to union bargaining power, this can lead to the targeting of union jobs (Golden 1997). In a similar vein, Leduc and Liu (2024) argue that automation reduces worker power in wage negotiations.

However, we contend that the effects of automation on unions are ambivalent and contingent. Theoretically, worker mobilization and bargaining are missing from most existing accounts of automation. To make progress, we link the automation debate to a longstanding literature on labor unions highlighting the importance of union organization and collective bargaining between firms and unions (for reviews, see Ahlquist 2017, OECD 2019). We integrate strategic union mobilization and collective bargaining into a task model of automation (in the spirit of Acemoglu and Restrepo 2019). Specifically, we set up and analyze a formal model in which a profit-maximizing firm, which employs a task-based production function, bargains with a union over wages under the threat of firm relocation (or capital flight). Crucially, we extend existing models of decentralized collective bargaining (Cahuc and Zylberberg 2004; Hays 2009) by endogenizing the union's efforts to mobilize workers before bargaining as well as the firm's decision to automate in the first place. Our model underlines that automation can empower as well as disempower unions. It recovers the negative impact of automation on unions highlighted in the current literature. But it also shows that the opposite can occur. Automation enhances the strength of unions when it reduces firms' threat to relocate production abroad (e.g., by reducing capital mobility and increasing the dependence on co-located skilled labor). The enhanced bargaining power leads to stronger incentives to mobilize workers to join or form unions.[2]

One important—and so far underappreciated—empirical implication of this logic is that the impact of automation on region-level union strength should be heterogeneous. In theory, how automation shapes union strength depends on several factors, such as the region's cost of capital, integration into global production networks, workers' skills and outside wages, as well as leadership qualities and workers' propensity to organize. These factors are difficult to observe but unlikely to be

[1] Earlier models of skill-biased technological change and unions do not feature job displacement through automation. One theory is that (skill-based) technological change weakens labor unions by undermining wage solidarity (Acemoglu, Aghion, and Violante 2001).

[2] This mechanism is not present in Leduc and Liu (2024)'s closed economy bargaining model without mobilization.

constant across regions. To empirically assess this heterogeneity, we build on and extend work that leverages an instrumental variable to assess the effect of robotization on local economies. Research on robots and manufacturing employment in economics uses arguably exogenous variation in robotization based on robot adoption in the same industries in other advanced economies as an instrumental variable (Acemoglu and Restrepo 2020). This empirical approach has also been applied to outcomes such as voting (Anelli, Colantone, and Stanig 2021; Frey, Berger, and Chen 2018) and union density (Balcázar 2023). Departing from the literature's focus on average effects, our focus is on unbundling the effect of robots on unions and to characterize its distribution. For this purpose, we draw on advances in instrumental variable models for quantile treatment effects (Chernozhukov and Hansen 2006; Chernozhukov, Hansen, and Wüthrich 2020).

We find that the effect of automation in the form of robots on unionization varies significantly across local labor markets. While the average effect is negative, in line with previous research on robotization exposure, we find significant effect heterogeneity. Our estimates reveal that robots are not bad for unions everywhere. Some effects are positive or null, others are negative, and the largest effects are about double the mean effect. This result is robust to excluding the auto industry, which has been most exposed to robots, and to accounting for offshorability of jobs in the region and import exposure. Moreover, we show that the heterogeneity cannot simply be explained by observable socio-demographic characteristics, sectoral composition, state-laws regulating unions, or historical legacies relating to worker organization. This is consistent with the theoretical perspective, which suggests that many factors that shape whether automation weakens or strengthens unions are in the residual.

Recent technological change is often seen as undermining workers' ability to organize, thereby weakening unions as a countervailing power in democratic capitalism, with consequences for economic and political inequality. While we agree that automation technology constitutes a significant challenge to worker organization, we argue that the consequences of automation for organized labor do not reduce to a simple race between productivity-increasing machines versus displaced workers. Strategic worker mobilization and bargaining also matter. The resulting heterogeneous effects imply that automation through robots do not equally weaken unions across the board. But they may increase inequalities in worker mobilization and political representation across regions.

2 Automation, Worker Mobilization, and Collective Bargaining

This section presents our theoretical framework. We begin by sketching the argument. Then we analyze a formal model to sharpen the logic and further motivate the empirical analysis.

2.1 Anatomy of argument

The effects of automation on worker organization work, at least in part, through strategic mobilization and bargaining. In addition to job displacement and efficiency effects that have been the focus of much of the literature on the labor market effects of automation technology, it is important to consider what we call a bargaining effect, which comprises strategic worker mobilization by unions and collective bargaining between firms and unions. Automation shapes what workers can get at the bargaining table, and as such it influences the incentives of unions to mobilize workers and the willingness of workers to remain or join a union.

Following much of recent work, we build on the task-based framework of the automation of work (Acemoglu and Autor 2011; Acemoglu and Restrepo 2020). In this framework, tasks are the "fundamental unit of production". Producing a product requires multiple tasks, and firms choose labor and capital inputs that minimize costs. The production of an electric car, for example, requires completing several production tasks (e.g., building the frame, battery, and engine) as well as non-production tasks like marketing or logistics. The task approach captures that automation enables some tasks previously performed by workers to be performed by machines, such as a robot or software. This is the job displacement effect of automation. At the same time, automation can also make workers in non-replaced tasks more productive, increasing labor demand.

While the task-based framework constitutes a significant advance in the study of automation, it currently has little to say about unions. The standard model assumes perfectly competitive markets (for a review, see Acemoglu and Restrepo 2019), implying no room for collective bargaining. Workers are conceived as atomized individuals whose wages are determined by demand and supply entirely beyond the control of firms. Implicitly, this assumption is also shared by much of the political science scholarship on the political effects of automation. However, this contrasts with research on imperfect competition in labor and product markets (Manning 2021; Yeh, Macaluso, and Hershbein 2022). The evidence on wage markdowns (and price markups) implies that there is scope for bargaining. Moreover, millions of private sector workers in major economies are union members, many more are covered by a collective bargaining agreement, and public support for unions is significant (Ahlquist, Grumbach, and Kochan 2024; Macdonald 2023; OECD 2019).[3]

We argue that it is fruitful to integrate the task-based approach into a model that captures worker mobilization and collective bargaining, connecting to earlier strands of research. To do so, we focus on decentralized, firm-level bargaining common in the United States, Australia, Britain, Canada, New Zealand, or Poland (OECD 2019: 49). We build on and extend the generalized Nash bargaining model with rent-sharing between firms and its employees (Cahuc and Zylberberg 2004: ch.7; Hays 2009). This is the most widely adopted approach to study collective bargaining because

[3]For recent evidence on what type of workplace representation American workers want, see Hertel-Fernandez, Kimball, and Kochan (2022); Mazumder and Yan (2024).

it is grounded in non-cooperative bargaining theory, captures the importance of outside options and asymmetric bargaining power, and can be embedded into richer strategic environments (Cahuc and Zylberberg 2004: 390).

Collective bargaining between employers and unions takes place under the threat of firm relocation (Choi 2006). At the bargaining table, the firm and the union bargain over the allocation of quasi-rents to profits for the firm (or its shareholders) versus wages for workers. The firm wants to maximize profits. Its threat point is the profit it can earn when it moves production abroad (or to a different location in the country). The union cares about wages and employment and its threat point is the outside wage available to workers in the region. In addition to outside wage and the firm's exit option, the general Nash bargaining model captures that the wages workers can negotiate at the bargaining table also depends on other sources of union bargaining power, such as membership mobilization (Abowd and Lemieux 1993; Addison, Portugal, and de Almeida Vilares 2023).[4]

In most collective bargaining models, technology and unions' numerical strength are taken as given. Going further, we endogenize them. Before coming to the bargaining table, firms decide whether to adopt an automation technology and union leaders' decide how much effort to put into organizing workers. Research has shown that the adoption of industrial robots as well as the more recent adoption of AI entails a large capital investment that is undertaken by large and productive firms (Brynjolfsson et al. 2023; Koch, Manuylov, and Smolka 2021). Automation at such firms has spillovers for local economies.

Importantly, technology adoption alters firms' exit threat and thus shapes bargaining and union mobilization. There are several reasons. First, a large investment into physical capital increases the cost of moving production in the short-run. For example, when production is moved, machines must be dismantled, transported and installed at the new location and the workers there must be trained (or the investment has to be written off and the old technology is used). Not surprisingly, prior research has linked asset mobility based on the relative importance of physical capital to taxes levied on firms (Langenmayr and Simmler 2021; Pond and Zafeiridou 2020). Moreover, regulations concerning data sovereignty and data privacy may also limit mobility of AI-based investments.

Second, automation technology can be more productive in their current than in the alternative location. For example, the smooth functioning of robots in the production process is enhanced by specialized companies that integrate robots into the production process, so-called robot integrators, which tend to be concentrated in robot hubs (Brynjolfsson et al. 2023). They may not be as easily available in alternative locations (e.g., their services may be costlier or response times

[4]As do previous models of bargaining but different from the general task model of production, we take a partial equilibrium perspective. We assume that there are rents available for bargaining, consistent with the evidence on imperfect competition, without modeling how they arise.

longer). Relatedly, productivity gains from automation can depend on the spatial co-location of complementary skills used in non-automated tasks or in new tasks created by technological change advancements (Iversen and Soskice 2019).

Looking at the impact of automation on region-level worker mobilization, our theory captures the argument that automation can weaken unions through a compositional mechanism: it displaces workers from unionized jobs without generating offsetting increases in worker mobilization (Agnolin et al. 2025). This occurs when automation destroys more jobs in relatively unionized establishments than it creates in complementary tasks, and when it does not substantially change firms' exit threat, perhaps because the new technology is mobile.

But our theory underlines that automation can also strengthen unions through a bargaining effect, by weakening firms' power at the bargaining table and opening the door for higher union mobilization to get a larger share of the pie. This possibility is not lost on workers and union organizers. For example, in April 2024 workers at Volkswagen's plant in Chattanooga, Tennessee, voted overwhelmingly to unionize (after previously unsuccessful attempts in 2014 and 2019) making it the first successful unionization of a foreign automaker's plant in the US South in recent history. The vote came a couple of years after the company made a heavy investment at the plant into more than 1,000 robots for car body production and battery assembly (Verpraet 2020). "I do not feel that the plant will leave Chattanooga or the South," a worker told a reporter after the vote. "Volkswagen has too much invested in this area." (Boudette 2024)[5] Anticipating the bargaining effect, firms will rationally invest in automation if the productivity-driven profit increase from automation is large enough to compensate for the reallocation of rents at the bargaining table.

The aggregate, region-level impact of automation on unions depends on the importance of the compositional and the bargaining effect. On balance, the theory highlights that the impact of automation is ambivalent. Whether automation empowers or disempowers unions depends on the bargaining situation, characterized by factors such as the dependence of production on co-specific skills, costs of capital and relocation, and firms' abilities to productively use the technology in alternative location. These factors are likely to vary across regional economies. Thus, in the empirical part we study the heterogeneity of the effect of automation on union strength.

2.2 Model

The model considers strategic interactions between a profit-maximizing firm (F) and a union leader (U) in a regional labor market. We extend a standard bargaining model with rent-sharing between firms and its employees (Cahuc and Zylberberg 2004: ch.7), where technology and union strength are taken as given, by incorporating the firm's choice to invest in automation technology at the

[5]For a union organizer's view into strategic mobilization, see McAlevey (2019: ch. 5).

beginning of the game and the union leader's mobilization strategy. The model also captures the threat of firm relocation (Choi 2006; Hays 2009), which shapes bargaining and union mobilization. The firm's leadership represents management or shareholders maximizing profits; the union leader represents workers interested in wages and employment. The firm should be thought of as being a relevant player in the regional economy, as it is generally large companies that are able to make investments in expensive production technology.

To capture that automation can hurt the mobilization of workers in unions through a job displacement effect, we follow the recent literature on automation in economics and adopt a task-based approach to modeling production and automation. We assume that displaced workers go to a different sector with lower unionization. This is in line with recent evidence (Agnolin et al. 2025), descriptive variation in unionization across sectors (Hirsch, Macpherson, and Even 2026), and stacks the deck against the result that automation may nonetheless strengthen unionization in the region. In the task-based approach, tasks are the "fundamental unit of production" (Acemoglu and Restrepo 2019: 6). The production of a good requires a variety of tasks, and automation enables the firm to produce some tasks previously performed by workers to be performed by machines. For tractability, we assume that the production of output y requires two tasks $i \in \{1, 2\}$. The tasks can all be performed by labor. However, the first task is technologically automated. This means that if the firm decides to invest in a new technology at the beginning of the game, a machine (e.g., robots, physical AI, software) will replace workers in the task. The second task can only be performed by labor. Formally, the firm produces outcome y according to the following production function:

$$y = \begin{cases} \min\{\theta_1 l_1^\alpha, \theta_2 l_2^\alpha\} & \text{if } a = 0 \\ \min\{\lambda_1 k_1^\alpha, \theta_2 l_2^\alpha\} & \text{if } a = 1 \end{cases} \tag{1}$$

Without automation ($a = 0$), production uses labor to produce each task in fixed proportions. Labor productivity is higher in the second task ($\theta_2 > \theta_1 > 0$). With automation ($a = 1$), production relies on capital, k_1, for the first task and labor, l_2, for the second task. Inputs have declining marginal returns ($\alpha \in (0, 1)$). The productivity gain from automation is captured by $\lambda_1 > \theta_1$. Total employment in the firm for a given choice about technology adoption (a) is denoted by $L_F(a) = l_1(a) + l_2(a)$. If the firm decides to automate, labor is only used in the second task.

The sequential game consists of the following four stages, and all players observe the history of play:

1. *Automation.* The firm decides whether to make a large capital investment into automation, $a \in \{0, 1\}$. Automation denoted by $a = 1$ and non-automation by $a = 0$. The non-zero cost of the investment is represented by c_a.

2. *Union mobilization.* The union leader observes the firm's decision and then chooses how much effort to put into mobilizing workers to become (or remain) union members. By doing

so, the union leader shapes the relative power of the union at the bargaining table in the next stage, represented by $\delta_F(a) \in [0,1]$. Choosing a higher $\delta_F(a)$ is costly, and we assume a convex and twice differentiable cost function, $c(\delta_F)$.

3. *Bargaining.* The firm and the union leader bargain over wages and employment. Following a well-established literature, the bargain is characterized by a generalized Nash bargaining solution, which depends on each player's outside option or threat point, and the union's relative strength ($\delta_F(a)$).

4. *Relocation.* Finally, the firm decides whether to relocate production, $m \in \{0,1\}$, where staying is denoted by $m = 0$ and moving by $m = 1$.

There is inelastic labor supply L in the region, and workers not employed by the firm are employed at the outside wage x, which can be thought of as the expected income from finding employment elsewhere and from being unemployed and receiving whatever level of income support is provided by the state. To capture the threat of job displacements for unions, we assume union strength is lower in the rest of region than inside the firm in the absence of automation, $\delta_O \leq \delta_F^*(0)$. Average union strength in the region, called $\bar{\delta}$, can be conceptualized as an employment weighted average between union leader's best-responding mobilization effort at the firm, $\delta_F(a)^*$, and union mobilization elsewhere in the regional economy, δ_O, which we take as given:

$$\bar{\delta}(a) = \frac{L_F(a)^*}{L}\delta_F(a)^* + \frac{L - L_F(a)^*}{L}\delta_O. \tag{2}$$

In this extensive form game, the analysis focuses on subgame perfect Nash equilibrium concerning the firm's strategy on automation and relocation, (a^*, m^*), and the union leader's mobilization strategy, $\delta_F^*(a)$. Employment and wages are characterized by the Nash bargaining solution, which accounts for the firm's relocation strategy.[6]

2.3 *The firm's decision to relocate*

At the last stage, the firm moves production if the expected profit from the move is strictly larger than the profit from staying and implementing the employment and wage level agreed at the bargaining table with the union. If the firm did not pursue automation ($a = 0$), which means both tasks are produced by labor and total firm employment is $L_F^* = l_1^* + l_2^*$, the profit from producing at home is $\Pi(a = 0) = y(l_1^*, l_2^*) - w^* L_F^*$, where the price of the output y, produced according to the task-based production function (equation 1), is normalized at one, and w^* is the uniform wage negotiated with the union. If the firm automated task 1 ($a = 1$), task 1 is performed by capital and

[6] Under automation, as will become apparent below, given the production function and efficient bargaining k_1 is residually determined by the choice of l_2^*.

task 2 by labor. Before the fixed cost of adopting the automation technology, c_A, the profit from keeping production at home is $\Pi(a = 1) = y(k_1^*, l_2^*) - wl_2^* - rk_1^*$, where capital k_1^* is remunerated at exogenous rate $r \leq x$. The profit from moving is denoted by $\Pi_m(a)$. It is a function of the firm's automation decision and it includes the non-zero cost of relocation, which may vary with the capital investment in automation. As a special case, it includes the zero profit condition used as the threat point in models without offshoring. Following Choi (2006) and others, we do not model how wages and employment are set in the alternative location.[7]

2.4 What do workers get at the bargaining table?

Working backwards, we next analyze bargaining over wages and employment for a given automation decision and union leader's mobilization effort. The union leader wants to maximize worker utility based on total employment in the firm, $L_F(a)$, and uniform wage, w, subject to the threat point that workers can be employed outside the firm at alternative wage x. The firm wants to maximize profits ($\Pi(a)$) subject to exit threat of moving production and earning the alternative profit ($\Pi_m(a)$). The bargaining outcome depends on players' outside options and the union's prior mobilization effort. This is captured by the generalized Nash bargaining approach. Accordingly, labor L_F and wage w are chosen to maximize $\big(L_F(w-x)\big)^{\delta_F(a)}\big(\Pi(a)-\Pi_m(a)\big)^{1-\delta_F(a)}$, where $\delta_F(a)$ is the parameter capturing the strength of the union, resulting from the union leader's mobilization effort before bargaining. The left term in the Nash formulation includes the union leader's goal of employment and wages as well as the alternative x as the threat point. The right term represents the firm's profit-maximizing objective and the firm's exit threat is captured by the profit earned after moving.

Regarding automation, there are two different scenarios, one in which the firm did not adopt the automation technology ($a = 0$) and another in which it did ($a = 1$). In each case, the bargaining problem can be expressed as function of two endogenous variables, labor input into task 2 (l_2) and the wage (w), as the efficient use of complementary inputs across tasks in the production function implies that they are used in fixed proportions (see Online Appendix A.1). If the firm's profit from relocation is larger than the profit at home when the union leader accepts the lowest feasible wage given the outside wage x, then there is no interior bargaining solution. In what follows, all analyses focus on an interior solution where non-trivial bargaining takes place and the firm is better off staying at the end of the game. The relocation threat nonetheless matters and forces the union leader to be more accommodating. The exit option matters, but is not so attractive to exclude the making of a deal.

In general, the solution to the bargaining problem underlines that the negotiated wage is sensitive to the outside wage, the union's bargaining strength, and the firm's threat point. If the firm did

[7] For instance, labor rights or the productivity of labor and capital may differ (Mosley 2010).

not automate at the start of the game, the negotiated wage is

$$w^*(a=0) = x + \delta_F(0)\left(\frac{1-\alpha}{\alpha}x - \frac{\Pi_m(a=0)}{L_F^*(a=0)}\right). \tag{3}$$

Employment in task 2 is $l_2^* = \left(\frac{\alpha\theta_2}{\phi x}\right)^{1/(1-\alpha)}$, and total employment is $L_F^*(a=0) = \phi l_2^*$, where $\phi \equiv 1 + \left(\frac{\theta_2}{\theta_1}\right)^{(1/\alpha)}$ is a multiplier reflecting the complementarity of labor inputs across tasks. Bargaining is efficient in the sense that employment, and thus firm output, is shaped by the productivity of labor (and capital) inputs but not union bargaining power. If the firm did decide to automate, the bargaining solution is

$$w^*(a=1) = x + \delta_F(1)\left(\frac{1-\alpha}{\alpha}\left(x + r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}\right) - \frac{\Pi_m(a=1)}{L_F^*(a=1)}\right). \tag{4}$$

Workers are employed only in task 2, as task 1 is performed by machines, and total employment in the firm is $L_F^*(a=1) = \left(\frac{\alpha\theta_2}{x+r(\theta_2/\lambda_1)^{1/\alpha}}\right)^{1/(1-\alpha)}$. Crucially, the firm's outside option and the union's mobilization effort depend on the prior automation decision. Now we are in a position to analyze how automation shapes worker mobilization and union strength.

2.5 How does technology adoption shape worker mobilization and union strength?

At the mobilization stage, the union leader takes the firm's automation decision as given and anticipates what happens at the bargaining table. The union leader chooses the mobilization effort $\delta_F(a)$ to maximize the negotiated wage w subject to cost function $c(\delta_F)$.[8] This formulation captures that mobilization is hard work for the leader. In practice, this includes holding meetings with workers, identifying leaders and holdouts, addressing union busting, preparing for strikes, and engaging local stakeholders (McAlevey 2019). The cost of mobilizing depends on leadership quality (Ahlquist and Levy 2013) as well as workers' pre-existing propensity to organize, which is shaped by policies and institutions regulating union formation (Feigenbaum, Hertel-Fernandez, and Williamson 2018), beliefs about the feasibility of collective action (Rothstein 2022), intergenerational transmission of the taste for unions (Ahlquist and Downey 2023), or social networks (Naidu 2022). Given an interior solution to the bargaining problem, at the union leader's best response the marginal cost of mobilization is equal to the marginal wage gain from mobilization.[9]

[8] There are several ways to micro-found the choice of δ. Building on models of political participation (Herrera, Morelli, and Nunnari 2016), one approach is to consider non-strategic workers facing heterogeneous costs and benefits of membership and a strategic leader choosing mobilization effort; group models with ethical motivations provide another approach.

[9] Given efficient Nash bargaining over wages and employment, the focus on w is without loss of generality: δ_F changes the distribution of quasi-rents but not employment.

This logic highlights that the union leader's mobilization effort increases in the outside wage and decreases in the firm's profit from relocation normalized by labor input at the current location, which may both vary with automation. Formally, the conditions characterizing the union leader's best-responding mobilization strategy for the case without and with automation can be written as:

$$c'(\delta_F) = \frac{1-\alpha}{\alpha}x - \frac{\Pi_m(a=0)}{L_F^*(a=0)} \tag{5}$$

$$c'(\delta_F) = \frac{1-\alpha}{\alpha}\left(x + r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}\right) - \frac{\Pi_m(a=1)}{L_F^*(a=1)} \tag{6}$$

From these two conditions, it is straightforward to deduce when the adoption of automation technology increases the union leader's mobilization effort. The result is summarized in Proposition 1. In substantive terms, it states that automation increases the union leader's effort to mobilize workers when, after automation is adopted, the firm's threat to exit by relocating production becomes relatively less attractive than it would be without automation. We call this the bargaining effect of automation. (All proofs are in Online Appendix A.1.)

Proposition 1. *The adoption of automation technology by the firm increases the union leader's mobilization effort if it reduces the firm's relocation threat. Formally,* $\delta_F(1)^* > \delta_F(0)^*$ *if* $\frac{\Pi_m(0)}{L_F^*(0)} - \frac{\Pi_m(1)}{L_F^*(1)} + (\frac{1-\alpha}{\alpha})r(\frac{\theta_2}{\lambda_1})^{1/\alpha} > 0$*, and* $\delta_F(1)^* < \delta_F(0)^*$ *if the inequality is reversed.*

The first part on the right-hand side of the condition contains the change in relocation profits per worker due to technology adoption. The second part accounts for how automation changes the scope for rents, which are split at the bargaining table, through the use of capital. Since the second part is always positive, automation can increase mobilization even when it increases firm's absolute relocation profit ($\Pi_m(1) > \Pi_m(0)$), as long as the productivity gains in the current location are sufficiently large. Automation strengthens unions when it makes the firm more profitable in its current location compared to its outside option.

At the local economy level, the effect of automation on union strength depends on both employment effects and bargaining effects. The impact of technology adoption on region-level union strength is captured by the difference between average union mobilization in the region with and without automation, $\bar{\delta}(1) - \bar{\delta}(0)$. After substitution, this can be written as

$$\bar{\delta}(1) - \bar{\delta}(0) = \frac{L_F(1)^*}{L}\left(\delta_F(1)^* - \delta_O\right) - \frac{L_F(0)^*}{L}\left(\delta_F(0)^* - \delta_0\right) \tag{7}$$

where union mobilization elsewhere in the local economy, δ_O, is taken as given. For a moment, assume that there is no strategic response of the union leader to automation, so mobilization effort is constant (i.e., $\delta_F(1) = \delta_F(0)$). Then all that matters is the relative balance of job displacement in automated tasks and job growth in non-automated tasks due to higher productivity, captured by the difference between total firm employment due to automation. This is a compositional effect.

If the job displacement effect is larger, unionization declines because of a shift of workers from more to less unionized establishments. If the productivity effect is larger, unionization grows. However, the model underlines that this comparison is incomplete. It is not generally the case that the union leader's optimal mobilization effort is the same with and without automation.

To account for both compositional and strategic effects, consider how regional-level union strength is shaped by an exogenous automation shock. This mirrors the focus in many empirical studies on arguably exogenous changes in technological diffusion. Proposition 2 summarizes the core implication of our theory that the effect of automation on region-level union strength is ambivalent.

Proposition 2. *The effect of automation on region-level union strength is ambivalent. Assuming $c(\delta_F) = \frac{1}{2}\delta_F^2$, the effect of an exogenous automation shock is positive if the following condition holds and negative if it is reversed:*

$$\Pi_m(0) - \Pi_m(1) > L_F^*(0)\left(\frac{1-\alpha}{\alpha}x - \delta_O\right) - L_F^*(1)\left(\frac{1-\alpha}{\alpha}\left(x + r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}\right) - \delta_O\right).$$

The condition balances two channels through which automation affects regional union strength. The left-hand side, $\Pi_m(0) - \Pi_m(1)$, captures how automation changes the firm's relocation threat. When positive, automation reduces the firm's outside option—for instance, because automated production depends more on co-located skilled labor or because physical capital investments are costly to relocate. The right-hand side captures the employment composition effect, weighted by mobilization incentives not related to the firm's outside option. Each term represents employment at the firm, $L_F^*(a)$, weighted by the scope for mobilization above the regional baseline, δ_O, given the production technology and factor costs. This term reflects both direct employment changes (job displacement in automated task 1 versus productivity-driven gains in complementary task 2) and how automation affects the technological scope for rent extraction through changes in the capital-labor ratio and factor costs.

Proposition 2 underlines that the claim about the firm's outside option is relative to what happens if the firm does not relocate. If the productivity gain from automation is large, the right-hand side term is negative. Then automation can strengthen unions even when $\Pi_m(1) > \Pi_m(0)$ as long as it increases the firm's relocation profit less than it increases potential quasi-rents from staying.

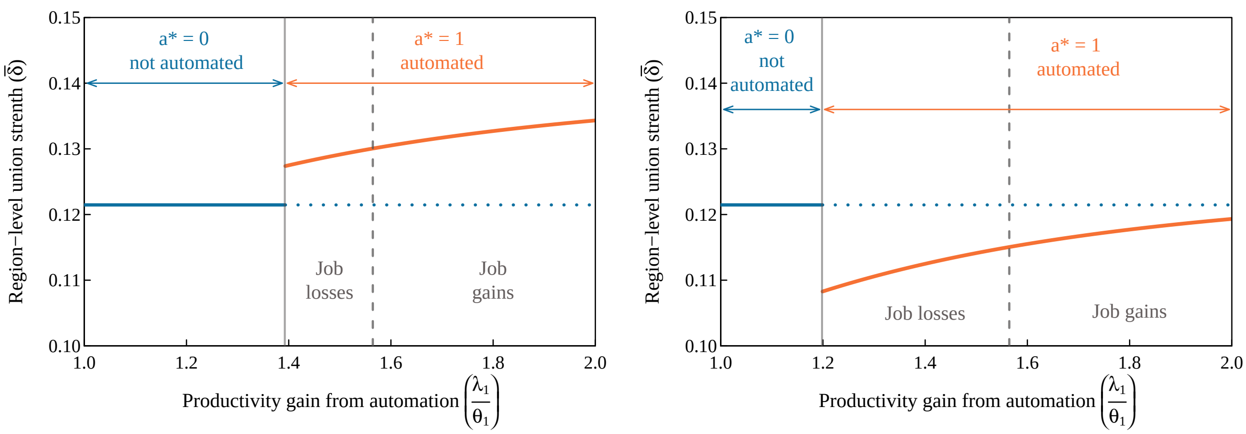
Going one step further, the model captures that the firm optimally chooses whether to automate or not—anticipating the union leader's mobilization strategy and collective bargaining. The firm automates if it is profitable to do so, $\Pi(1)^* - c_a > \Pi(0)^*$, given expected outcomes with and without automation. In equilibrium, three different outcomes can emerge. First, the firm decides not to automate. This occurs if the expected productivity gains are small relative to costs. It can also occur if there are sizable productivity gains but the firm believes that it will have to share too much of them with workers at the bargaining table. Second, the firm automates and region-level union strength declines. Third, the firm automates and region-level union strength increases.

Proposition 3 states that the equilibrium effect of automation on union strength remains ambivalent when automation is endogenous.[10] Under some conditions, the firm will automate despite anticipating increased rent-sharing with a stronger union at the bargaining table. This occurs when automation makes the firm's outside option less attractive relative to producing at home, so that the bargaining effect boosts worker mobilization, but productivity gains from automation are

[10]The proof in Appendix A.1 solves the profit condition given optimal behavior in subsequent nodes of the game.

sufficiently large so that the relative decline in the firm's bargaining power is compensated by increased productivity and profits. Under other conditions, the firm's automation decision is more straightforward because automation increases productivity and strengthens the firm's relative bargaining power by making its outside option more attractive.

Proposition 3. *When automation is endogenous, the equilibrium effect of automation on regional union strength remains ambivalent. The effect is positive if the firm chooses to automate and the condition from Proposition 2 holds.*



(a) Automation strengthens unions **(b) Automation weakens unions**

Figure I
Varying equilibrium effects of automation on region-level union strength

Note: The solid line shows expected regional-level union strength under different scenarios. The only difference is the firm's outside profit under automation: in panel (a), $\Pi_m(a = 1) = 2.5 \cdot \Pi_m(a = 0)$ (before c_a), and in panel (b) $\Pi_m(a = 1) = 4 \cdot \Pi_m(a = 0)$. Calculated using the following parameter values: $\alpha = 0.5$, $\theta_1 = 100$, $\theta_2 = 105$, $x = r = 0.25$, $c_a = 1500$, $\Pi_m(a = 0) = 1000$, labor supply $L = 100,000$, union leader cost function $c(\delta_F) = \frac{1}{2}\delta_F^2$, and union mobilization outside the firm $\delta_x = 0.1$.

Accounting for the firm's optimal automation decision, Figure I illustrates the equilibrium impact of automation on region-level union strength as a function of the productivity gain from automation in task 1 (θ_1/λ_1) for plausible parameter values. Panel (a) shows that automation can *increase* region-level unionization through a reduced threat of firm relocation even when the effect of automation on the firm's employment is neutral or negative, though it becomes larger when the efficiency gain from automation increases. If the productivity gain from automation is relatively small, the firm does not automate. One reason is that the firm knows that automation increases the power of the union at the bargaining table. Once the productivity gain becomes large enough, it is a best response for the firm to pursue automation nonetheless. There is a discontinuous jump in mobilization effort once the firm switches to machines. Panel (b) show the opposite case. If automation enhances the firm's relocation threat, bargaining power and worker mobilization decline. The effect is mitigated as the new technology become more productive.

Because the firm anticipates the bargaining effect, the productivity threshold for technology adoption (the solid vertical line) varies in the two cases. It is lower when the bargaining effect hurts rather than benefits worker mobilization. Figure I also illustrates that automation may shape union strength even if it is employment neutral (the dashed vertical line), which occurs when the job displacement effect and productivity effect cancel each other out. In this case, the bargaining effect alone can increase (decrease) unionization in the region due to an increase (reduction) in the mobilization effort at the intensive margin.

Our theoretical analysis suggests a new direction for the empirical study of automation and worker organization. While recent studies provide credible evidence of a negative effect of automation through robots on region-level union strength (Agnolin et al. 2025; Balcázar 2023), our theory suggests that the impact should be heterogeneous. Proposition 2 and 3 underline that whether automation strengthens or weakens unions depends on the interplay of several region-specific factors: how automation affects the firm's relocation threat, the magnitude of productivity gains and job displacement, the cost of capital, workers' outside options, and unionization in the rest of the economy. These factors are shaped by the region's integration in technology hubs, global value chains, skill composition, propensity of workers to unionize, among others—characteristics that vary substantially across local economies and are not straightforward to measure. Thus, we are interested in the distribution of effects, not only the average effect.

3 Empirical strategy

Our main empirical analysis estimates the distribution of effects of robotization exposure on union strength in local labor markets in the US. Between the early 1990s and 2007, the stock of industrial robots grew about fourfold in the US and other advanced economies in Western Europe for which comparable data is available (Acemoglu and Restrepo 2020). We examine the effects of robotization on union membership at the level of 722 regional labor markets, called commuting zones, in the continental US. This enables us to disentangle technological change from other economic changes that may affect unionization, such as import competition (Autor, Dorn, and Hanson 2016; Ahlquist and Downey 2023).

Our theory has stressed the fact that the impact of automation technology on union organization is shaped by a host of region-level factors, many of which are not easy to measure. Thus our empirical strategy focuses on characterizing this distribution rather than investigating a set of interactive regressions. In a subsequent step, we explore whether observed characteristics explain the heterogeneity.

3.1 Data and variables

Union strength To measure union strength we draw on administrative data on unions compiled by Becher, Stegmueller, and Kaeppner (2018) and used in other research on the effects of automation and import competition on unions (Balcázar 2023; Becher and Stegmueller 2026). They use mandatory reports, so-called LM forms, filed by each local union to the Department of Labor each year, excluding the public sector. Each report includes the union's membership size and address. Based on more than 350,000 individual reports covering almost 30,000 unions, the count of union members was mapped onto commuting zones based on the unions' geolocation. A comparison of LM-form data aggregated to the state level with CPS-based union density estimates reveals a very high degree of correspondence. We define union density as the share of union members among the working population in a given commuting zone. Panel (a) of Figure II shows changes in (logged) union density during the exposure period. The histogram reveals considerable variation across commuting zones. While the plurality of commuting zones experienced declining union density, a sizable number saw moderate to large increases.[11]

Robotization To measure a geographic unit's exposure to robotization, we follow the seminal approach of Acemoglu and Restrepo (2020). Using data from the International Federation of Robots, they first measure the growth industrial robots at the industry-level (approximately the three-digit level for manufacturing and two-digit in other sectors). Second, they measure each regional unit's exposure to robotization through a shift-share approach, which weights each industry's growth in robots with the industry's employment share in a given unit. Panel (a) of Figure III plots the intensity of robotization exposure across commuting zones in the early 2000s. Robotization is geographically clustered and heavily driven by the automotive industry (a point we return to below). Many of the commuting zones most exposed to robotization are in the corridor from Michigan to Indiana to Tennessee, with the Detroit-Flint and Saginaw-Bay City–Midland as well as the Indianapolis-Muncie labor markets being the most exposed. However, there is considerable variation across commuting zones (and within states).

Endogeneity is a challenge for scholars trying to estimate the effect of robotization on unions. As the literature documents, and panel (a) of Figure III illustrates, robotization is not randomly distributed across the US geography (Brynjolfsson et al. 2023). Robots may cluster in places where unions are strong to begin with for multiple reasons. For instance, firms in more productive areas should find it easier to pay union wages and compete internationally, and for the same reasons be able to shoulder expensive investments into industrial robots. Perhaps unions increase efficiency by addressing commitment problems, fostering skill formation, or reducing workplace turnover (Freeman and Medoff 1984). On the other hand, firms may also be tempted to use robots to replace

[11] Note that we also examine our results when using a definition of union density change where we express changes in union membership relative to a fixed denominator (the year 2000 employed population). See Appendix A.3.

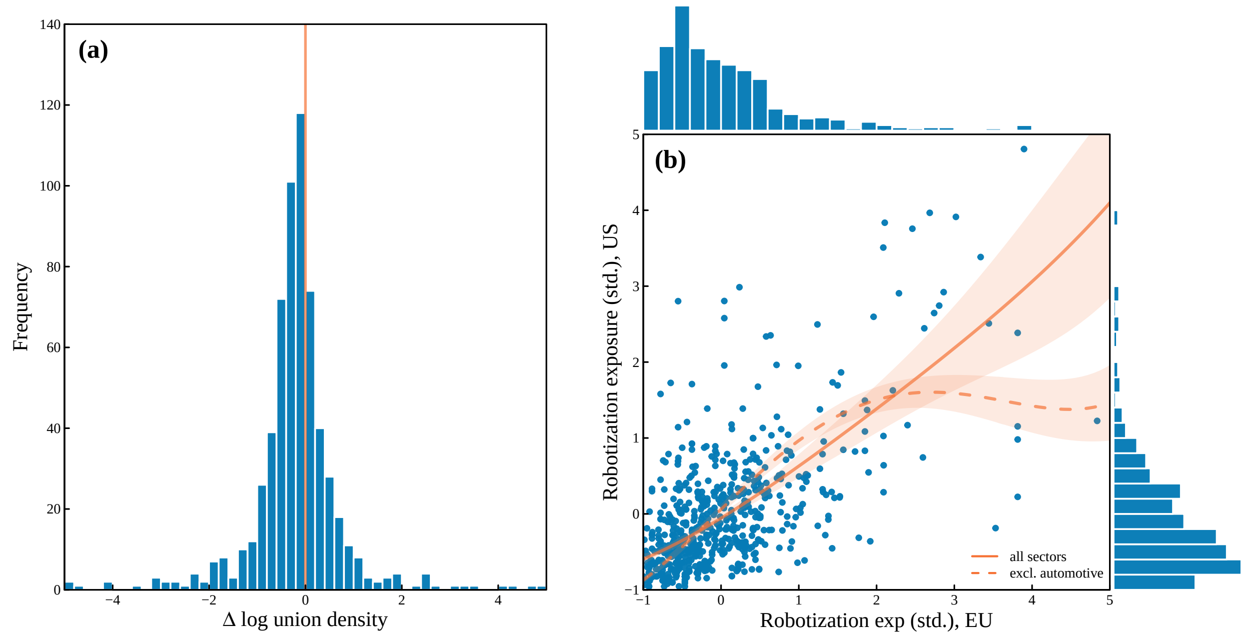


Figure II
Distribution of key variables

Note: Panel (a) plots a histogram of commuting zone-level changes in union density. Panel (b) plots (standardized) 10-year equivalent robotization exposure on the US (y-axis) against its instrument (x-axis): 10-year equivalent robotization exposure in five large EU countries. Superimposed in orange are polynomial smoothers (using 4th degree polynomials). The solid line represents the relationship between exposure and instrument calculated using all industrial sectors as in Acemoglu and Restrepo (2020); the dashed line represents the relationship computed using an alternative measure which excludes the automotive sector.

unionized workers or strategically invest where labor unions are weak to avoid having to share the productivity gains from automation with workers.

To mitigate the endogeneity problem, we leverage arguably exogenous variation in robotization across regions over time. While it is not possible to randomize robotization at national scale, we build on the approach of Acemoglu and Restrepo (2020) and employ an instrumental variable for commuting zone-level robot exposure based on robotization at the industry-level in five other advanced economies. Panel (b) of Figure II plots the exposure in the US against the instrument with marginal densities shown as histograms on both axes. The solid red line represents a polynomial smoother and shows a strong and almost linear relationship.

As mentioned above, robotization is heavily driven by capital investments made by the auto industry. This is the case both in the US and in Europe. Calculating Rotemberg weights for each industry (following the approach in Goldsmith-Pinkham, Sorkin, and Swift 2020) reveals the considerable influence the automotive sector can have on estimates. The Rotemberg weight for the automotive sector is 0.764, while the next highest weight (for Plastics and Chemicals) is only 0.167. The remaining weights are quite low (< 0.04; cf. table A.1 in the appendix). It is thus

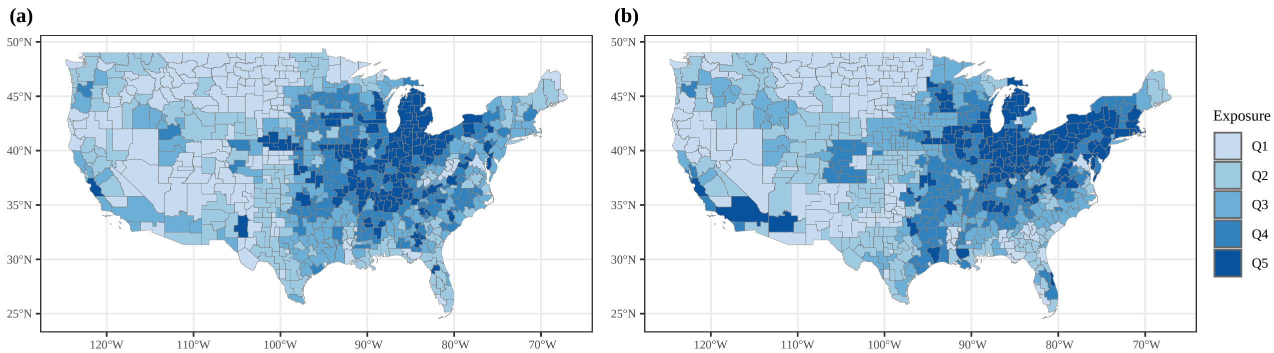


Figure III
Exposure to industrial robots in the US.

Note: The map shows 10-year equivalent changes for commuting zone-level robotization exposure measured for 2004-2007. Panel (a) includes all industries. Exposure in panel (b) calculated without automotive sector. Color coding corresponds to quintiles of each exposure.

germane to ask if the relationship between union strength and robotization is *solely* driven by the automotive sector and if previous results regarding robotization apply to other industries (Gallego and Kurer 2022: 468). Thus, we calculate an alternative measure of exposure and a corresponding instrument that excludes the automotive sector and allows us to use the variation in robotization outside the automobile industry. The dashed line in panel (b) of Figure II shows the polynomially smoothed relationship using the alternative measure. The biggest difference emerges at the top of the distribution, now truncated due to the absence of heavily exposed car manufacturing areas. Panel (b) of Figure III shows the spatial distribution. The main pattern still follows panel (a) due to auto-industry suppliers, though relatively higher exposure is now evident in areas like the Erie-to-Buffalo corridor and the Hartford-Stamford labor market, suggesting we can examine the effect of robotization even when excluding the car industry

With measures of exposure and suitable instruments in hand, we can ask whether the arguably exogenous change in robot exposure affects changes in union density. Going beyond existing work, we are not only interested in the average effect of robotization but in its heterogeneity. This is why we adopt a quantile instrumental variable approach, as is explained in more detail below.

Controls In some specifications we adjust for a low dimensional vector of commuting zone level controls produced via dimension reduction of a large number of district characteristics (see Appendix A.2.6). Sociodemographic controls are calculated from the 2000 Census SF1 and SF3 files and mapped to commuting zones. We account for the share of the Black and Hispanic population, the share of women, foreign born, highly educated (with college degree and above). We also account for employment in construction, manufacturing, and the share of women employed in manufacturing. In extended specifications, beginning-of-period offshorability is measured following Autor and Dorn (2013). Note that the measure is one of *potential offshorability*, i.e., a measure to what extent jobs in a given district are likely at risk of outsourcing, not one of jobs actually lost (Autor and Dorn 2013: 1584). In the light of research on important competition and union strength (Ahlquist and Downey 2023; Becher and Stegmueller 2026), we also estimate models where we adjust for either pre-treatment levels or for changing levels of Chinese import exposure calculated from the data provided by Autor, Dorn, and Hanson (2016).

3.2 Estimating heterogeneous treatment effects

In this section we describe how we estimate the heterogeneous effect of automation on union density using an instrumental variable quantile treatment effect estimator (Chernozhukov and Hansen 2005, 2013; Chernozhukov, Hansen, and Wüthrich 2020). A more detailed technical discussion is available in Appendix A.2. Quantile regressions allow us to study the impact of automation at different points of the outcome distribution. Rather than estimating a single average effect of robotization—which, as our theory suggests, may mask important variation—we estimate how the effect differs across the distribution of an unobserved 'proneness' toward unionization. Commuting zones that are otherwise similar in observed characteristics may differ in hard-to-measure features of their bargaining environment, such as firms' relocation options, or union leadership quality. The quantile treatment effect (QTE) captures how robotization shifts the outcome at different points of this unobserved heterogeneity distribution. Formally, the QTE is defined as $QTE(\tau) = Q_{Y_d}(\tau|x) - Q_{Y_{d'}}(\tau|x)$, where $Q_{Y_d}(\tau|x)$ represents the τ-th conditional quantile of the potential outcome variable Y_d under robotization exposure d conditional on covariates, and $Y_{d'}$ denotes a counterfactual (e.g., lower) level of exposure (cf. Appendix A.2.1).

As in prior studies and noted above, we address the endogeneity of robotization exposure by (i) estimating the model in differences, thus accounting for time-constant commuting-zone level unobservables, and (ii) by using an instrumental variable, discussed above, that is correlated with robotization exposure but independent of the unobserved heterogeneity in potential outcomes. The analysis of heterogeneous effects rests on three key identifying assumptions: a standard IV independence assumption (potential outcomes are independent of the instrument conditional on covariates), a monotonicity assumption of the quantile functions (the quantile functions for each robotization level are strictly increasing in τ conditional on covariates), and assuming rank similarity (in unobservables) across treatment states.

Substantively, the latter requires that a commuting zone's relative position in the unobserved proneness-to-unionize distribution does not systematically shift depending on the level of robotization exposure it receives. Firms may adopt robots based on unobservable local characteristics. This is why we need an instrument. But their investment decisions should not be based on precise knowledge of how a specific commuting zone would rank in unionization outcomes relative to others at a particular exposure level. This allows for noisy variation in ranks across exposure levels while ruling out the exact sorting that would undermine identification. This assumption is consistent with the theoretical model in Section 2, where firms optimize over their own expected profits given local conditions, including productivity gains, relocation options and expected bargaining outcomes. They do not select into automation based on their local economies' relative position in the cross-sectional distribution of unionization residuals. Moreover, the instrument isolates variation in robotization driven by technological change in other countries. It further limits the scope for the kind of domestic cross-regional sorting that could shift residual ranks. Appendix A.2.2 provides a formal discussion.

In our empirical analysis, we use the following linear-in-parameters specification: $Q_{\Delta y_i}(\tau) = d_i\alpha(\tau) + x_{i0}'\beta(\tau)$. Here, $d_i \equiv \Delta R_i$ is the 10-year equivalent change in robotization exposure R_i in commuting zone i ($i = 1, \ldots, N$), Δy_i is the 10-year equivalent change in log union density, and x_{i0} are pre-exposure commuting zone characteristics. Thus, $\alpha(\tau)$ captures the QTE of robotization at quantile τ and $\beta(\tau)$ captures (quantile-specific) effects of controls. We estimate the full quantile process (Chernozhukov and Hansen 2006: 503) from the 2nd to the 98th quantile and present our key quantities of interest graphically. We estimate the model using the smoothed generalized methods of moments estimator (de Castro et al. 2019). Appendix A.2.3 provides more details.

We examine the first-stage characteristics of the robotization instrument (which are more involved in quantile GMM models) in Appendix A.2.4 and find it to be sufficiently strong (even when excluding the automotive sector). In addition, Appendix A.2.5 shows that an alternative k-class limited information maximum likelihood estimator of the quantile model produces substantially similar results (which, too, reduces concerns about potential quantile-specific instrument weakness).

4 Results

4.1 Heterogeneous effects of robotization on union density

Figure IV plots quantile treatment effects of robotization changes on changes in union density for a range of specifications. Before discussing these in detail, a quick glance across the plots already reveals one of the key results of our analysis: the existence of substantial effect heterogeneity. Panel (f) provides a formal test via Kolmogorov-Smirnov statistics for the null hypothesis of constant effects: $\forall\tau : \alpha(\tau) = \alpha$ (Heckman 1990). The blue bars plot the resulting test statistic while the gray bars plot the 95% critical value calculated via simulation using 500 resampling draws (Chernozhukov and Hansen 2006: 506f). It reveals that under a range of different specifications, the null hypotheses of a constant treatment effect is clearly rejected. This underscores that there is indeed significant variation in the impact of robotization exposure across ranks U_d.

Panel (a) of Figure IV shows quantile-specific treatment effects estimates with robust 95% confidence intervals. Note that these represent the effect of robotization exposure on *differences* in

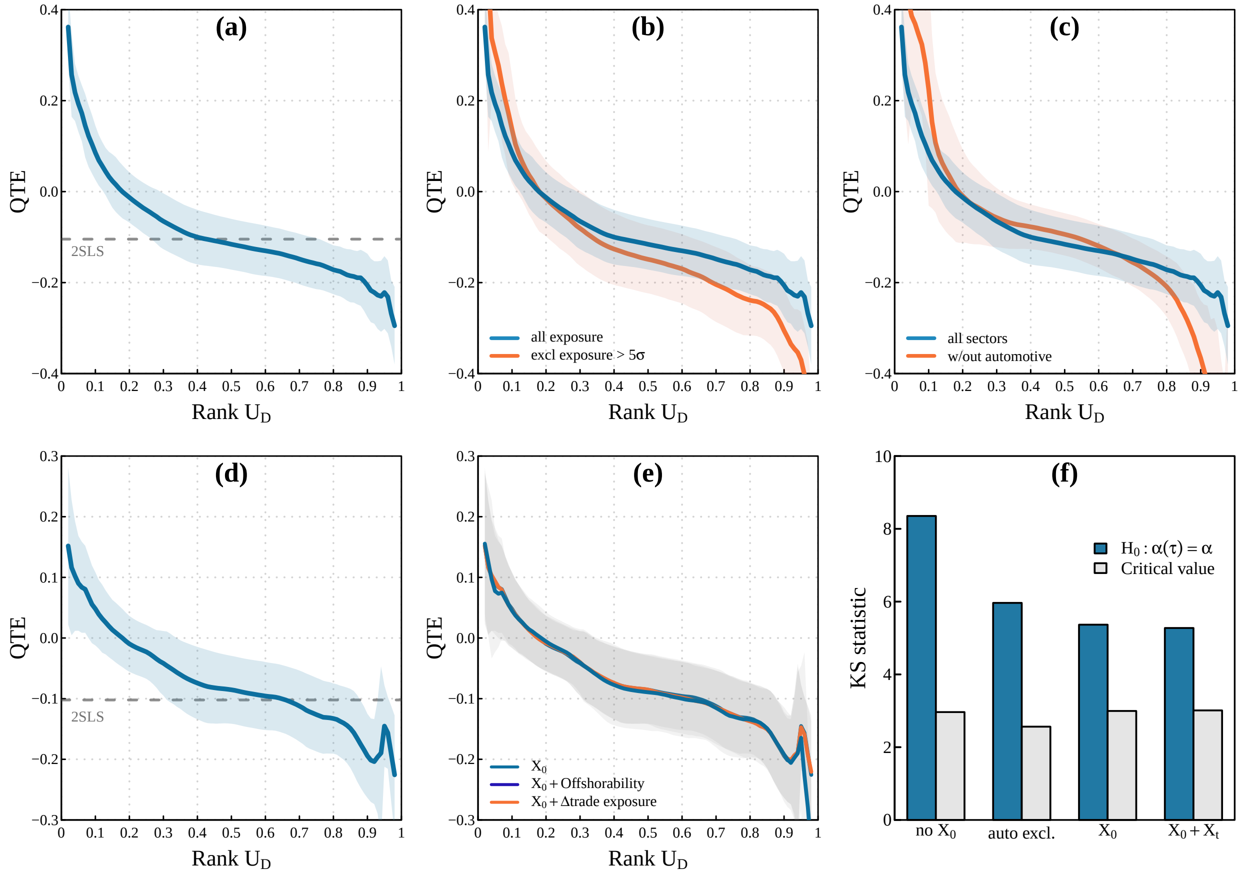


Figure IV
Quantile treatment effects of robotization exposure on union density

Note: QTE for a standard deviation increase in 10-year equivalent robotization exposure on 10-year equivalent changes in union density in commuting zones. For panels (a) to (e), estimates $(\partial q(d, x, \tau)/\partial d)$ are on the vertical axis, while the quantile index is on the horizontal axis. Shaded regions represent the 95% confidence interval using robust standard errors. Panel (f) shows KS statistics and critical values for tests of the null hypothesis of no effect heterogeneity $(\forall\tau : \alpha(\tau) = \alpha)$. The specification in panel (a) only uses the robotization instrument and an intercept. Panel (b) excludes highly exposed commuting zones (5σ above the mean). Panel (c) uses the alternative measure excluding the automotive sector. Panel (d) adds pre-exposure commuting zone characteristics and trade exposure, X_0, while panel (e) adds pre-exposure levels of offshorability and during-exposure levels of Chinese imports, X_t. Based on smoothed GMM estimates with nonparametric robust standard errors.

union density, i.e., time-constant unobservables at the commuting zone levels are removed in our analysis. The dashed horizontal line represents a standard 2SLS estimate which assumes homogeneity in the impact of robotization. Our results reveal that the effect is clearly not constant and decreases almost monotonically with increasing U_d. At the center of the unobservable heterogeneity distribution, the impact of robotization is not systematically different from the standard linear IV estimate. However, for both high and low levels of U_d the impact of robotization is quite heterogeneous. Most notably, while the QTE is predominantly negative, for areas with very low U_d ranks, changes in robotization exposure do lead to an *increase* in unionization. The model specification underlying panel (a) only includes an intercept in X_0 (the matrix of pre-treatment covariates) and thus relies on the instrument and the long-differencing of exposure and outcome. We will examine the impact of observables on heterogeneity below.

Panel (b) plots QTEs from a specification that removes highly exposed commuting zones (those with z-standardized exposure greater 5σ). This mostly includes areas in Michigan exposed to changes in robotization in the car manufacturing industry and its suppliers. In panel (c) we use our alternative measure of robotization exposure which excludes the automotive sector completely. Both specifications show even more pronounced heterogeneity. Notably, when removing the robotization changes in the automotive sector from the exposure, areas with low U_D levels see a more pronounced positive impact of robotization on union strength. The relationship between robotization and the fate of unions in the US is not limited to changes in the car industry.

The remaining analyses include pre-treatment by observables. Panel (d) accounts for pre-treatment sociodemographic characteristics (race, gender, education), employment composition (manufacturing, construction), and pre-robotization Chinese import exposure. The results reveal that the degree of heterogeneity is somewhat diminished. Nonetheless, there is still substantial variation in treatment effects, especially between commuting zones with low and high U_D values. Panel (e) extends this analysis in two ways. First, it adds pre-exposure levels of offshorability. Second, it adds over time changes of trade exposure (instead of levels). These alternative specifications do not reveal a substantive change in heterogeneity. This is confirmed in the last entry of panel (f), which again rejects the null hypothesis of constant treatment effects.

4.2 Correlates of effect heterogeneity

Panel (a) of Figure V shows the estimated QTE for each commuting zone. It illustrates the existence of considerable effect heterogeneity both within and across states. To examine whether this heterogeneity of the robotization effect found in this analysis can be explained by observable commuting zone characteristics, panel (b) of Figure V plots the pairwise correlation between the estimated QTE and 26 variables. We include a broad set of characteristics measured at the beginning of the period: sociodemographic variables (education, race, income, population, urbanization), labor market indicators (sectoral employment, unemployment), exposure to other technological change and globalization (routine task intensity, offshorability), existing union membership stocks, and historical variables capturing legacies of anti-union sentiment (from 1930s Gallup surveys), immigration and slavery (1910 Census), as well as right-to-work legislation and Old South location.[12]

[12]Appendix A.6 provides details on sources and operationalization.

If effect heterogeneity is mainly due to a compositional mechanism, by which union workers displaced by robots are reemployed in more or less unionized jobs, then these variables should do a good job of predicting it. For example, right-to-work laws make it more difficult to organize the growing but less unionized service sector (Feigenbaum, Hertel-Fernandez, and Williamson 2018); construction tends to be more unionized than other non-manufacturing industries (Hirsch, Macpherson, and Even 2026); higher education was linked (until the early 2000s) to lower union membership (Farber et al. 2021). A related possibility is that variation in exposure to the automation of routine tasks through computers or offshorability are drivers of heterogeneity (Meyer 2019). However, Panel (b) of Figure V reveals that there is no strong correlation between the size of the QTE and any of these observable characteristics.

For a more systematic exploration we analyze the predictive capacity of all variables. We estimate a random forest regression where all commuting zone characteristics are used jointly to predict the magnitude of the QTE.[13] We then compute permutation-based importance, which captures how much prediction accuracy decreases when a single variable is randomly shuffled while all others are left unchanged. This is measured via the resulting increase in prediction error for observations not used to grow each tree. This approach quantifies each variable's contribution to the model's predictive performance (Hastie, Tibshirani, and Friedman 2009: 15.3.2).

Panel (c) of Figure V plots the variable importance for each variable. It reveals that the observed commuting-zone characteristics have limited predictive power for explaining heterogeneity in the robotization effect. Altogether, the pattern suggests that compositional factors or other structural changes at best partially explain it. This is consistent with the theoretical argument. Propositions 2 and 3 show that whether automation strengthens or weakens unions depends on the interplay of firms' relocation incentives, the productivity gains from new technology in the current versus alternative locations, and the costs of worker mobilization, which are shaped by a region's (changing) position in production networks, the specificity of its capital and skills, and the quality of local union leadership. These characteristics are not well captured by sociodemographic or economic indicators, nor entirely captured by state-level policies and historical measures of union sentiment.

To be sure, the finding that observables do not predict the heterogeneity is also compatible with other interpretations. The variation could partly reflect unmeasured local shocks unrelated to bargaining or dimensions of industrial composition not captured here. However, recall that the heterogeneity persists after controlling for manufacturing employment shares, offshorability, trade exposure, a range of institutional and historical variables and that it is robust to excluding the automotive sector.

[13] We conduct the analysis using 1000 trees and tune hyperparameters $n_{\min} \in \{1, 3, \ldots, 10\}$ (minimum node size) and $m_{try} \in \{2, 4, \ldots, 26\}$ (variables tried per split) using grid search selecting the pair with the lowest out-of-bag prediction error.

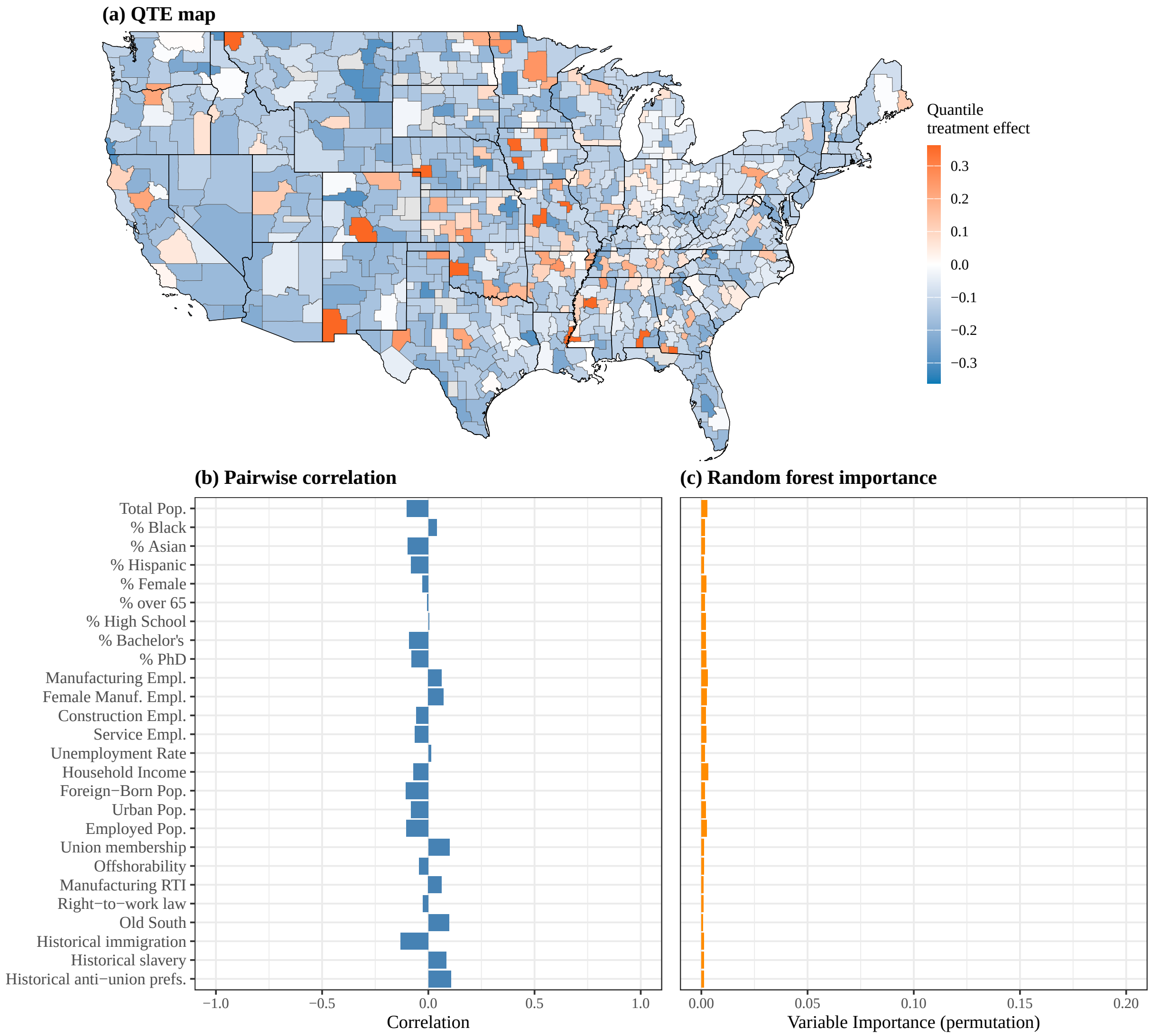


Figure V
Spatial distribution of QTE and predictors of effect heterogeneity

Note: Panel (a) plots the estimated QTE by commuting zone. Panel (b) shows the correlation between QTE and commuting-zone characteristics; panel (c) plots permutation-based variable importance from a random-forest regression predicting the estimated QTE (Hastie, Tibshirani, and Friedman 2009: 15.3.2). Importance is measured as the increase in out-of-bag prediction error when a variable is randomly shuffled.

5 Conclusion

Does the increasing automation of work undermine the organization of workers in labor unions? While the existing evidence is incomplete, the dominant view in the emerging literature is that automation should weaken unions and thus the collective power of workers in the workplace and in democratic politics—at least in the United States with its system of decentralized and combative wage bargaining that makes unions vulnerable to economic shocks. This view has a long pedigree. For instance, a historical account of labor unions in the US suggests that "[d]espite its obvious benefits, technology had been the bane of the American worker." (Dray 2010: 549)

However, the theory and evidence we presented qualifies this view and suggests that the impact of automation on unionization is heterogeneous. Our theoretical contribution is to bring strategic worker mobilization and bargaining to the political economy literature on automation. Our model illustrates that automation, in some contexts, can reduce capital's threat of exit and thus increase unions' bargaining position and ability to mobilize workers to become or remain members. In other contexts, automation weakens unions. Empirically, we have investigated the link between robots and union membership at the regional level with a novel focus on effect heterogeneity. Drawing on quantile treatment effect models with endogenous covariates, we found that there is a mixture of effects. While the (local) average effect of robotization is negative, it hides a lot of heterogeneity.

Industrial robots are the focus of our empirical investigation, reflecting how pervasive they have become in workplaces over the last decades. Of course, advances in information technology and AI are transforming the workplace beyond robotization. While challenges to worker mobilization in service and tech sectors are significant, qualitative work indicates that workers sometimes nonetheless mobilize (Doellgast 2022; Rothstein 2022). Relatedly, the increasing computing requirements for training cutting-edge AI models have led to a surge of physical investments, turning previously asset-light firms into asset-heavy and potentially less mobile ones (Tan and Thelen 2026). Moreover, surveys show the rise of union-curious workers across the workforce (Ahlquist, Grumbach, and Kochan 2024).

Our analysis has implications for research on the political consequences of technological change. If the impact of automation on worker organization varies across regions due to features of the bargaining environment that are difficult to observe, then the downstream political consequences of automation—for elections, policymaking, and political equality—are also likely to be uneven in ways that average effects cannot capture. Automation may widen geographic inequalities not only in economic outcomes but also in the collective capacity of workers to exercise voice in democratic politics.

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Online Appendix

Contents

Online Appendix

A.1 Theoretical Model

In this Online Appendix section, we provide a formal proof of the theoretical propositions stated in the main text.

Proof of Proposition 1

Bargaining stage Start by considering the case when the firm has not adopted the automation technology at the start of the game, $a = 0$. To avoid notational clutter, we omit variables' dependence on a where not strictly necessary. Given the production function and efficient use of resources in this case without automation, $l_1 = \left(\frac{\theta_2}{\theta_1}\right)^{1/\alpha} l_2$ and total employment can be written as $L_F = \phi l_2$, where $\phi \equiv 1 + \left(\frac{\theta_2}{\theta_1}\right)^{1/\alpha}$. Hence, the generalized Nash bargaining solution can be written as choosing employment l_2 in task 2 and wage w to maximize

$$\big(\phi l_2(w-x)\big)^{\delta_F(0)}\big(\theta_2 f(l_2) - w\phi l_2 - \Pi_m(0)\big)^{1-\delta_F(0)} \tag{A.1}$$

subject to $w \geq x$, $0 \leq L_F \leq L$ and $\Pi(0) \geq \Pi(0)_m$. At an interior solution, there are two first-order conditions:

$$w^*(0) = x + \delta_F(0)\left(\frac{\theta_2 f(l_2)}{\phi l_2} - x - \frac{\Pi_m(0)}{\phi l_2}\right) \tag{A.2}$$

$$w^*(0) = x + \delta_F(0)\left(\frac{\theta_2 f(l_2)}{\phi l_2} - \frac{\Pi_m(0)}{\phi l_2}\right) + (1-\delta_F(0))\left(\frac{\theta_2 f'(l_2)}{\phi}\right) \tag{A.3}$$

Setting $w^*(0) = w^*(0)$ and rearranging yields $x = \frac{\theta_2 f'(l_2)}{\phi}$. Substituting $f(l_i) = l_i^{\alpha}$, we get employment in task 2

$$l_2^*(0) = \left(\frac{\alpha\theta_2}{\phi x}\right)^{1/(1-\alpha)}. \tag{A.4}$$

Hence, employment in task 1 is $l_1^*(0) = \left(\frac{\theta_2}{\theta_1}\right)^{1/\alpha} l_2$ and total employment is $L_F^*(0) = \phi\left(\frac{\alpha\theta_2}{\phi x}\right)^{1/(1-\alpha)}$. Note that it depends only on the outside wage and labor productivity (efficient bargaining). By substitution, the wage equation can be written as

$$w^*(0) = x + \delta_F(0)\left(\frac{1-\alpha}{\alpha}x - \frac{\Pi_m(0)}{L_F^*(0)}\right). \tag{A.5}$$

Next, consider the case when the firm has automated, $a = 1$. Similar to above, the bargaining problem can be described as choosing employment in the second task l_2 and wage w to maximize

$$(l_2(w-x))^{\delta_F(1)}\left(\theta_2 f(l_2) - wl_2 - r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha} l_2 - \Pi_m(1)\right)^{1-\delta_F(1)}. \tag{A.6}$$

The expression has substituted $k_1 = \left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha} l_2$. Given the production function and efficient use of resources, capital in task 1 is used in fixed proportions to labor in task 2. At an interior solution, there are the following two first-order conditions:

$$w^*(1) = x + \delta_F(1)\left(\frac{\theta_2 f(l_2)}{l_2} - x - r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha} - \frac{\Pi_m(1)}{l_2}\right) \tag{A.7}$$

$$w^*(1) = \delta_F(1)\left(\frac{\theta_2 f(l_2)}{l_2} - \frac{\Pi_m(1)}{l_2}\right) + (1-\delta_F(1))\theta_2 f'(l_2) - r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha} \tag{A.8}$$

Following the same steps as above, setting $w^*(1) = w^*(1)$ and rearranging yields $x = \theta_2 f'(l_2) - r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}$. Given $f(l_i) = l_i^\alpha$ and $f(k_1) = k_1^\alpha$, we get employment in the non-automated task 2

$$l_2^*(1) = \left(\frac{\alpha\theta_2}{x + r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}}\right)^{1/(1-\alpha)} \tag{A.9}$$

which is total employment in the firm, $L_F^*(1)$. Labor demand only depends on the outside wage, the productivity of capital (task 1) and labor (task 2) and the exogenous cost of capital (efficient bargaining). By substitution, the wage equation can be written as

$$w^*(1) = x + \delta_F(1)\left[\left(\frac{1-\alpha}{\alpha}\right)\left(x + r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}\right) - \frac{\Pi_m(1)}{L_F^*(1)}\right]. \tag{A.10}$$

Mobilization stage For a given a and anticipating the outcomes from the bargaining stage, the union leader chooses $\delta_F(a)$ to maximize $w - c(\delta_F)$, where $c(\delta_F)$ is a convex and twice-differentiable cost function (not changing with a). In an interior solution, respectively for $a = 0$ and $a = 1$, this yields

$$c'(\delta_F) = \frac{1-\alpha}{\alpha}x - \frac{\Pi_m(0)}{L_F^*(0)} \tag{A.11}$$

$$c'(\delta_F) = \left(\frac{1-\alpha}{\alpha}\right)\left(x + r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}\right) - \frac{\Pi_m(1)}{L_F^*(1)} \tag{A.12}$$

where $L_F^*(0) = \phi(\frac{\alpha\theta_2}{\phi x})^{1/(1-\alpha)}$ and $L_F^*(1) = \left(\frac{\alpha\theta_2}{x + r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}}\right)^{1/(1-\alpha)}$ from above. Hence, we have $\delta_F^*(1) > \delta_F^*(0)$ if the right-hand side of equation A.12 is larger than the right-hand side of equation A.11. This holds if $\frac{\Pi_m(0)}{L_F^*(0)} - \frac{\Pi_m(1)}{L_F^*(1)} + \left(\frac{1-\alpha}{\alpha}\right) r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha} > 0$, which is the condition stated in Proposition 1. □

Proposition 2

Given the above and assuming quadratic mobilization cost, $c(\delta_F) = \frac{1}{2}\delta_F^2$, region-level union strength given no automation (a=0) can be written as

$$\begin{aligned}\bar{\delta}(0) &= \frac{L_F(0)^*}{L}\delta_F(0)^* + \frac{L - L_F(0)^*}{L}\delta_O \\ &= \delta_O + \frac{1}{L}\left[L_F(0)^*\left(\frac{1-\alpha}{\alpha}x - \delta_O\right) - \Pi_m(0)\right].\end{aligned} \tag{A.13}$$

Recall that the firm's overall labor demand is $L_F(0)^* = \phi\left(\frac{\alpha\theta_2}{\phi x}\right)^{1/(1-\alpha)}$. Similarly, region-level union strength given automation (a=1) can be written as

$$\bar{\delta}(1) = \delta_O + \frac{1}{L}\left[L_F(1)^*\left(\frac{1-\alpha}{\alpha}\left(x + r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}\right) - \delta_O\right) - \Pi_m(1)\right] \tag{A.14}$$

where the firm's total employment is $L_F(1)^* = \left(\frac{\alpha\theta_2}{x + r\left(\frac{\theta_2}{\lambda_1}\right)}\right)^{1/(1-\alpha)}$.

Hence, an exogenous automation shock increases region-level worker mobilization, $\bar{\delta}(1) > \bar{\delta}(0)$, if

$$\Pi_m(0) - \Pi_m(1) > L_F(0)^*\left(\frac{1-\alpha}{\alpha}x - \delta_O\right) - L_F(1)^*\left(\frac{1-\alpha}{\alpha}\left(x + r\left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}\right) - \delta_O\right), \tag{A.15}$$

and it reduces mobilization if the inequality is reversed.

Proposition 3

For this proposition, consider the firm's optimal decision whether to automate at the beginning of the game given optimal behavior in the subsequent nodes of the game. Given an interior solution of the bargaining problem, the firm automates task 1 ($a^* = 1$) if $\Pi^*(1) - c_a > \Pi^*(0)$ and does not automate otherwise ($a^* = 0$), where $\Pi^*(a)$ is the firm's equilibrium profit given optimal mobilization effort $\delta^*(a)$ and negotiated wage $w^*(a)$. Let $\Omega(0) \equiv \left(\frac{\theta_2}{\theta_1}\right)^{1/\alpha}$ and $\Omega(1) \equiv \left(\frac{\theta_2}{\lambda_1}\right)^{1/\alpha}$. By substitution, in case of $a = 0$ the firm's profit can be written as

$$\Pi(0)^* = y(l_1^*(0), l_2^*(0)) - w^*(0)L_F^*(0) \tag{A.16}$$

$$= \theta_2 f(l_2(0)^*) - w^*(0)\phi l_2^*(0) \tag{A.17}$$

$$= \theta_2\left(\frac{\alpha\theta_2}{(1+\Omega(0))x}\right)^{\alpha/(1-\alpha)} - (x + (\delta^*(0))^2)(1+\Omega(0))\left(\frac{\alpha\theta_2}{(1+\Omega(0))x}\right)^{1/(1-\alpha)}, \tag{A.18}$$

where $\delta^*(0) = \left[\frac{1-\alpha}{\alpha} x - \left(\frac{\Pi_m(0)}{(1+\Omega(0))\left(\frac{\alpha\theta_2}{(1+\Omega(0))x}\right)^{1/(1-\alpha)}} \right) \right]$. For $a = 1$, profit can be written as

$$\Pi(1)^* = y(k_1^*, l_2^*(1)) - w^*(1) l_2^*(1) - r k_1^* \tag{A.19}$$
$$= \theta_2 f(l_2(1)^*) - w^*(1) l_2^*(1) - r k_1^* \tag{A.20}$$
$$= \theta_2 \left(\frac{\alpha\theta_2}{x + r\Omega(1)} \right)^{\alpha/(1-\alpha)} - (x + (\delta^*(1))^2) + r\Omega(1)) \left(\frac{\alpha\theta_2}{x + r\Omega(1)} \right)^{1/(1-\alpha)}, \tag{A.21}$$
$$\tag{A.22}$$

where $\delta^*(1) = \left[\frac{1-\alpha}{\alpha} (x + r\Omega(1)) - \left(\frac{\Pi_m(1)}{\left(\frac{\alpha\theta_2}{x+r\Omega(1)}\right)^{1/(1-\alpha)}} \right) \right]$. Hence automation is a best response if

$$\theta_2 \left(\frac{\alpha\theta_2}{x + r\Omega(1)} \right)^{\alpha/(1-\alpha)} - (x + (\delta^*(1))^2 + r\Omega(1)) \left(\frac{\alpha\theta_2}{x + r\Omega(1)} \right)^{1/(1-\alpha)} - c_a$$
$$> \theta_2 \left(\frac{\alpha\theta_2}{(1+\Omega(0))x} \right)^{\alpha/(1-\alpha)} - (x + (\delta^*(0))^2)(1+\Omega(0)) \left(\frac{\alpha\theta_2}{(1+\Omega(0))x} \right)^{1/(1-\alpha)}, \tag{A.23}$$

and not automating is best if the inequality is reversed.

A.2 Statistical model details

In this section we describe the idea and assumptions behind quantile treatment effects in the potential outcomes framework, detail estimation via smoothed general methods of moments, and explore instrument strength.

A.2.1 Quantile treatment effects

Within the standard potential outcomes framework, consider robotization exposure which takes on values $d \in D$. Union density potential outcomes are indexed against treatment d and are denoted by Y_d.[1] Covariates are denoted by X. Since we are interested in the heterogeneity of the robotization effect we consider the full distribution of potential outcomes and focus on quantiles of the potential outcomes

$$\left\{Q_{Y_d}(\tau \mid x),\ \tau \in (0,1)\right\}. \tag{A.24}$$

The main quantity of interest is the Quantile Treatment Effect (QTE; e.g., Doksum 1974) of robotization exposure given by

$$QTE(\tau) \equiv Q_{Y_d}(\tau \mid x) - Q_{Y_{d'}}(\tau \mid x) \tag{A.25}$$

which represents an intuitive way to describe the effect of exposure d on different points of the marginal distribution of potential outcomes.

To derive the model, represent the potential outcomes given covariates $X = x$ and exposure state d as:

$$Y_d = q(d, x, U_d) \text{ with } U_d \mid D \sim U(0,1). \tag{A.26}$$

In this representation (Lehmann 1974; Chernozhukov and Hansen 2005) $q(d, x, \tau) = Q_{Y_d}(\tau|x)$ is the conditional τ quantile of potential outcome Y_d; U_d is a (non-separable) unobservable (structural error) which induces effect heterogeneity. In other words, U_d creates differences in potential outcomes among observationally equivalent commuting zones for a given level of robotization exposure d. If we think of U_d as a preference or "proneness" (Doksum 1974) for unionization, we can intuitively understand its role as determining the relative ranking of observationally equivalent commuting zones in the distribution of potential outcomes (conditional on observables) and thus interpret the quantile index τ as the rank in the preference distribution. This makes this model setup useful for examining the structure of treatment effect heterogeneity while accounting for unobserved heterogeneity (Doksum 1974; Heckman and Smith 1997; Koenker 2005).

Of course, in an observational study such as this one exposure to robotization is likely endogenous to the system under study. Selection of robot exposure might depend not just on observable characteristics of a commuting zone, such as the prevalence of manufacturing, but also on unobserved characteristics or the potential outcomes themselves. Thus, we consider endogenous robotization exposure shaped by a systematic component, which includes observed

[1] The potential outcomes are latent states, since only one component of $\{Y_d\}$ for any given commuting zone is observed.

commuting zone characteristics, X, and the robotization instrument, Z, as well as a stochastic component. More precisely, given $Z = z$, $X = x$, and a random vector ν, the selection equation is given by

$$D \equiv \delta(z, x, \nu) \tag{A.27}$$

where δ is an unknown function. Note that ν is an unobserved component that captures unobservables driving robotization and that is allowed to depend on $\{U_d\}$.[2] Note further that the model does not impose independence of Z and ν, i.e., it does not require that the instrument is independent of the error in the selection equation. Thus, the endogenous extension of eq. (A.26) is:

$$Y_d = q(d, x, U_d),\ U_d \mid Z \sim U(0,1). \tag{A.28}$$

Here, the robotization instrument is correlated with D but independent of U_d.

A.2.2 Identification

This model structure is addressed in the instrumental variable quantile regression model (Chernozhukov and Hansen 2005, 2006; Chernozhukov, Hansen, and Wüthrich 2020). Chernozhukov and Hansen (2006: 495) show that identification without functional form assumptions of the QTE is possible under the following conditions: (1) a monotonicity assumption on the structural function (the quantile functions for each d are strictly increasing in τ conditional on X); (2) a standard IV independence restriction (potential outcomes are independent of Z given X); (3) and a rank similarity assumption, which restricts U_d to be similar across exposure states. The latter assumption is central. Intuitively, this assumption restricts how ranks can vary across treatment states. In the strictest version, ranks are invariant (for each d and d', $U_d = U_{d'}$), that is, a commuting zone's position on U does not change with exposure levels. See Heckman and Smith (1997) for a pointed critique. A more realistic version relies on rank *similarity*: given (X, Z, ν) for each d and d', $U_d \sim U_{d'}$. This allows for noisy variation in U_d positions across d (termed "slippages" by Heckman and Smith 1997): assume that deviations in ranks $U_d - U$ from a common level U are identically distributed across exposure states. Then, in substantive terms, this implies that selection of robotization exposure can depend on unobservables and even on the distribution of slippages, but not on exact knowledge of the value of $U_d - U$ (Chernozhukov and Hansen 2013: 63, cf. Wüthrich 2020). As discussed in the main text, under the assumption firms may adopt robots based on unobservable (to the data analysts) local characteristics to maximize profits, as long as their investment decisions are not based on precise knowledge of how a specific commuting zone would rank in unionization outcomes relative to others at a particular exposure level.[3]

[2] It is the dependence between ν and the $\{U_d\}$ that induces endogeneity and violates standard quantile regression assumptions. This issue is solved by the use of the instrument.

[3] Wüthrich (2020) discusses transformation conditions for the equivalence of the IVQTE estimands discussed here to the local quantile treatment effect estimands of Abadie, Angrist, and Imbens (2002) and some of the resulting desirable robustness properties of the IVQTE (Wüthrich 2020: 446f.).

A.2.3 Smoothed GMM estimation details

In our analysis, we employ the linear-in-parameters version of the model with

$$Q_{\Delta y_i}(\tau) = d_i\alpha(\tau) + x_{i0}'\beta(\tau), \tag{A.29}$$

where $d_i \equiv \Delta R_i$ is the 10-year equivalent change in robotization exposure R_i in commuting zone i ($i = 1, \ldots, N$), Δy_i is the 10-year equivalent changes in log union density, and x_{i0} are pre-exposure commuting zone characteristics.[4] We estimate specifications with and without covariates (i.e., the assumptions discussed above are assumed valid conditionally on covariates). We estimate the full quantile process $\tau \mapsto q(d, x, \tau)$ for τ in $\mathscr{T}$ (Chernozhukov and Hansen 2006: 503).

We estimate the model using the smoothed GMM (generalized methods of moments) estimator (de Castro et al. 2019). The smoothing bandwidth is the feasible minimum for each element of the quantile process (following Kaplan and Sun 2017: 111). Smoothing of the discontinuous moment condition not only increases numerical stability but also reduces bias. We use robust standard errors calculated using nonparametric density estimation via an Epanechnikov kernel with bandwidth determined using Silverman's rule (Silverman 1986).

In more detail, consider the finite sample analog of the population moment condition implied by the model (Chernozhukov and Hansen 2006: 499):

$$g_n(\alpha, \beta; \tau) = n^{-1} \sum_{i=1}^{n} \hat{\Psi}_i \left[\tau - \mathbf{1}\left(\Delta y_i - d_i\alpha - x_{i0}'\beta \leq 0 \right) \right],$$

where $\hat{\Psi}_i \equiv \hat{\Psi}(x_{i0}, z_i)$ is the vector of instruments and exogenous covariates used in the estimating equations (here formed from x_{i0} and the projection of d_i on x_{i0} and z_i). The indicator function $\mathbf{1}(\cdot)$ equals 1 if its argument is true and zero otherwise. The sharp discontinuity introduced by this function makes computing the estimator more difficult. Thus, following Kaplan and Sun (2017), we use the smoothed moment condition

$$g_{n,h}(\alpha, \beta; \tau) = n^{-1} \sum_{i=1}^{n} \hat{\Psi}_i \left[\tau - \tilde{\boldsymbol{I}}\left(\frac{\Delta y_i - d_i\alpha - x_{i0}'\beta}{h} \right) \right],$$

where $\tilde{\boldsymbol{I}}(\cdot)$ is a smooth approximation to the indicator function and h is the smoothing bandwidth selected such that it minimizes the mean squared errors of the estimating equations (Kaplan and Sun 2017: 117). The estimator minimizes the quadratic GMM criterion based on $g_{n,h}(\alpha, \beta; \tau)$.

Figure A.1 plots the h values used in our analysis for each τ. We also conducted a robustness test where we set h to a single value ($h = 0.13$; the mean of the h values in the 20th to 80th τ quantiles) to ensure that our results are not driven by the slightly higher chosen optimal bandwidth for low values of τ.

[4] Note that in order to ease notation, symbols used in this section have no relationship to the ones used in the formal model.

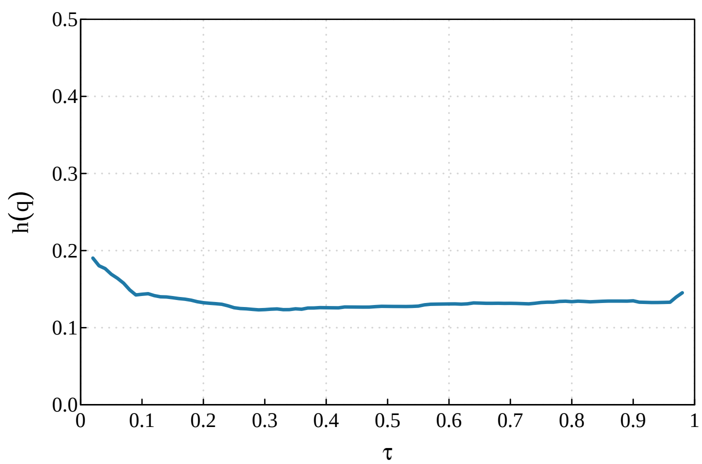


Figure A.1
Bandwidths of smoothed estimating equations

A.2.4 First-stage IV characteristics

In this section we examine the first-stage characteristics of the instrument, which is less straightforward in the quantile IV setting due to its nonlinear nature. We present two approaches to assessing instrument strength in Figure A.2. Entries in panel (a) are measures of instrument strength $T(\alpha)$ which depend on the structural (second stage) parameters. We use the robust inference procedure proposed by Alejo, Galvao, and Montes-Rojas (2023) which evaluates $T(\alpha)$ along a sequence of values $\alpha(\tau) \in \mathscr{T}$. We plot results for a lower ($\tau = 0.2$) and an upper ($\tau = 0.8$) quantile and for the instrument computed with and without the automotive sector. We find that the instrument is quite strong across $\alpha(\tau)$ when τ is set to 0.2. This is the case no matter if the automotive sector is excluded or not. When τ is 0.8 we see a decline in instrument strength for larger values of $\alpha(\tau)$ for the full instrument, but not when excluding the automotive sector.

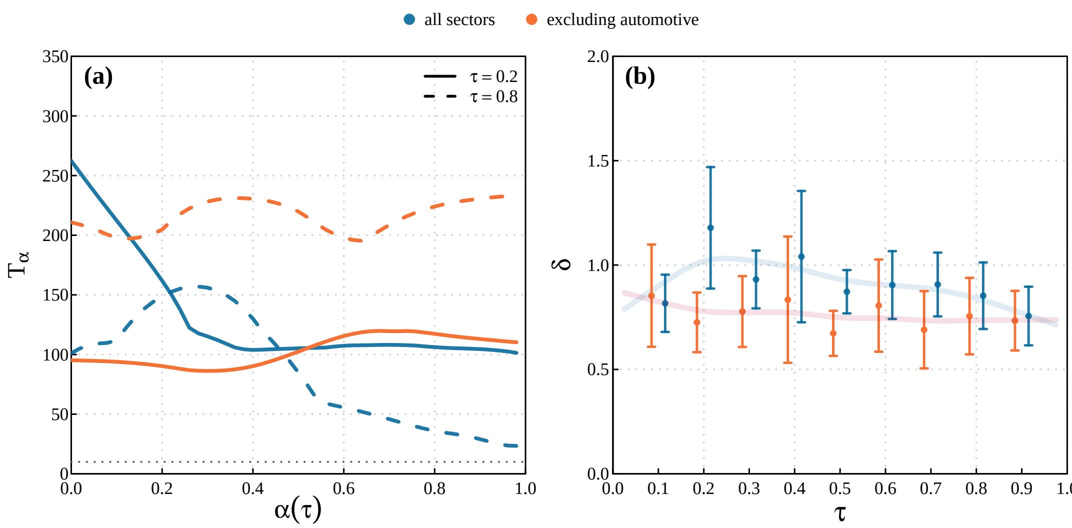


Figure A.2
First-stage characteristics

Note: Panel (a) displays robust first stage statistic $T(\alpha)$ calculated following (Alejo, Galvao, and Montes-Rojas 2023) along fixed possible values of $\alpha(\tau)$ for treatment effects evaluated at the 20th (solid line) and 80th quantile (dashed line) of U_D. $T(\alpha)$ is smoothed using a Nadaraya-Watson estimator with a bandwidth of 0.10 and Epanechnikov kernel. Panel (b) plots the first-stage parameter δ (cf. Alejo, Galvao, and Montes-Rojas 2023: 355) of the instrument. Results for the Acemoglu and Restrepo (2020) instrument are shown in blue, results using the instrument excluding the automotive sector in orange.

Panel (b) uses an alternative approach to evaluate instrument relevance. It assumes consistent estimates of the structural parameters and estimates the first-stage coefficient δ which directly represents the effect of the instrument (Alejo, Galvao, and Montes-Rojas 2023: 357). A validity test of the instrument can be carried out via the (quantile-specific) weak instrument hypothesis $H_0 : \delta = 0$. In our case, we inspect visually if the 95% confidence intervals cross zero. We find that across all values of τ the instrument is strongly and significantly related to robotization. This is true whether the automotive sector is included or not.

A.2.5 Comparison of GMM and k-class estimators

Panel (a) of Figure A.3 presents results from models estimated using smoothed GMM (de Castro et al. 2019) as in the main text compared to a k-class estimator for the instrumental variable QR model (Kaplan and Liu 2024) in panel (b). We specify two values of k. One that produces a limited-information maximum likelihood estimator (a data-dependent choice of k) and one set at $k = 1.1$ (somewhat above the "2SLS-like" value of $k = 1$). Both choices are intended to produce results more robust to weak instruments and small sample sizes (at the cost of higher variance). The resulting QTE estimates do not show any substantive deviation from the pattern we found using smoothed GMM.

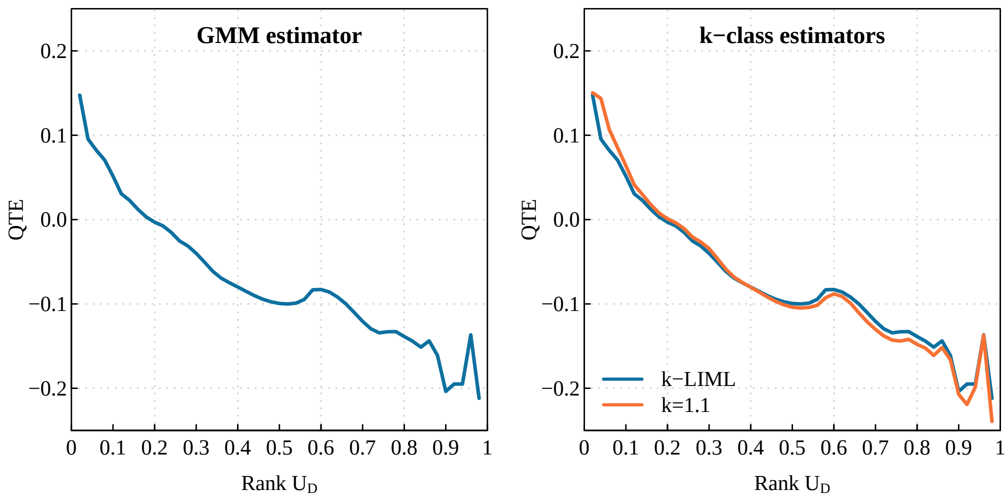
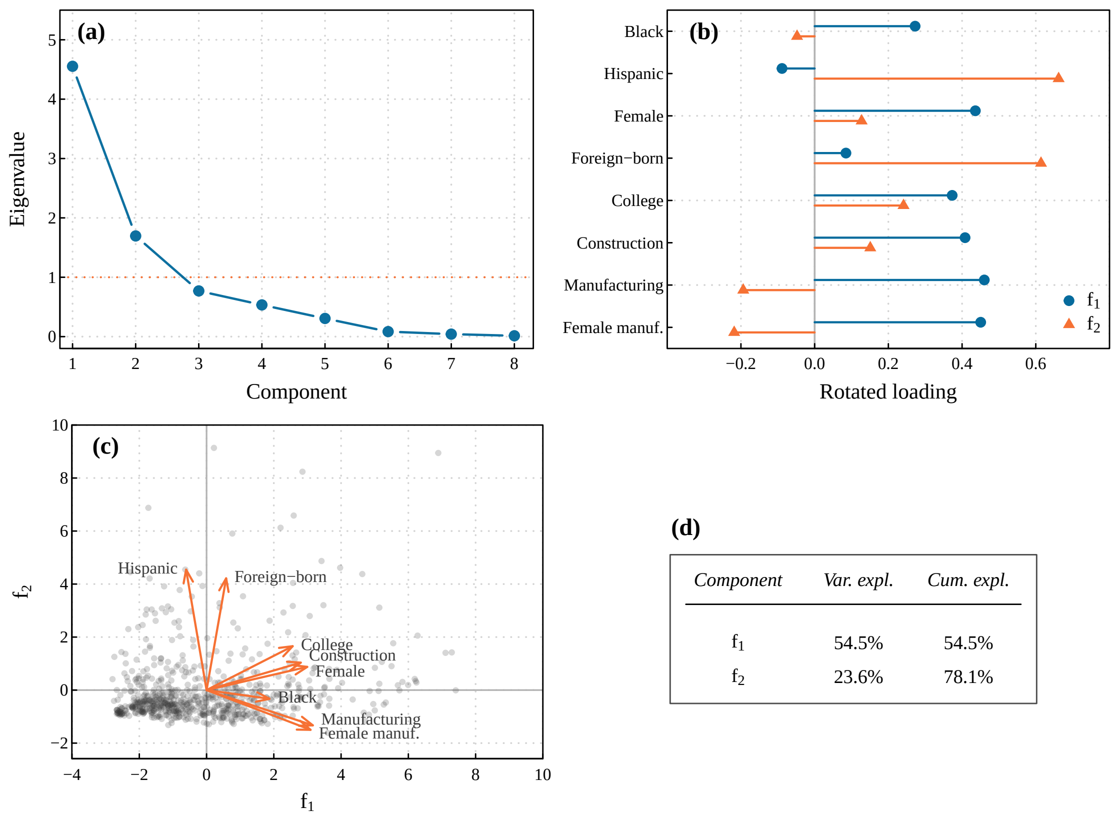


Figure A.3
Comparison of GMM and k-class estimators

Note: The left panel shows QTE from a smoothed GMM estimator (de Castro et al. 2019) as used in the main analyses; the right panel shows k-class instrumental variable estimates calculated following Kaplan and Liu (2024).

A.2.6 Dimension reduction of controls

We adjust for a low dimensional vector of commuting zone level controls produced via a dimension reduction of a large number of district characteristics. As shown in Figure A.4, we use principal components analysis to extract the first two components, which explain about 78% of the total variance. The first three eigenvalues are 4.55, 1.70, and 0.77. The biplot in panel (c) shows the broad separation of an industrial-education dimension (f_1) from an immigration dimension (f_2; note the different location of Hispanic versus Black population shares).



(d)

Component	*Var. expl.*	*Cum. expl.*
f_1	54.5%	54.5%
f_2	23.6%	78.1%

Figure A.4
Principal component analysis of commuting zone controls

Note: Principal component analysis. Panel (a) shows a scree plot of eigenvalues. Panel (b) shows variable loadings on the first two components after varimax rotation. Panel (c) shows a biplot of commuting-zone scores and variable loading vectors in the rotated two-component space. Panel (d) reports the variance and cumulative variance explained by the first two components.

A.3 Alternative definition of dependent variable

Figure A.5 compares our main results to an alternative definition of the dependent variable. In the main text, union density is defined as the number of union members in a commuting zone at a point in time relative to the number of employed individuals in this commuting zone and point in time. Thus, the dependent variable captures changes in the (logged) share of union members. Union density so defined is a common variable in the analysis of the politics of labor unions. However, a concern with this approach is that it combines two sources of change: changes in the number of union members and changes in commuting-zone level employment. To address this concern, we also define the dependent variable as the change in the number of union members in a commuting zone relative to the beginning-of-period employed population (i.e., we hold the denominator fixed at year 2000 employment numbers). Overall, we find the same pattern of nonlinearity in the relationship between robotization and union density. However, the QTE estimates are slightly smaller (but still positive) at lower U_D values and noticeably smaller for U_D values above the median. We still clearly reject the null hypothesis of a constant treatment effect (KS test of 8.35 with a critical value of 2.96).

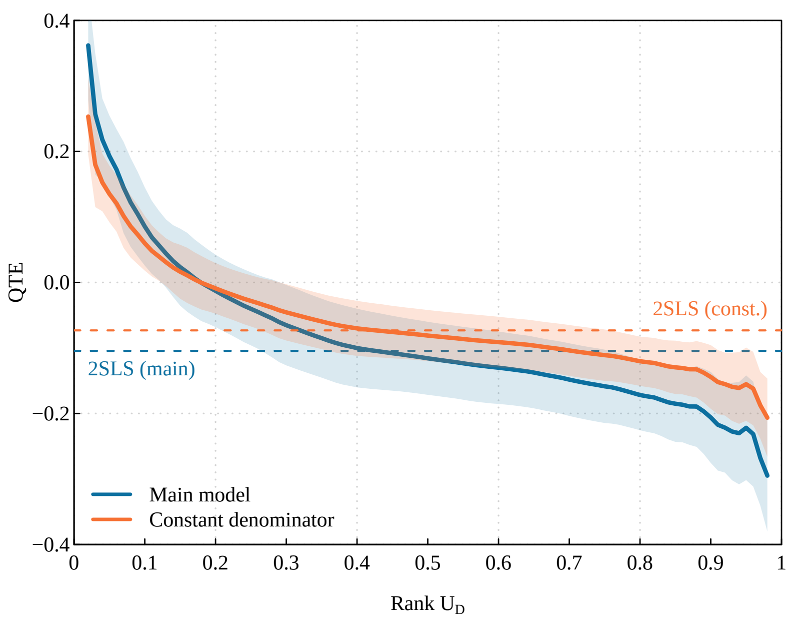


Figure A.5
Comparison of results when using a fixed denominator in union change calculation

Note: QTE for a standard deviation increase in 10-year equivalent robotization exposure on 10-year equivalent changes in union density in commuting zones. The alternative model (orange line) shows QTEs when using a fixed denominator (the number of employed individuals in the year 2000) in the calculation of union density changes. Dashed lines represent standard 2SLS estimates; shaded regions represent 95% confidence intervals.

A.4 Alternative model specifications

Figure A.6 presents robustness tests of the main model specification. The left panel shows the QTE from a model that allows for (some) nonlinearity in the instrument by estimating it as restricted cubic splines (Harrell 2001). The middle panel shows estimates when using the generalized quantile regression estimator (Powell 2020) where the full set of district, offshorability, and trade covariates is specified as proneness variables. Figure A.1 showed a slightly higher bandwidth of the GMM smoothing function at lower quantiles. To ensure that this does not drive our results, the right panel of Figure A.6 shows QTE estimates when setting a fixed bandwidth h for all τs. The bandwidth is set to the mean of the selected optimal bandwidths of the 20th to 80th quantile.

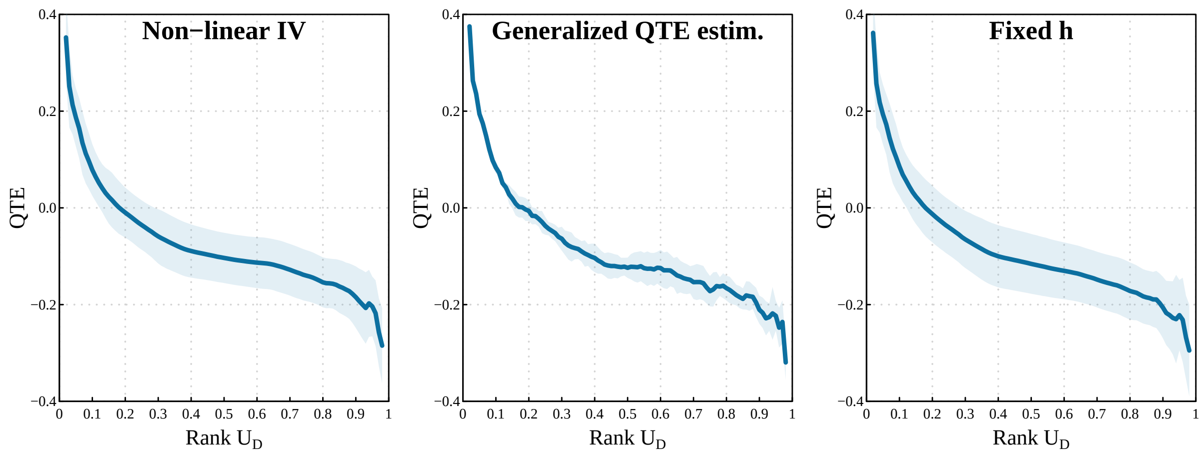


Figure A.6
Alternative model specifications

Note: The left panel shows QTE from a model using allowing for possible nonlinearity in the instrument by estimating it as restricted cubic regression splines (with 4 knots). The middle panel shows estimates when using the generalized quantile regression estimator (Powell 2020) where the full set of district, offshorability, and trade covariates is specified as proneness variables. The right panel shows QTE estimates when setting a fixed bandwidth h for all τs. Bandwidth is set to the mean of the selected optimal bandwidths of the 20th to 80th quantile.

A.5 Additional tables

Table A.1 presents the Rotemberg weights of the five most influential industries in our analysis. The Rotemberg weights are calculated following Goldsmith-Pinkham, Sorkin, and Swift (2020).

Table A.1
Rotemberg weights of five most influential industries

Industry	α_k
Automotive	0.764
Plastics and Chemicals	0.167
Basic Metals	0.037
Metal products	0.037
Electronics	0.010

A.6 Additional variables used to predict QTEs

Historical anti-union sentiment For our measure of historical anti-union sentiment, we follow Becher, Stegmueller, and Kaeppner (2018) and use national public opinion surveys conducted by Gallup in 1936-7 (available from the Roper Center for Public Opinion Research, `ropercenter.cornell.edu`). Reflecting the large salience of the union issue at the time, the surveys (dataset USAIPO1936-3637) include several items on the respondents' view about organized labor. We use a question that asks respondents whether the military should be "called out whenever strike trouble threatens" (N=2,904). Respondents answering yes take a clear anti-union stand. We aggregate responses to the state level (there are no sub-state identifiers). As the surveys were conducted using quota-control methods rather than random sampling, which can lead to systematic deviations between the survey samples and the population, we follow Berinsky (2006) and employ a post-stratification weighting adjustment. Using 1940s state-level census estimates of population proportions, we compute a weighted distribution of sampled groups that correspond to the population. This state-level measure is then spatially mapped to commuting zones. For a number of commuting zones this mapping is one-to-one (i.e., the commuting zone is wholly contained within a state). For commuting zones crossing state boundaries, we map anti-union sentiment values by weighting them by the share of the Census housing units in each spatial intersection.[5]

Right-to-work legislation and Old South We include indicator variables for right-to-work (RTW) legislation and being part of the "Old South". For commuting zones wholly encased in a state, these values are simply the values of the corresponding state. For commuting zones that cross state boundaries, we assign RTW values equal to one if more than 50% of a commuting zone's Census housing units lie in a RTW state (and mutatis mutandis for the Old South indicator).

Historical stocks of immigration and slavery Using the 1910 Census, we compute shares of immigrants (the share of the White Census population that is foreign-born) and the share of the Black population to capture legacies of slavery and immigration (Acharya, Blackwell, and Sen 2019). We use the IPUMS 100% sample (providing about 92.4 million cases). The 1910 Census does not provide information about which commuting zone respondents reside in. Instead, it includes State Economic Areas (SEA), which were introduced in the 1940 Census and have been added to the IPUMS 1910 Census release. We use geographic shapefiles for 1910/1940 SEAs and calculate their polygon area intersection with commuting zones using standard GIS tools (the GEOS library). Based on this crosswalk we spatially weight the Black and foreign-born population in 1910 to contemporary commuting zones.

Other variables Commuting zone total Population, % Black, % Asian, % Hispanic, % Female, % aged over 65, % with high school degree, % with Bachelor's degree, % with PhD, manufacturing employment, female manufacturing employment, construction employment, unemployment rate, median household income, foreign-born population, urban population, employed population are measured at the beginning of the analysis period and calculated from NHGIS county-level values from the 2000 Census SF1a and SF3a files aggregated to commuting

[5]The Census block level shares are obtained from the MABLE/Geocorr database.

zones. Offshorability and routine task intensity in manufacturing are from Autor, Dorn, and Hanson (2015).

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