The Impact of Automation Risk on Union Membership

Ben Kim

University of Virginia

Department of Economics

Distinguished Majors Thesis

April 28, 2025

Abstract

This paper examines the impact of automation on unionization trends across 15 robot-exposed U.S. industries from 2004 to 2021. To estimate causal effects, I implement a first-differences regression design, leveraging variation in European robot adoption as an instrument for U.S. robot density. My IV estimates indicate that, for a given industry, a one-unit increase in robots per hundred workers leads to a 0.9 to 1.2 percentage point decline in the unionization rate — a substantial impact relative to baseline rates of 5 to 15%.

From the bottom of my heart, thank you to my advisor Professor Emma Harrington, DMP Director Kerem Cosar, and my lovely cohort members for their invaluable guidance and support — this endeavor would not have been possible without you. Lastly, which is ironic given the subject of this paper, thank you to ChatGPT for its help with brainstorming ideas, making stylistic improvements, and editing my messy R code. You are the reason I wanted to study this topic, and the reason I will have to join a union one day.

1 Introduction

In October 2024, over 47,000 members of the International Longshoremen's Association (ILA), a major North American labor union representing dockworkers, went on strike over contract disputes and concerns about automation; in particular, the deployment of semi-automated cranes.[1] [2] Though not explicitly stated, the ILA's message was clear: the union sought to act as a 'safe haven' protecting workers from automation-driven displacement. This episode sparked my research question: *Does increased exposure to automation drive workers to join or to leave unions?*

1.1 Observation #1: Falling Unionization

To frame this research question, it is helpful to consider historical trends in unionization and automation. Figure 1 shows that the average union membership rate in the United States has declined steadily over recent decades.[3] However, the decline is not uniform across sectors. Industries characterized by routine physical tasks, such as manufacturing and mining, exhibit sharper declines compared to service-oriented industries. This suggests that industries more exposed to automation may have experienced faster declines in unionization. This trend is not unique to the United States. Appendix A shows that unionization rates across Europe have also fallen since 1980.

Why has unionization declined?

Balcázar (2024) identifies three key explanations. First, the *institutional thesis* emphasizes legal changes, such as Right-to-Work laws, which have weakened unions' bargaining frameworks. More and more states have adopted these over the years, including Indiana (2012), Wisconsin (2015), Kentucky (2017), and West Virginia (2016) within the last fifteen years.[4] Second, the *structural thesis* attributes union decline to structural shifts in employment from historically-unionized manufacturing sectors toward less-unionized service sectors. Third, the *market competition thesis* posits that globalization and technological competition have weakened the incentives for both firms and workers to support unionization, since the cost of offshoring is lower. These forces together have exerted steady downward pressure on unionization rates.

Why does this matter?

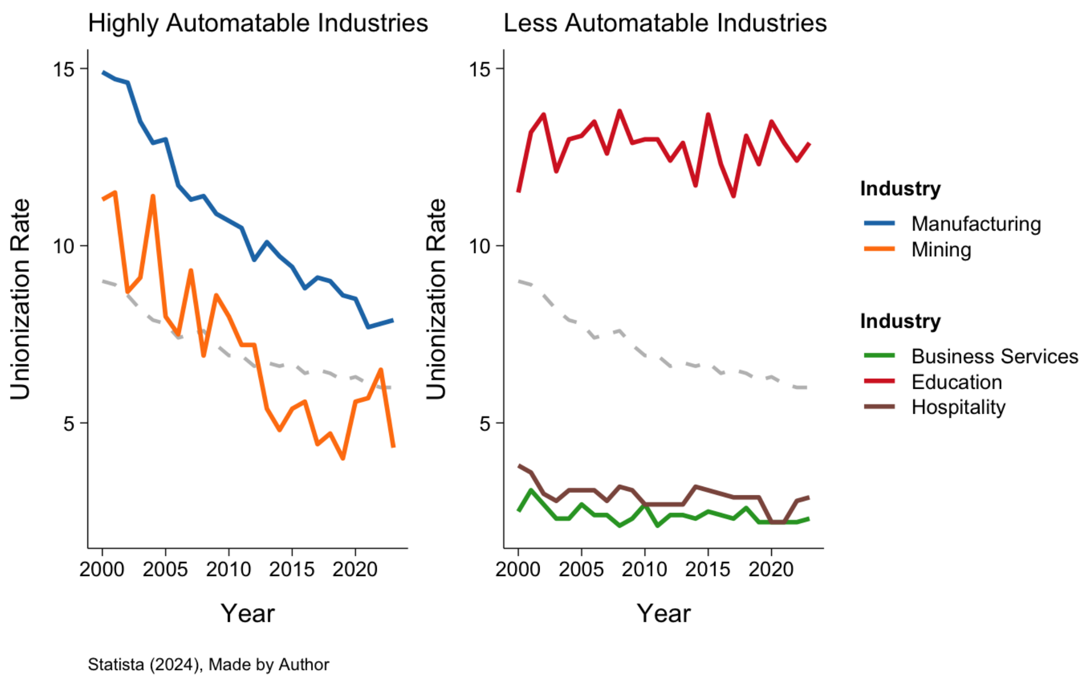
[1] Doyinsola Oladipo and David Shepardson, "US Dockworkers Strike, Halting Half the Nation's Ocean Shipping," Reuters, October 1, 2024.

[2] Lori Ann LaRocco, "Ila Union and Port Owners Held Secret Meeting on Automation as New Strike Looms," CNBC, January 7, 2025.

[3] Statista. "Labor Unions in the U.S." 2024.

[4] "Right-to-Work Resources," National Conference of State Legislatures, December 19, 2023, `https://www.ncsl.org/labor-and-employment/right-to-work-resources`.

Figure 1: U.S. Labor Union Membership Trends, 2000–2024 (Source: Statista)



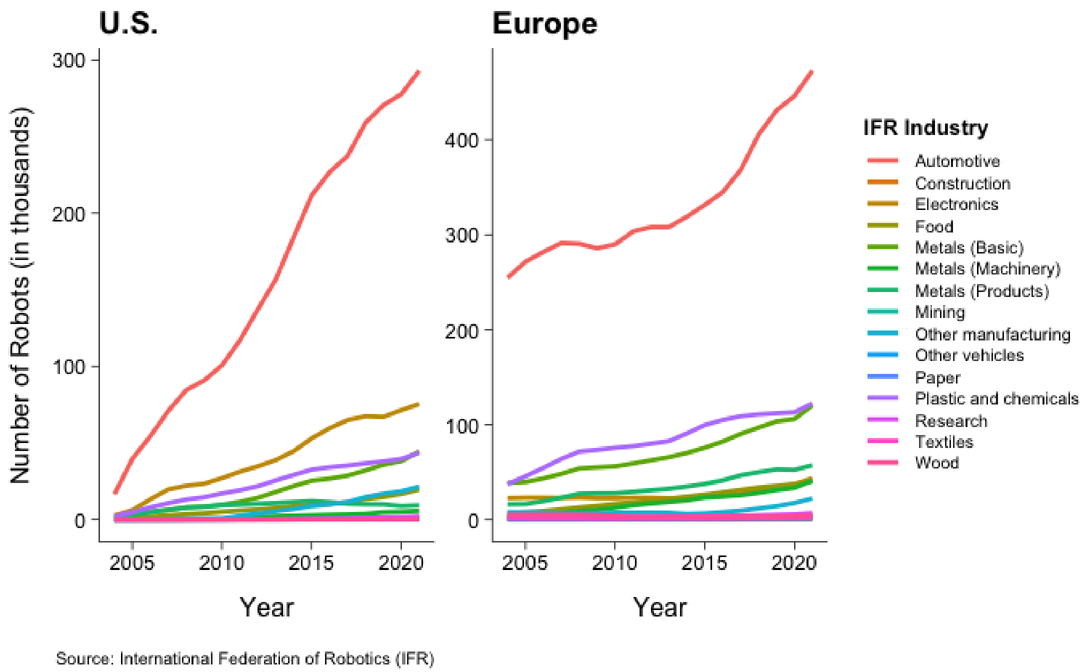
The sharp decline in unionization in 'highly automatable' industries relative to stable unionization in the services industries provided initial evidence for the paper.

Declining unionization has significant consequences for labor markets. Unions have historically raised wages, improved working conditions, and amplified workers' political voice. Card, Lemieux, and Riddell (2004) show that unions reduce wage inequality, particularly among men. Beyond wages, unions have historically secured non-wage benefits like healthcare, retirement plans, and workplace protections. Their decline likely contributes to deteriorating job quality and a weakening of labor's political influence.

1.2 Observation #2: Rising Robots

In contrast to the declining unionization trend, robot adoption has risen dramatically across all major industries. Figure 2 shows that the stock of operational robots has expanded significantly in both the United States and Europe across sectors. While the magnitude is somewhat higher in Europe, the trends are strikingly similar. I use the number of operational robots per hundred workers—a measure of 'robot exposure'—as my primary proxy for automation exposure, building upon but slightly simplifying previous measures discussed in the Data and Variables section.

Figure 2: Robot Stock by Industry in the U.S. vs Europe (Source: IFR)



The U.S. and Europe have very similar robot adoption trends for each industry. This correlation will be helpful in instrumented U.S. Robot Density in the specifications.

Observation #3: Robot Exposure Displaces Routine Jobs

Acemoglu and Restrepo (2020) find that increased robot adoption leads to significant displacement of manufacturing jobs, particularly those involving routine tasks. Their findings, illustrated in Appendix B, reveal a strong negative correlation between employment and robot exposure. Autor and Dorn (2013) show that routine-biased technological change has polarized labor markets, eroding middle-skill employment while boosting low- and high-skill service jobs (See Appendix C). Together, these studies imply that robot exposure erodes sectors traditionally associated with strong unionization, reinforcing the plausibility of a negative effect on union membership.

Observation #4: Unions Have Power Against Automation, But That Power is Weakening

Recent research suggests that unions still retain some power to resist the disruptive effects of automation. Lewandowski and Szymczak (2024) find that higher trade union coverage significantly mitigates the adverse effects of robot adoption on 'atypical employment', which refers to jobs that deviate from traditional full-time arrangements. Increases in atypical employment are common when workers in traditional roles are displaced. Lewandowski and Szymczak conclude that "higher unionisation significantly reduces robots' impact on atypical employment," suggesting that collective bargaining plays a meaningful role in shielding workers from technological displacement.

However, other evidence indicates that this protective power is eroding. Balcázar (2024) estimates that an increase in one robot per a thousand workers per year reduces the unionization rate by 0.07 percentage points and the likelihood that congresspeople vote with unions' interests by two percentage points. This effect is large and relevant considering that union density has decreased on average 0.3 percentage points per year from 1964-2021 (Hirsch, Macpherson and Even, 2025). In this view, while unions may retain the ability to moderate some immediate impacts of automation, their structural position in the labor market is gradually deteriorating as technological change accelerates.

Taken together, these findings suggest a nuanced story: unions do have some capacity to buffer workers against automation-induced disruptions, but this capacity is being increasingly undermined over time. As robot intensity continues to rise across industries, the ability of unions to meaningfully resist labor market polarization and erosion may diminish further.

Contribution

Most research examines how automation affects firms' labor demand, but relatively little is known about how it influences workers' decisions regarding collective organization. Understanding how automation reshapes union membership is critical for designing labor policies that are adaptive rather than merely prescriptive. As Lewandowski and Szymczak (2024) emphasize, unions play a "particularly relevant role in shaping the labor market impacts of automation." Recognizing whether unions can act as a buffer against technological disruption, or whether they are themselves undermined by it, is central to understanding the evolving balance of power between labor and capital.

Prior studies offer valuable insights into how automation reshapes labor market outcomes, particularly wages and employment. This paper draws heavily from Acemoglu and Restrepo (2020) for methodological inspiration and from Balcázar (2024) as a benchmark for comparison. However, my paper differs from the existing literature in three key respects.

First, in data construction: I use CPS-based union estimates from IPUMS, while Balcázar (2024) relies on union filings collected by Becher, Stegmueller, and Kappner (2018), who collect data from annual Department of Labor reports and harmonize this data at the congressional district level. Second, in time horizon: I extend the sample to 2021, whereas previous studies focus only through 2014. This is important because robot installations and technological advancements have accelerated significantly since then. These additional seven years allow me to examine more long-run effects, and how the impact of automation exposure changes post-2014. Third, I experiment with alternative measures of automation exposure, such as robot density per hundred workers in each industry, offering a simpler and more interpretable proxy relative to the commuter-zone adjusted metrics used elsewhere. Overall, my goal is to update, extend, and complement prior work on the relationship between automation and unionization, capturing more recent trends in technological adoption and labor market transformation. In particular, I seek to examine whether the accelerating spread of industrial robotics has contributed to the strengthening of unions in the United States.

Research Question and Hypotheses

Motivated by these considerations, the study is guided by the following research question and corresponding hypotheses:

> **Research Question (RQ):** Does increased robot density influence unionization rates across industries?
>
> **Null Hypothesis (H_0):** Changes in robot density have no effect on unionization rates.
>
> **Alternative Hypothesis (Positive) (H_{A1}):** Changes in robot density positively affect unionization rates.
>
> **Alternative Hypothesis (Negative) (H_{A2}):** Changes in robot density negatively affect unionization rates.

Initially, I hypothesized a *positive* causal relationship, reasoning that greater exposure to automation might spur workers to organize collectively as a defense against technological displacement. Rising automation risk, under this logic, could incentivize unionization as a mechanism for securing job protections, retraining programs, or severance benefits. However, as the results presented later demonstrate, the evidence instead supports the *negative* hypothesis: greater automation exposure is associated with a decline in unionization rates. One plausible explanation is that automation reduces the costs firms incur during labor disputes, thereby weakening workers' bargaining power. In environments where capital can readily substitute for labor, the traditional threat of work stoppages becomes less effective, diminishing unions' leverage and eroding incentives to organize.

To rigorously test these hypotheses, I employ both ordinary least squares first-differences (OLS-FD) and two-stage least squares first-differences (IV-FD) designs. The use of both OLS and IV approaches enables assessment of the stability of the estimated causal relationship across alternative specifications. Full details of the regression designs and identification strategies are presented in the Empirical Strategy section.

2 Data and Variables

This study utilizes several high-quality datasets to examine automation exposure, labor market characteristics, and unionization trends across U.S. industries. These data sources enable the construction of robust empirical measures and facilitate causal inference regarding the relationship between automation and unionization.

Robots

Precisely defining automation exposure presents several challenges. Building on prior work by Acemoglu and Restrepo (2020), I utilize data from the International Federation of Robotics (IFR), the leading source of industry-level robot adoption statistics. The IFR reports data at the national-industry level using an adjusted version of the ISIC Revision 4 classification. A sample of the IFR data is presented in Table 1:

Year	Industry Code	Industry Name	Country Code	Operational Stock
2004	0	All Industries	US	123,663
2004	90	All other non-manufacturing branches	US	0
2004	2939	Other (AutoParts)	US	0
2004	2934	Glass (AutoParts)	US	0
2004	2933	Electrical/electronic (AutoParts)	US	0
2004	2932	Rubber and plastic (AutoParts)	US	0

Table 1: Sample of U.S. Industry Data (2004)

While the IFR data are invaluable, they have limitations. Data are reported only at the national level, and not all robots are assigned to one of the 15 main IFR industries, potentially omitting some automation activity. Mismatches between IFR and U.S. industry classifications may introduce measurement error, and earlier years often have zero robots, particularly for less robot-intensive industries. Additionally, differences in adoption timing between Europe and the U.S. may complicate comparative analysis. Despite limitations, IFR data remain the standard for measuring automation exposure across sectors due to their broad international coverage and consistent reporting methodology.

For my main explanatory variable, rather than replicating Acemoglu and Restrepo's "Adjusted Penetration Rate" (APR), I adopt a simpler, realized measure: Robot Density, defined as the number of operational robots per hundred workers within an industry. Total employed workers are computed using EARNWT from the IPUMS CPS dataset.

$$\text{Robot Density}_{it} = \frac{\text{Number of Robots}_{it}}{\text{Total Employed Workers}_{it}} \times 100$$

Unions

Unionization measures are constructed using data from the Integrated Public Use Microdata Series (IPUMS) version of the Current Population Survey (CPS). The CPS provides detailed annual information on union membership and labor market outcomes. A sample of the CPS data is presented below in Table 2:

Year	**State Code**	**IND1990 Code**	**Union**	**Income**	**ASECWT**	**EARNWT**
2004	23	601	0	28,000	289	2,238
2004	23	641	0	2,500	304	2,112
2004	23	761	0	4,185	289	2,238
2004	23	360	0	52,863	289	2,088
2004	23	831	0	35,000	298	2,365
2004	23	840	0	69,000	239	2,279

Table 2: Sample of IPUMS Microdata (Selected Columns)

Union membership is reported through the UNION variable, categorized as "No response (0)," "No union coverage (1)," "Member of a labor union (2)," and "Covered by a union but not a member (3)." I recode this into a binary indicator ($UNION_{Binary}$): UNION=2 is classified as a union member (1), while UNION=1 or UNION=3 are classified as non-members (0), and no responses are removed from the data.

$$\text{Unionization Rate}_{it} = \frac{\text{Unionized Workers}_{it}}{\text{Total Employed Workers}_{it}}$$

$$\text{where} \quad \text{Unionized Workers}_{it} = \sum_{j \in \{i,t\}} \text{EARNWT}_j \times UNION_{Binary\,j}$$

$$\text{and} \quad \text{Total Employed Workers}_{it} = \sum_{j \in \{i,t\}} \text{EARNWT}_j \quad \text{for all } j \text{ in the labor force}$$

Despite its advantages, the CPS data has limitations. Union membership data suffer from high nonresponse rates (over 95% of the sample), limiting representativeness. No certified crosswalk exists between

IND1990 and the IFR's ISIC Rev. 4 industries, requiring manual mapping (See Appendix D). Survey weights (EARNWT) are imperfect, and static industry classifications may not fully capture structural shifts. Nevertheless, IPUMS CPS remains the best available source for analyzing long-term unionization trends across U.S. industries.

Additional Covariates

To address potential confounders, I include (i) industry-level average wages and (ii) total employment. Average wage is calculated as:

$$\text{Mean Wage}_{it} = \frac{\sum_{j \in \{i,t\}} \text{EARNWT}_j \times \text{INCWAGE}_j}{\sum_{j \in \{i,t\}} \text{EARNWT}_j}$$

Industries with higher average wages may exhibit lower unionization rates if workers perceive less marginal benefit to union representation or face higher opportunity costs to organizing. Total workforce size reflects organizational capacity and bargaining leverage and serves as both a control variable and regression weight. One shortcoming is that Income (INCWAGE) is self-reported and prone to measurement error and missingness; it reflects annual income without adjusting for hours worked, and is not inflation-adjusted. High earners may also skew industry averages.

Excluded Variables

Right-to-Work laws (RWLs) are omitted from the baseline specification because RWL adoption may itself be endogenous to automation exposure. Although RWLs are an important determinant of unionization, its inclusion could bias estimates. Future work will incorporate RLWs more explicitly as a robustness check. Import exposure, offshorability exposure, and capital growth are similarly excluded. These variables are likely important for unionization outcomes but would require extensive external datasets and adjustments beyond the scope of this analysis. In future research, I aim to more closely replicate frameworks like those in Acemoglu and Restrepo (2020) and Autor, Dorn, and Hanson (2013) by integrating broader trade and economic dynamics.

Summary Tables

After cleaning, Table 3 is a sample of the main dataframe for each industry in each year:

Year	Industry	Workers	Union Rate	Robot Density	Mean Wage	Euro Robots
2004	Automotive	1,743,705	0.324	0.949	44,275	254,687
2004	Construction	10,224,495	0.164	0	36,511	350
2004	Electronics	2,121,138	0.0678	0.123	54,436	22,688
2004	Food	2,063,676	0.119	0.0304	36,775	6,521
2004	Metals (Basic)	783,618	0.331	0.176	40,752	38,601
2004	Metals (Machinery)	2,183,939	0.0629	0	50,089	2,285

Table 3: Sample of Industry-Level Data

We will compute absolute and percentage differences between variables of two different years (ex. 2004 and 2007) for our main regressions, outlined below.

3 Empirical Strategy: First Differences Model

Having constructed measures of industry-level automation exposure, unionization rates, and relevant covariates, I now turn to the empirical strategy. The primary objective is to estimate the causal effect of robot adoption on unionization outcomes across U.S. industries. To do so, I implement a first-differences regression framework that exploits continuous variation in robot density across industries over time. This approach removes time-invariant industry characteristics and enables identification of the impact of changes in automation exposure on changes in unionization rates.

Following the conceptual approach of Acemoglu and Restrepo (2020), I exploit differences in the intensity of automation exposure across industries, rather than a binary treatment. While a standard panel fixed-effects model could still suffer from bias if industries inherently differ in unobserved trends correlated with automation, differencing outcomes over time controls for persistent industry-specific factors. By examining changes between specific periods, this framework mitigates concerns over structural differences and isolates the relationship between automation and unionization dynamics. To strengthen causal inference and address potential endogeneity, I estimate both OLS first-differences regressions and an instrumental variables (IV) version that leverages European robot adoption as a source of exogenous variation.

3.1 OLS First-Differences Specification

The baseline OLS specification relates changes in unionization rates to changes in robot density and additional covariates:

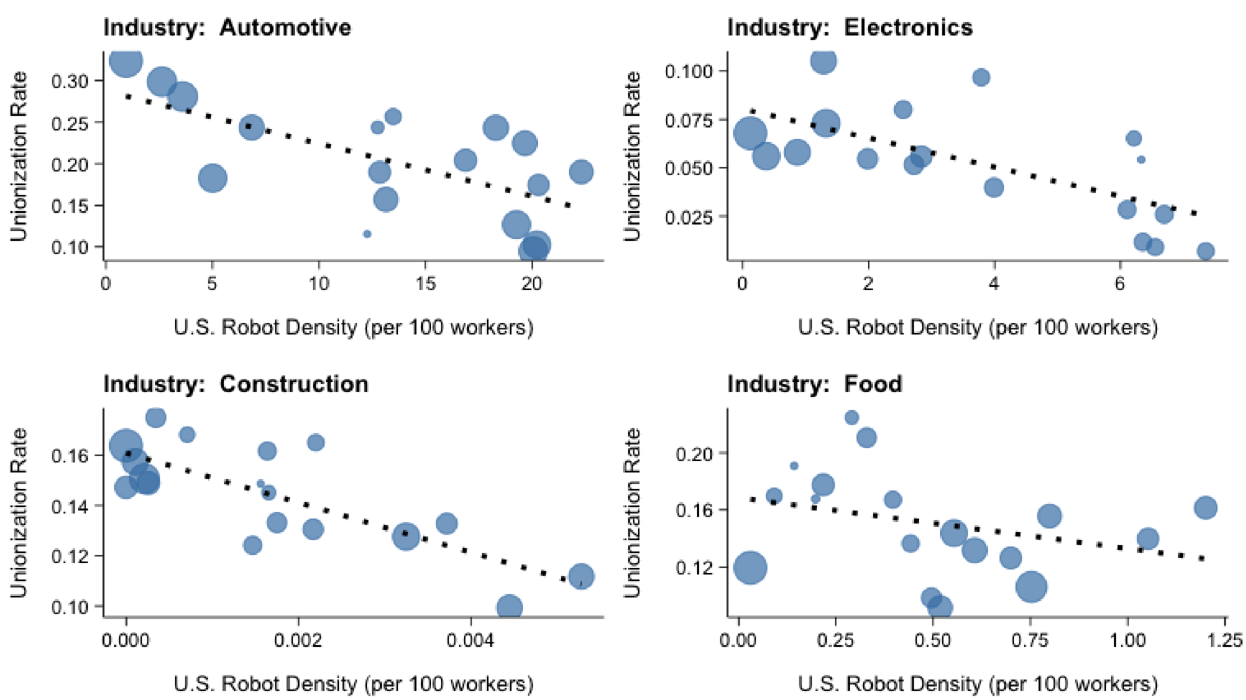
$$\Delta UnionizationRate_{i,t_1,t_2} = \gamma_0 + \gamma_1 \Delta RobotDensity_{i,t_1,t_2} \tag{1}$$

$$+ \gamma_2 \Delta\% MeanWage_{i,t_1,t_2} \tag{2}$$

$$+ \gamma_3 \Delta\% WorkerPopulation_{i,t_1,t_2} + \epsilon_{i,t_1,t_2} \tag{3}$$

In Equation 1, $\Delta UnionizationRate_{i,t_1,t_2}$ denotes the change in the unionization rate for industry i between years t_1 and t_2, $\Delta RobotDensity_{i,t_1,t_2}$ captures the change in robot density (robots per hundred workers), and $\Delta\% MeanWage_{i,t_1,t_2}$ and $\Delta\% WorkerPopulation_{i,t_1,t_2}$ control for changes in mean wages and total workforce size, respectively. Figure 3 shows the negative correlation between U.S. Robot Density and the Unionization Rate for some of the industries in my sample.

Figure 3: U.S. Robot Density vs. Unionization by Industry (Sources: IPUMS, IFR)



Within industries, robot density is negatively correlated with unionization rates from 2004-2021. Figure 3 depicts the OLS plots for four of the fifteen IFR industries used in this analysis.

Although the first-differences model controls for time-invariant differences across industries, it may still be vulnerable to endogeneity if industries that adopt robots more rapidly also experience other simultaneous shocks that independently affect unionization rates. Moreover, there is a potential concern of reverse causality: industries experiencing a decline in unionization could become more attractive targets for automation investment, if lower union strength reduces the costs or resistance associated with adopting new technologies. In such cases, observed correlations between rising robot density and falling unionization could reflect strategic behavior by firms rather than a causal impact of automation itself. Finally, OLS estimates could suffer from measurement error in robot density or other omitted variables that evolve jointly with both automation exposure and unionization outcomes. To address these concerns and strengthen causal identification, I also consider an instrumental variables (IV) strategy.

3.2 IV First-Differences Specification

To mitigate endogeneity concerns, I extend the analysis to an instrumental variables (IV) framework. Following Acemoglu and Restrepo (2020), I instrument changes in U.S. robot density using changes in European robot adoption patterns. European automation trends are plausibly exogenous to U.S. labor market conditions, offering a credible source of quasi-random variation. As Acemoglu and Restrepo (2020) note,"European robot adoption is a powerful predictor of U.S. industry-level robot penetration and, given the geographic separation, unlikely to be directly influenced by U.S. labor market shocks." Confidence in the instrument relies on three core assumptions: relevance, exclusion, and the absence of unmeasured confounders. First, European robot adoption must strongly predict changes in U.S. robot density (relevance). Second, European robot use must affect U.S. unionization only through its impact on U.S. robot adoption and not directly (exclusion restriction). Third, there must be no omitted variables simultaneously influencing European robot adoption, U.S. robot adoption, and U.S. unionization outcomes. Based off of preceding research findings, theoretical backing, and strong first stage F-statistics (as shown in Table 5), I am confident in using European robot adoption to instrument U.S. Robot Density[5]. The first-stage regression estimating predicted changes in U.S. robot density is specified as:

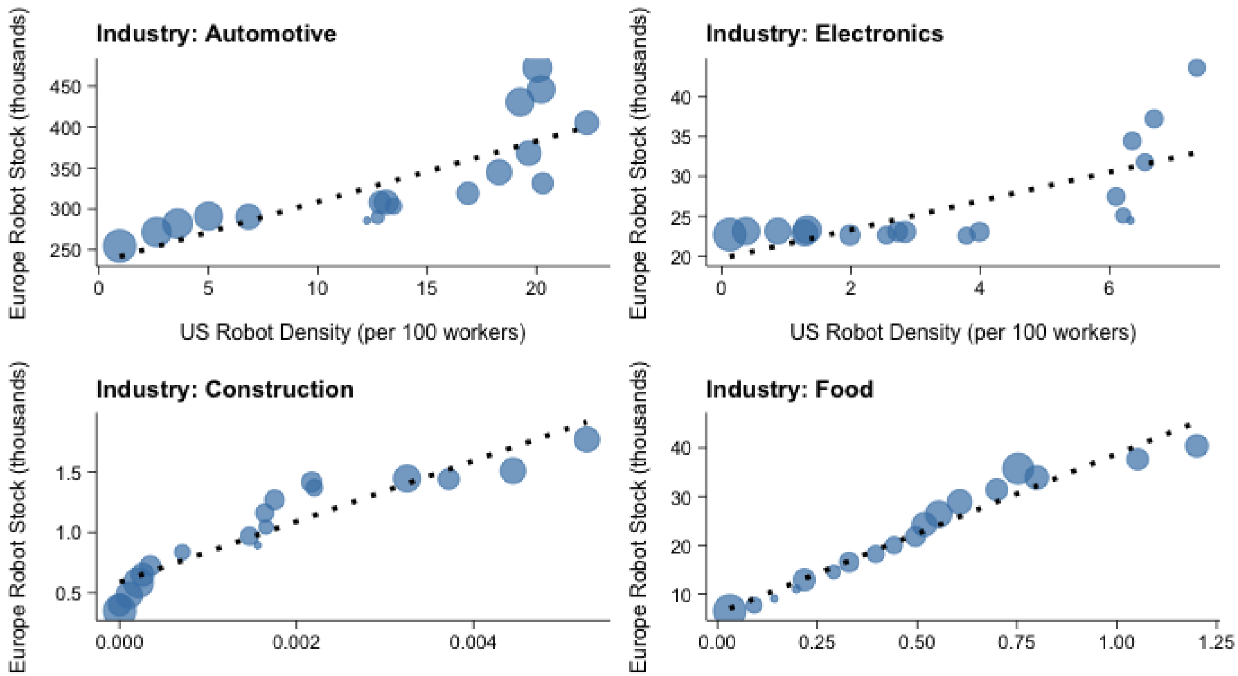
$$\Delta Robot\widehat{Density}_{i,t_1,t_2} = \pi_0 + \pi_1 \Delta EuropeanRobots_{i,t_1,t_2} \tag{4}$$

$$+ \pi_2 \Delta \% MeanWage_{i,t_1,t_2} \tag{5}$$

$$+ \pi_3 \Delta \% WorkerPopulation_{i,t_1,t_2} + \nu_{i,t_1,t_2} \tag{6}$$

[5]While this strategy builds on established precedent, one limitation arises: I am unable to replicate the exact one-to-one mapping from European robots per worker to U.S. robots per worker employed by Acemoglu and Restrepo (2020). Attempts to reconstruct this measure using the EUKLEMS dataset were hindered by missing data for post-2014 years, particularly regarding hours worked variables. Consequently, I use changes in total European operational robot stock at the industry level as the instrument in the first stage (See Equation 4). Preliminary scatterplots shown in Figure 4 reveal a strong positive relationship between changes in European robot stock and changes in U.S. robot density, supporting the instrument's strength.

Figure 4: U.S. Robot Density vs. European Robot Stock by Industry (Sources: IPUMS, IFR)



U.S. Robot Density and European Robot Stock appear to be highly correlated. While a 1-1 metric as the instrument is preferred, this will suffice.

Whereas the second stage uses the predicted change in robot density to estimate the causal effect on unionization rates:

$$\Delta UnionizationRate_{i,t_1,t_2} = \beta_0 + \beta_1 \Delta \widehat{RobotDensity}_{i,t_1,t_2} \tag{7}$$

$$+ \beta_2 \Delta\% MeanWage_{i,t_1,t_2} \tag{8}$$

$$+ \beta_3 \Delta\% WorkerPopulation_{i,t_1,t_2} + \epsilon_{i,t_1,t_2} \tag{9}$$

3.3 Timeframe

The analysis focuses on multiple time windows selected to capture distinct economic contexts. I first examine changes from 2004 to 2007 to align with Acemoglu and Restrepo's pre-recession focus and to exploit a short-run horizon where automation shocks began to intensify but major macroeconomic disruptions had not yet occurred. The 2004 to 2014 window extends the analysis to include the Great Recession and the early recovery period, allowing an assessment of whether automation's impact on unionization differed during periods of economic stress. Finally, the 2004 to 2021 window captures the full available period, including the acceleration of automation in the mid-to-late 2010s. Comparing across these intervals enables assessment of the stability or variation of robot adoption effects across different macroeconomic environments. Overall, the combination of a first-differences regression approach with an instrumental variables strategy provides a credible empirical framework for estimating the causal impact of automation on unionization trends. While limitations remain, this design mitigates key sources of bias and strengthens the validity of the findings.

4 Results

With the empirical framework established, I now turn to presenting the results. I first examine baseline estimates from ordinary least squares (OLS) first-differences regressions, which exploit continuous variation in robot density across industries. I then present results from instrumental variables (IV) specifications that address potential endogeneity concerns by using exogenous variation in European robot adoption. Throughout, I assess the robustness of the findings across different time horizons and discuss their implications for the evolving relationship between automation and unionization in the U.S. labor market.

4.1 OLS First-Differences Results

Table 4 presents estimates from OLS first-differences regressions examining the relationship between changes in robot density and changes in industry unionization rates across three time horizons: 2004–2007, 2004–2014, and 2004–2021. Weighted regressions are done based on $Population_{i,2004}$ for each industry i. Across all specifications, the results consistently reveal a negative association between increases in robot density and subsequent changes in unionization rates.

Table 4: OLS First-Differences Regressions: Δ Unionization vs Δ Robot Density

	Dependent variable:					
	Δ Unionization Rate					
	2004–07	2004–07	2004–14	2004–14	2004–21	2004–21
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Robot Density	-0.0409**	-0.0341**	-0.0064***	-0.0071***	-0.0079***	-0.0076**
	(0.0138)	(0.0126)	(0.0018)	(0.0021)	(0.0023)	(0.0027)
Δ Wages (%)	-0.0945	-0.0528	0.0263	-0.0095	-0.0724	-0.0668
	(0.1222)	(0.1130)	(0.0628)	(0.0625)	(0.0655)	(0.0654)
Δ Population (%)	0.0779	-0.0166	-0.0533**	-0.0338	-0.1663**	-0.1449**
	(0.0999)	(0.0821)	(0.0223)	(0.0348)	(0.0582)	(0.0585)
Constant	0.0281	-0.0014	-0.0511**	-0.0260	-0.0308	-0.0372
	(0.0317)	(0.0226)	(0.0202)	(0.0187)	(0.0412)	(0.0373)
Weighted		✓		✓		✓
Observations	15	15	15	15	15	15
R^2	0.4792	0.3995	0.6065	0.5127	0.6623	0.6037
Adjusted R^2	0.3372	0.2358	0.4992	0.3798	0.5702	0.4956

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

In the short-run period of 2004–2007 (columns 1 and 2), a one-unit increase in robot density per hundred workers is associated with a 4.09 to 3.41 percentage point decline in unionization rates, significant at the 5% level. In longer periods, such as 2004–2014 and 2004–2021, the estimated effects shrink to approximately 0.64 to 0.79 percentage points but remain statistically significant. These patterns suggest that the immediate effects of automation were particularly disruptive to organized labor, with the magnitude of the impact diminishing over longer horizons as industries adapted. However, given potential concerns about reverse causality and measurement error, these OLS results should be interpreted cautiously.

4.2 IV First-Differences Results

Table 5 presents instrumental variables (IV) estimates of the causal impact of changes in robot density on changes in industry unionization rates, using changes in European robot stock as an instrument for U.S. robot adoption. Again, weighted regressions are done based on $Population_{i,2004}$ for each industry i. Across all specifications, the IV results consistently reveal a negative relationship between robot exposure and unionization outcomes.

Table 5: IV First-Differences Regressions: Δ Unionization vs Δ Robot Density

	Dependent variable:					
	Δ Unionization Rate					
	2004–07	2004–07	2004–14	2004–14	2004–21	2004–21
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Robot Density	-0.0371*	-0.0338*	-0.0088***	-0.0115**	-0.0098***	-0.0102***
	(0.0169)	(0.0161)	(0.0026)	(0.0037)	(0.0028)	(0.0032)
Δ Wages (%)	-0.0935	-0.0524	0.0213	0.0021	-0.0591	-0.0438
	(0.1226)	(0.1140)	(0.0677)	(0.0741)	(0.0682)	(0.0697)
Δ Population (%)	0.0801	-0.0164	-0.0580**	-0.0455	-0.1680**	-0.1460**
	(0.1003)	(0.0825)	(0.0243)	(0.0417)	(0.0600)	(0.0609)
Constant	0.0267	-0.0015	-0.0466*	-0.0284	-0.0330	-0.0469
	(0.0321)	(0.0227)	(0.0220)	(0.0221)	(0.0425)	(0.0393)
Weighted		✓		✓		✓
First-Stage F	22.931	17.236	12.998	9.006	31.235	31.829
Observations	15	15	15	15	15	15
R^2	0.4757	0.3995	0.5452	0.3220	0.6415	0.5695
Adjusted R^2	0.3327	0.2357	0.4212	0.1371	0.5437	0.4521

Note: *p<0.1; **p<0.05; ***p<0.01

In the short-run period from 2004 to 2007 (columns 1 and 2), a one-unit increase in robot density per hundred workers leads to an estimated 3.71 to 3.38 percentage point decline in unionization rates, with statistical significance at the 10% level. Over the 2004–2014 horizon (columns 3 and 4), the effect size remains negative, ranging from 0.88 to 1.15 percentage points, significant at the 1% and 5% levels depending on weighting. In the full 2004–2021 period (columns 5 and 6), the estimates are smaller in magnitude (approximately 0.99 to 1.01 percentage points), but highly statistically significant. Notably, the IV estimates are often larger in magnitude than the corresponding OLS estimates. This suggests that the OLS results may have been biased toward zero, possibly because of measurement error in robot density. In other words, the OLS approach may have understated the true impact of automation on unionization rates. Instrumental variables correct for this by isolating exogenous variation, producing larger and more accurate coefficient estimates. Nevertheless, the persistence of negative and statistically significant effects across all periods strengthens the evidence for a causal interpretation.

Control variables again exhibit mixed patterns across time horizons. Wage changes are negatively associated with unionization in early periods but are not consistently statistically significant. Changes in workforce size flip signs across periods, reflecting longer-term compositional shifts in the industrial base. Overall, the IV estimates provide robust evidence that increases in robot density causally contributed to declines in industry-level unionization rates between 2004 and 2021.

5 Conclusion

I now return to the Research Question and Hypotheses outlined earlier. Based on the empirical evidence presented, I reject the null hypothesis (H_0) and instead accept the negative alternative hypothesis (H_{A2}). The analysis finds that increases in robot density are consistently associated with declines in industry-level unionization rates across multiple time horizons. This result is robust to the use of instrumental variables techniques that address potential endogeneity concerns.

The initial expectation (H_{A1}) that automation risk might spur greater unionization is not supported by the data. Rather than galvanizing collective action, increased automation exposure appears to undermine traditional mechanisms of worker power. A likely explanation is that automation erodes the leverage of unions by reducing firms' dependence on human labor, making work stoppages and strikes less costly and less effective.

5.1 Discussion of the Results

Taken together, the results suggest that automation had a meaningful and statistically significant negative impact on unionization trends across U.S. industries during the study period (2004-2021). Both OLS and IV estimates consistently point toward a negative relationship, but the IV specifications, which leverage exogenous variation from European robot adoption, provide stronger causal evidence that rising robot density suppressed unionization.

The magnitude of the estimated effects is not only statistically significant but also economically meaningful. Based on the IV estimates, a one-unit increase in robot density—equivalent to one additional operational robot per hundred workers—causes an approximately 0.9 to 1.2 percentage point decline in that industry's unionization rate. Given that baseline unionization rates in many industries were in the range of 5 to 15 percent during the early 2000s, even a 1 percentage point drop represents a substantial erosion of union power. Although the magnitude of the estimated coefficients declines modestly over longer horizons (likely reflecting industry adaptation through re-skilling, occupational shifts, and institutional evolution), the persistence of statistically significant effects underscores automation's durable influence on collective bargaining structures.

Comparing to Balcázar (2024), who estimates that an increase of one robot per 1,000 workers per year reduces unionization by approximately 0.07 percentage points, my results are highly consistent. Rescaling my IV estimates to Balcázar's units suggests that one additional robot per 1,000 workers would decrease unionization rates by roughly 0.09 percentage points. The similarity in magnitude and direction across settings provides strong external validation for the findings, reinforcing the conclusion that automation has played a modest but systematic role in weakening organized labor in the U.S. economy during the early twenty-first century.

5.2 Policy Implications

Beyond their immediate labor market effects, these results raise important policy considerations. If automation weakens the institutional capacity of workers to organize and advocate collectively, policymakers may need to consider new forms of labor protections and representation suited to an increasingly automated economy. Traditional union structures evolved under industrial-era production systems. As technological change accelerates, modern equivalents must adapt to sustain worker voice in an era of continuous disruption.

Moreover, as robot adoption continues and emerging technologies like artificial intelligence reshape white-collar occupations, policymakers must recognize that the erosion of union power may not be confined to historically unionized manufacturing sectors. Strengthening collective bargaining rights, supporting alternative worker organizations, and rethinking social safety nets may be critical components of a labor policy agenda responsive to technological transformation.

5.3 Limitations

Several limitations of the present study should be acknowledged. First, although the instrumental variables strategy strengthens causal identification, measurement error in robot counts and employment estimates may still introduce noise into the estimated effects. Second, the analysis focuses on industry-level averages, potentially masking important heterogeneity across occupations, demographic groups, or geographic areas within industries. Third, while the European robot stock instrument plausibly satisfies relevance and exclusion restrictions, its validity ultimately rests on the assumption that European automation trends are unrelated to unobserved shocks affecting U.S. unionization patterns—a condition that, while defensible, cannot be fully tested in this analysis. Fourth, the study does not account for other technological, political, or trade-related forces—such as import exposure from globalization, offshorability of jobs, or broader economic restructuring—that may simultaneously influence both automation and unionization. Finally, the analysis is confined to the pre-LLM (large language model) automation era; future waves of technological change may differ substantially in scope and nature from industrial robotics.

5.4 Future Steps

Building on these findings, future research should pursue several extensions. First, integrating measures of import competition and offshorability (following Autor, Dorn, and Hanson (2013)) would allow researchers to disentangle the effects of automation from broader globalization pressures on unionization. Second, analyzing routine-task intensity (RTI) as an alternative proxy for automation risk may capture subtler labor market transformations, particularly in industries where robot adoption data is limited. Third, expanding the analysis to include white-collar occupations—particularly in light of emerging automation risks from large language models (LLMs)—could reveal whether similar declines in organizational labor power are now affecting professional sectors. This may require the development of new metrics for automation risk, as traditional industrial robot measures may fail to capture software-based automation impacts. Finally, future work could explore cross-sectoral dynamics, investigating whether the erosion of union power in manufacturing spills over into related service industries, and whether certain legal or institutional environments (such as right-to-work laws) mediate the relationship between automation and collective bargaining. By addressing these topics, future research can further clarify how technological change reshapes not only the structure of employment but also the broader institutional landscape governing worker voice and power.

6 References

Daron Acemoglu & Pascual Restrepo, 2020. "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, University of Chicago Press, vol. 128(6), pages 2188–2244.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–1597.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103 (6): 2121–2168.

Balcázar, Carlos Felipe. "Unions and Robots: Automation and the Power of Labor." (2024). Available at SSRN: `https://ssrn.com/abstract=4360315`.

Card, D., Lemieux, T., & Riddell, W.C. (2004). Unions and Wage Inequality. *Journal of Labor Research*, 25(4), 519–559.

Flood, King, Rodgers, Ruggles, and Warren. 2023. Integrated Public Use Microdata Series, Current Population Survey: Version 11.0 [dataset]. IPUMS. `https://doi.org/10.18128/D030.V11.0`.

Hirsch, Barry T., David A. Macpherson, and William E. Even. (2025). "Union Membership, Coverage, and Earnings from the CPS." `https://unionstats.com`.

International Federation of Robotics. World Robotics: Industrial Robots 2023. Frankfurt: IFR Statistical Department, 2023.

LaRocco, Lori Ann. "Ila Union and Port Owners Held Secret Meeting on Automation as New Strike Looms." CNBC, January 7, 2025. `https://www.cnbc.com/2025/01/06/ila-union-ports-held-secret-meeting-on-automation-as-new-strike-looms.html`.

Lewandowski, Piotr, and Wojciech Szymczak. 2024. "Automation, Trade Unions and Involuntary Atypical Employment." *IBS Working Papers* 02/2024. `https://ideas.repec.org/p/ibt/wpaper/wp022024.html`.

Oladipo, Doyinsola, and David Shepardson. "US Dockworkers Strike, Halting Half the Nation's Ocean Shipping." Reuters, October 1, 2024. https://www.reuters.com/world/us/us-east-coast-dockworkers-head-toward-strike-after-deal-deadline-passes-2024-10-01/.

"Right-to-Work Resources." National Conference of State Legislatures, December 19, 2023. https://www.ncsl.org/labor-and-employment/right-to-work-resources.

Schnabel, Claus. "Trade Unions in Europe — CEPR." VoxEU, November 18, 2013. https://cepr.org/voxeu/columns/trade-unions-europe..

Statista. "Labor Unions in the U.S." 2024. https://www.statista.com/topics/10789/labor-unions-in-the-us/.

Stegmueller, Daniel, Michael Becher, and Konstantin Käppner. 2018. "Labor Unions and Unequal Representation." Available at SSRN: https://ssrn.com/abstract=3220032.

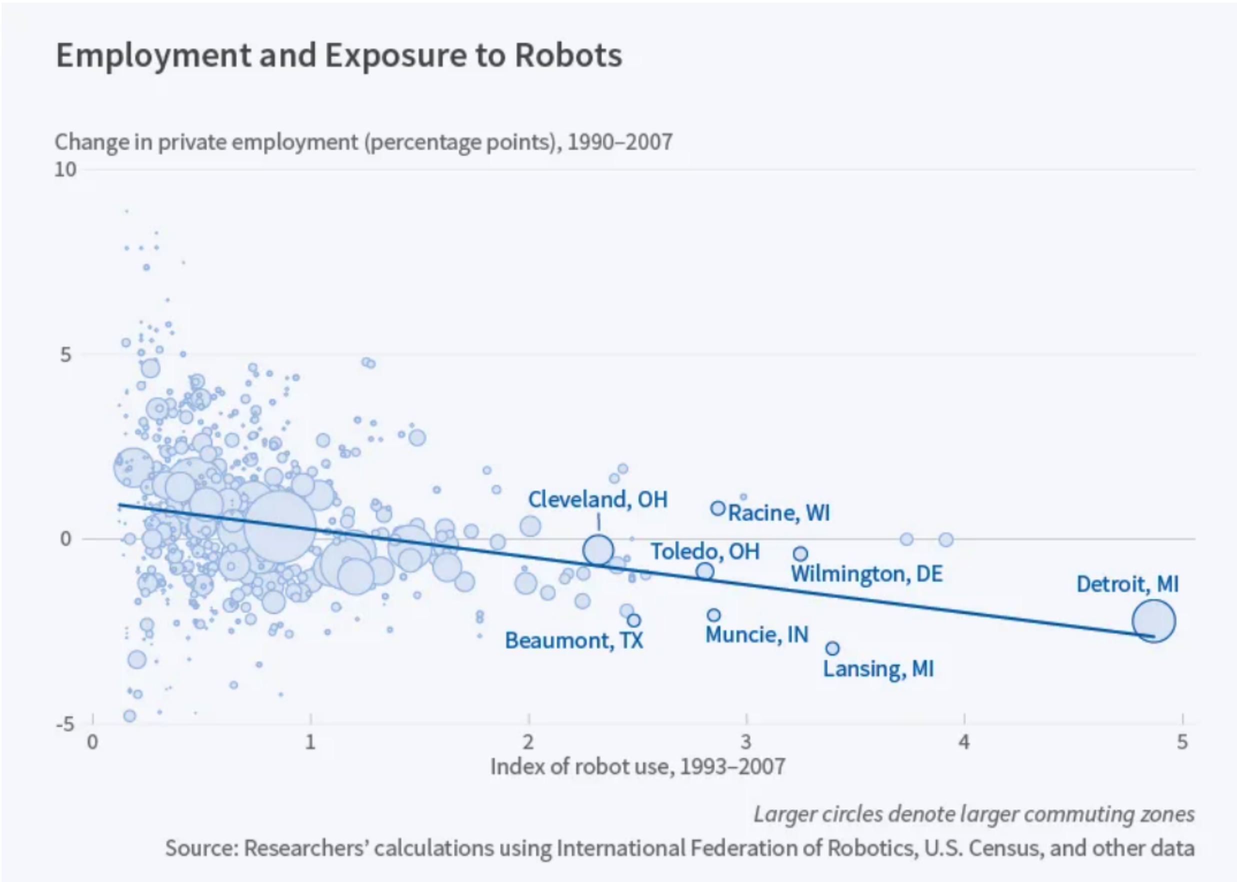
Appendix A: Declining European Unionization

European Union Densities (Source: CEPR)

country	union density (net membership/ employment, in %)				change (% points)
	1960	1980	2000	2011	1980-2011
Austria	67.9	56.7	36.6	27.8	-28.9
Belgium	41.5	54.1	49.5	50.4	-3.7
Denmark	56.9	78.6	74.2	68.5 1	-10.1
Germany	34.7	34.9	24.6	18.0	-16.9
Greece	---	39.0	26.5	25.4	-13.6
Finland	31.9	69.4	75.0	69.0	-0.4
France	19.6	18.3	8.0	7.9 1	-10.4
Ireland	46.4	58.4	37.2	36.1	-22.3
Italy	24.7	49.6	34.8	35.2	-14.4
Luxemburg	---	50.8	42.5	37.3 2	-13.5
Netherlands	40.0	34.8	22.6	19.0	-15.8
Norway	60.0	58.3	54.4	54.6	-3.7
Portugal	---	54.8	21.6	19.3 1	-35.5
Spain	---	18.7	16.7	15.6 1	-3.1
Sweden	72.1	78.0	80.1	68.9 1	-9.1
Switzerland	36.1	27.7	20.2	17.2 1	-10.5
UK	40.4	51.7	30.1	27.1 1	-24.6

Appendix A shows a decline (across all industries) in unionization in Europe from 1980-2011, paralleling U.S. trends.

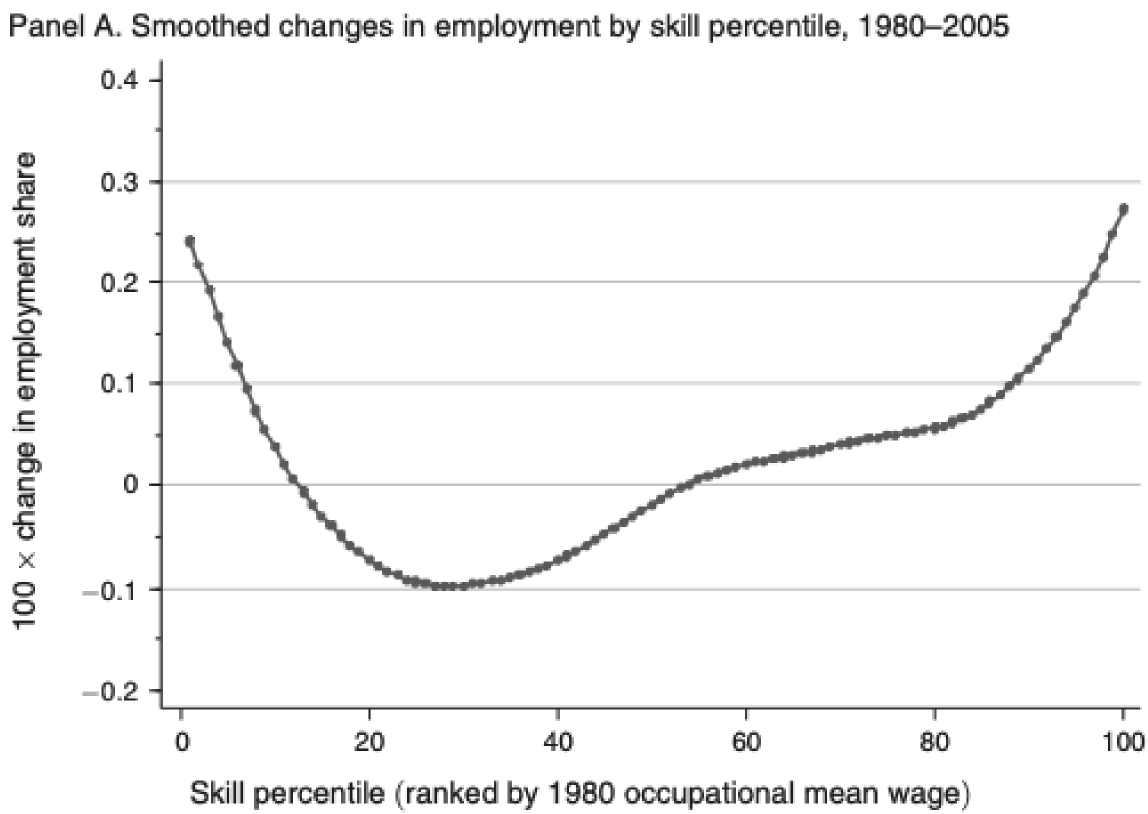
Appendix B: Negative Impact of Robots on Employment



Source: Acemoglu and Restrepo (2020)

Appendix B shows a negative relationship between robot use and private employment found in "Robots and Jobs."

Appendix C: Polarization of U.S. Labor Market



Source: Autor and Dorn (2013)

Appendix C shows low and high-skill jobs gaining employment shares in "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." I believe many unionized manufacturing jobs may fall in the 20-40th percentile range.

Appendix D: Industry Mapping

IND1990 CODE	Description	IFR Industry
351	Motor vehicles and motor vehicle equipment	Automotive
60	All construction	Construction
340	Household appliances	Electronics
100	Meat products	Food
101	Dairy products	Food
110	Grain mill products	Food
111	Bakery products	Food
112	Sugar and confectionery products	Food
120	Beverage industries	Food
121	Misc. food preparations and kindred products	Food
130	Tobacco manufactures	Food
271	Iron and steel foundries	Metals (Basic)
272	Primary aluminum industries	Metals (Basic)
280	Other primary metal industries	Metals (Basic)
310	Engines and turbines	Metals (Machinery)
311	Farm machinery and equipment	Metals (Machinery)
312	Construction and material handling machines	Metals (Machinery)
320	Metalworking machinery	Metals (Machinery)
321	Office and accounting machines	Metals (Machinery)
322	Computers and related equipment	Metals (Machinery)
282	Fabricated structural metal products	Metals (Products)
290	Screw machine products	Metals (Products)
291	Metal forgings and stampings	Metals (Products)
292	Ordnance	Metals (Products)
300	Miscellaneous fabricated metal products	Metals (Products)
40	Metal mining	Mining
41	Coal mining	Mining
42	Oil and gas extraction	Mining
371	Scientific and controlling instruments	Other manufacturing
380	Photographic equipment and supplies	Other manufacturing

IND1990 CODE	Description	IFR Industry
391	Miscellaneous manufacturing industries	Other manufacturing
352	Aircraft and parts	Other vehicles
360	Ship and boat building and repairing	Other vehicles
361	Railroad locomotives and equipment	Other vehicles
370	Cycles and miscellaneous transportation equipment	Other vehicles
432	Services incidental to transportation	Other vehicles
161	Miscellaneous paper and pulp products	Paper
162	Paperboard containers and boxes	Paper
171	Newspaper publishing and printing	Paper
181	Drugs	Plastic and chemicals
182	Soaps and cosmetics	Plastic and chemicals
191	Agricultural chemicals	Plastic and chemicals
192	Industrial and miscellaneous chemicals	Plastic and chemicals
200	Petroleum refining	Plastic and chemicals
201	Miscellaneous petroleum and coal products	Plastic and chemicals
210	Tires and inner tubes	Plastic and chemicals
212	Miscellaneous plastics products	Plastic and chemicals
842	Elementary and secondary schools	Research
850	Colleges and universities	Research
851	Vocational schools	Research
852	Libraries	Research
132	Knitting mills	Textiles
141	Carpets and rugs	Textiles
150	Miscellaneous textile mill products	Textiles
152	Miscellaneous fabricated textile products	Textiles
220	Leather tanning and finishing	Textiles
230	Logging	Wood
232	Wood buildings and mobile homes	Wood
241	Miscellaneous wood products	Wood
242	Furniture and fixtures	Wood

Appendix D is the crosswalk I created between the IPUMS IND1990 industry codes and the 15 IFR industries.