# Unions and Automation

Joe Tatarka and Anthony Tatarka*

**Abstract**

In this paper we examine the effects of labor unions on the adoption of automation using a difference-in-difference approach utilizing variation in Midwest states adopting Right-to-Work (RTW) laws. We find that RTW states have on average 0.3361 more robots per thousand workers than non-RTW states, which is significant at the 1% level. Since RTW laws are a proxy for weaker unions, this suggests that unions decrease automation; however, this estimate is not casual due to problems with the parallel trends assumption and non-exogenous adoption of RTW laws.

## 1 Introduction

One major concern with the advancement of technology in the workplace is that new automation will displace jobs. Acemoglu and Restrepo (2020) provide evidence that the adoption of robots reduces employment and decreases wages. This is of particular worry to labor unions as they represent the interest of workers, making the dynamic between unions

*Author Contributions: Anthony collected and analyzed the data. Both authors designed research and wrote the paper.

and automation in the workplace unclear. Understanding this dynamic between unions and automation is important to understand given a recent shift in how unions are viewed as shown by unionization attempts at large corporations such as Starbucks and Amazon.

There are two competing channels through which unions and automation interact which makes the effect of unions on automation a priori ambiguous. The first channel is that unions may use their bargaining abilities to make adopting technology more costly for employers. There are examples of unions making an effort to combat job losses to automation by bargaining for re-skilling of jobs and, at least in one case, requiring a six-month notice of any new technologies that may create job loss (Green, 2020; Meisburg and Quackenboss, 2020). Unions may have the power to fight back against automation through bargaining such as this.

The second channel is that unions may increase labor costs by increasing wages for workers which leads employers to substitute labor for capital, therefore increasing automation. In their paper, Alesnia et al. (2015) create a model of automation that includes labor market regulations and compare their model to empirical evidence. They find a correlation between union density and an increase in automation in low skill jobs. A similar idea is also investigated in a working paper which uses industry level data across OECD countries to look at the effect of labor friendly institutions on adoption of robots (Presidente, 2019). This paper estimates that an increase in union density by 10% is associated with an increase in 1.8 robots per thousand employees, although this is not a casual interpretation.

There is also literature on the effects of automation on unions. A working paper by Bálcazar and Quintana (2021) looks at automation and unions in the United States, in which they estimate that an increase in one robot per thousand workers is related to a 2.6 percent point reduction in the number of unionized workers and a 0.07 percentage point reduction in the share of unionized workers. They argue that increased automation reduces unionization through two channels: first by reducing the effectiveness of union strikes and second by reducing the number of workers through which unions draw their members from.

In this paper we explore the net effects of unions on automation in the United States with a difference-in-difference approach which leverages variation between Right-to-Work states and non-Right-to-Work states. Previous studies have not used the difference in Right-to-Work states in order to examine unions and automation. Also our study focuses on comparison within the United States while similar studies compare between OECD countries.

The rest of the paper is organized as follows. Section II discusses the history of Right-to-Work states. Section III describes the data used. Section IV explains the empirical strategy. Section V shows the empirical results and checks if the parallel trends assumption is satisfied. Section VI concludes.

## 2 Right-to-Work States

In 1935, the National Labor Relations Act, also known as the Wagner Act, allowed for workers to unionize and negotiate collective bargaining agreements with companies. Collective bargaining agreements could force all workers covered by these agreements to pay union dues even if they are not union members. In 1947, the Taft-Hartley act passed which allowed states to pass Right-to-Work (RTW) laws which prevent non-union workers from being forced to pay union dues. A RTW state is any state that has adopted these laws. As of today there are 27 RTW states (see Figure A.1) although unions have opposed them; the AFL-CIO claims that RTW laws are “designed to take away rights from working people” (AFL-CIO, 2022).

RTW laws essentially weaken a unions influence in the state which is reflected in our data. We find that there are lower rates of union membership and union coverage in RTW states (Figure 1) and that RTW is negative and statistically significant in explaining these union measures even with controls (Table A.2).

In the 2010’s three states in the Midwest adopted RTW laws; in 2012, Michigan and Indiana adopted Right-to-Work laws and Wisconsin followed suit in 2015, while the rest of the Midwest did not change their laws.

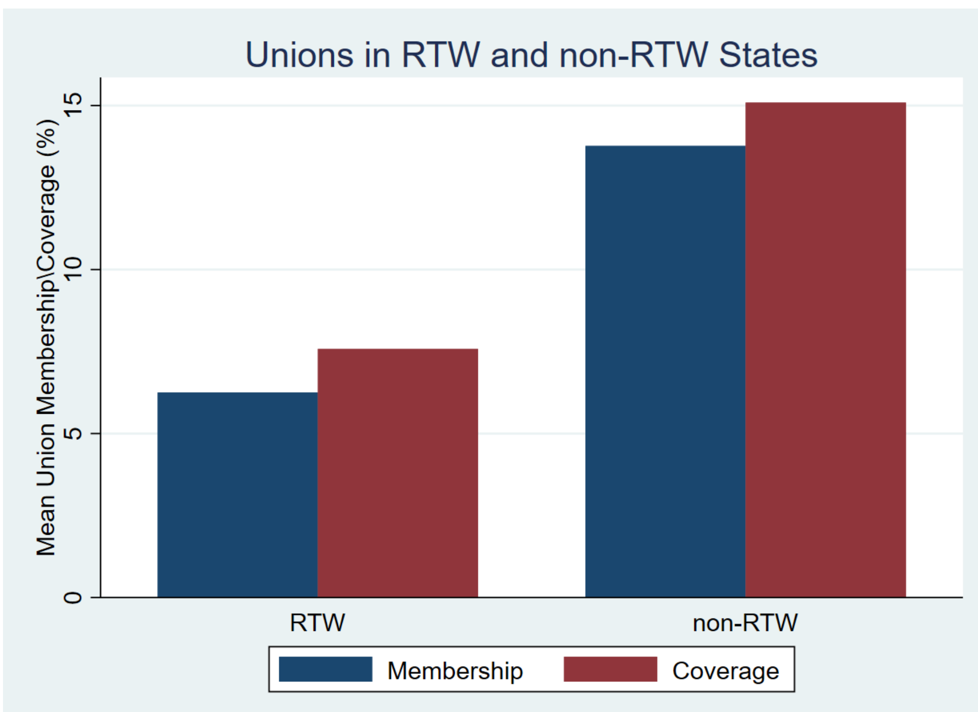


Figure 1: Union Membership and Coverage in RTW vs. non-RTW States

# 3 Data

We intend to use three main data sources: the first is the Union Membership and Coverage Database which is an internet data resource providing private and public sector labor union membership and coverage estimates compiled from the monthly household Current Population Survey (CPS) using BLS methods. From this dataset, we will use union membership and coverage by state from 2004-2017.

The second data source is a list of Right to work States and when they became introduced these laws. This data will indicate if a state is a Right to Work (RTW) state or not, over the time period of 2004-2017, giving us a binary variable for RTW.

The third data set contains data on industrial robot exposure by commuting zone from 2004-2017 which is a measure created by Acemoglu and Restrepo (2020) using data from the International Federation of Robotics. To create a state level dataset, we took the mean robot exposure over commuting zones within a given state and year. It is important to note that Alaska and Hawaii are not included, so the data is restricted to the 48 contiguous states.

There is also data for state unemployment and civilian non-institutional population from the Bureau of Labor Statistics and state median income from the U.S Census which will be used for additional controls.

In Table 3.1, we observe the 5 main variables used in this paper. The variable *Robot Exposure* is the robot exposure in a given state and year and it is measured in robots per thousand workers. On average, a given state in a given year has 1.35 robots per thousand workers. Next, the variable $\Delta$*Robot Exposure* is the difference in robot exposure in a given year from the previous year for a given state, thus giving us the change in robot exposure.

Table 3.1: Descriptive Statistics

| | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| Robot Exposure | 1.35 | 0.86 | 0.15 | 5.87 | 672 |
| $\Delta$ Robot Exposure | 0.07 | 0.06 | -0.08 | 0.45 | 624 |
| Union Membership | 10.28 | 4.97 | 1.60 | 26.10 | 672 |
| Union Coverage | 11.60 | 4.96 | 2.60 | 27.50 | 672 |
| RTW | 0.46 | 0.50 | 0.00 | 1.00 | 672 |

Note: An observation is for a given state (48 contiguous states) during a given year (2004-2017)

The reason for looking at this is to look at how quickly the exposure to robots is changing. Creating a variable in this way will drop one years worth of data, thus leaving us with only 624 observations compared to the other variables having 672 observations (we lose one observation for one of each of the 48 states that are in the data set). The variables *Union Membership* and *Union Coverage* are percentage of workers in a union or covered by a union for a given state and year, respectively. We find that on average 10.28% of workers are a member of a union and 11.60% of workers are covered by a union in a given state and year. Union coverage has a higher mean than union membership, but this is by construction of the estimate because union coverage includes union members and non-union members who are bargained for (thus "covered") by unions. The final variable $RTW$ is a binary variable for Right-to-Work and is equal to 1 if a state in a given year is a Right-to-Work state, and 0 otherwise.

# 4 Empirical Strategy

In order to understand the relationship between unions and automation we can run the following regression:

$$\text{robots}_{i,t} = \beta_0 + \beta_1 \text{union}_{i,t} + \alpha_t + \alpha_i + X_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $\text{robots}_{i,t}$ is either the robot exposure in state $i$ and year $t$ or $\Delta$ robot exposure ($\text{robotexposure}_{i,t} - \text{robotexposure}_{i,t-1}$) for state $i$ and year $t$. $\text{union}_{i,t}$ is either union membership or union coverage for state $i$ in year $t$. We also have $\alpha_t$ and $\alpha_i$ which are time and state fixed effects respectively. The variable $X_{i,t}$ is a set of controls which are unemployment, median income, and civilian non-institutional population for state $i$ and in year $t$. Finally, $\varepsilon$ is the error term.

The problem with this OLS regression is that there is potential of reverse causality. For example, an increase in automation could cause a reduction in union membership due to the displacement of workers, meaning that there are less people able to join the unions. There is also worry of omitted variable bias from union membership being positively correlated with politically left leaning states which could then be correlated with robot adoption, thus causing the OLS estimation to biased.

What we can do instead is utilize the variation in Indiana, Michigan and Wisconsin becoming Right-to-Work states in 2010s (Indiana and Michigan in 2012 and Wisconsin in 2015). We treat these states as our treatment group and the other Midwest states who remained non Right-to-Work (Illinois, Minnesota, Missouri, Nebraska, and Ohio) as our control group. This allows us to run the following regression:

$$\text{robots}_{j,t} = \beta_0 + \beta_1 \text{RTW}_{j,t} + \alpha_t + \alpha_j + X_{j,t} + \varepsilon_{j,t} \tag{2}$$

where $\text{RTW}_{j,t}$ is a dummy variable that is 1 if state $j$ in year $t$ is a Right to Work state, otherwise it is 0, and the rest of the variables are the same. One important note is that $j$ is restricted only to the 8 states mentioned above. This follows a difference-in-difference method, using the variation between states switching from non-RTW states to RTW states. The reason why we look at variation in RTW is because RTW is a good proxy for union membership, with non-RTW states having more union membership and RTW states having lower union membership. For our diff-in-diff approach to work, we will need to make sure that this does not violate the parallel trends assumption, as well as the adoption of RTW being exogenous. The parallel trends assumption will be checked later in empirical results. The latter assumption is of concern because RTW adoption is associated with states political leanings, which could be correlated with robot adoption. Also, unions might have knowledge that the law will pass so they will be able to prepare and mitigate the effects of the RTW laws. Therefore, the regression results will not be casual.

# 5 Empirical Results

## 5.1 Main Results

In Table 5.1 we record the simple OLS regression of union membership on robot exposure and change in robot exposure with results as specified in equation (1). Column (2) shows that union membership has a small negative relationship with robot exposure and column (4) shows that there is a positive small positive relationship with change in robot exposure although these results are only weakly significant.

Table 5.1: OLS Regression

| | Robot Exposure | | Δ Robot Exposure | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Union Membership | 0.0034 | -0.0108* | 0.0003 | 0.0025* |
| | (0.0052) | (0.0062) | (0.0004) | (0.0015) |
| *N* | 672 | 672 | 624 | 624 |
| Fixed Effects | No | Yes | No | Yes |

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. "Fixed Effects: Yes" refers to state and year fixed effects as well as controls being included in the regression.

In Table 5.2 we run the regression specified on the effect of Right-to-Work on robot exposure as specified in equation (2). We find that there are positive and significant (at the 1% level) estimates for robot exposure, with RTW states having 0.3361 more robots per thousand workers on average than non-RTW states. Similarly, there is a positive and significant effect (at the 5% level) on change in robot exposure with RTW states having 0.0391 more robots per thousand workers than the previous year on average than non-RTW states. This means that we find that weaker unions lead to more robot exposure and more quickly growing robot exposure, which gives evidence to the idea that unions slow the growth of automation.

Table 5.2: Midwest Difference-in-Difference Regression

| | Robot Exposure | | Δ Robot Exposure | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| RTW | 0.0520 | 0.3361*** | 0.0159 | 0.0391** |
| | (0.2502) | (0.0844) | (0.0170) | (0.0194) |
| *N* | 126 | 126 | 117 | 117 |
| Fixed Effects | No | Yes | No | Yes |

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

### 5.2 Parallel Trends Assumption

The diff-in-diff approach is only valid with the assumption that robot exposure would have trended similarly among the treatment and control states had Right-to-Work laws not been adopted by the treatment group. We examine for pre-trends as Makridis (2019) does in studying the effects of RTW laws on individuals' well-being; we estimate trends of the form:

$$\begin{aligned} \text{robots}_{i,t} = \gamma_0 + \gamma_1 \text{RTW}_{i,t-2} + \gamma_2 \text{RTW}_{i,t-1} + \gamma_3 \text{RTW}_{i,t} &+ \gamma_4 \text{RTW}_{i,t+1} + \gamma_5 \text{RTW}_{i,t+2} \\ &+ \alpha_t + \alpha_i + X_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where $\gamma_1$ and $\gamma_2$ provide an indication of the potential presence of pretrends and $\gamma_4$ and $\gamma_5$ provide indication of longer term effects of RTW laws. The results of the regression are reported in Table 5.3. It is important to note that this regression further restricts the number of observations being used.

The $\gamma_2$ coefficient ($RTW_{t-1}$) in column (2) is positive and statistically significant which indicates that there was a pretrend of increasing robot exposure before RTW laws were passed in the treatment group. This provides evidence that the parallel trends assumption is invalid. The difference-in-difference estimate of RTW on robot exposure is biased and overestimates the true effect.

The $\gamma_1$ and $\gamma_2$ estimates for the change in robot exposure are insignificant which provides evidence that the parallel trends assumption are met for this outcome. We find that only the $\gamma_3$ estimate is statistically significant which indicates that RTW only affected change in

Table 5.3: Parallel Trends Check-Midwest States

| | Robot Exposure | | Δ Robot Exposure | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $RTW_{t-2}$ | -1.9651*** | 0.0957 | -0.1044** | 0.0008 |
| | (0.7048) | (0.1140) | (0.0442) | (0.0263) |
| $RTW_{t-1}$ | 0.2247 | 0.1354*** | 0.0226 | 0.0039 |
| | (0.7537) | (0.0394) | (0.0406) | (0.0142) |
| $RTW_{t}$ | 0.6832 | 0.1568** | 0.0870*** | 0.0821*** |
| | (0.7357) | (0.0692) | (0.0272) | (0.0186) |
| $RTW_{t+1}$ | 0.1151 | -0.0532 | 0.0293 | 0.0084 |
| | (0.7398) | (0.0769) | (0.0283) | (0.0220) |
| $RTW_{t+2}$ | 0.7636 | 0.0646 | -0.0022 | 0.0031 |
| | (0.5367) | (0.0389) | (0.0277) | (0.0190) |
| $N$ | 80 | 80 | 80 | 80 |
| Fixed Effects | No | Yes | No | Yes |

Note: *** p<0.01, ** p<0.05, * p<0.10.

robot exposure in the year that the laws were introduced. Additionally, a visual look at the parallel trends assumption is included in A.4, which further suggests that the parallel trends assumption is violated.

# 6 Conclusion

There is an interesting dynamic between unions and the adoption of automation. Since automation can substitute labor this poses a threat to workers and to the goals of labor unions, who could potentially fight back. On the other hand, if unions are strong they could bargain for higher wages which would incentivize companies to substitute labor for capital through automation. These opposing channel means that there are a priori ambiguous effects between unions and the adoption of automation.

By utilizing the effects of Right-to-Work states in the Midwest in the 2010s we find that the net effects of unions decrease automation. We find that RTW states have on average 0.3361 more robots per thousand workers and 0.0391 more change in robots per thousand workers compared to non-RTW states. Since RTW states are a proxy for weaker unions, this means that the states with weaker unions have higher robot exposure and change in robot exposure and are therefore adopting more automation. However, it is important to note that these estimates are biased upwards as we found evidence of a pre-trend.

Another limitation of the study is that we were only able to look at the Midwest states with only 3 states being our "treatment" group, leaving questions as to whether or not this is able to be extrapolated to other parts of the United States.

Overall, this paper finds that there is some interaction of unions decreasing automation, but there still much analysis left to be done. Some further areas where this study can be expanded is looking into the exact channels in which unions interact with automation as well as industry level regressions to see effects of unions on automation in specific industries.

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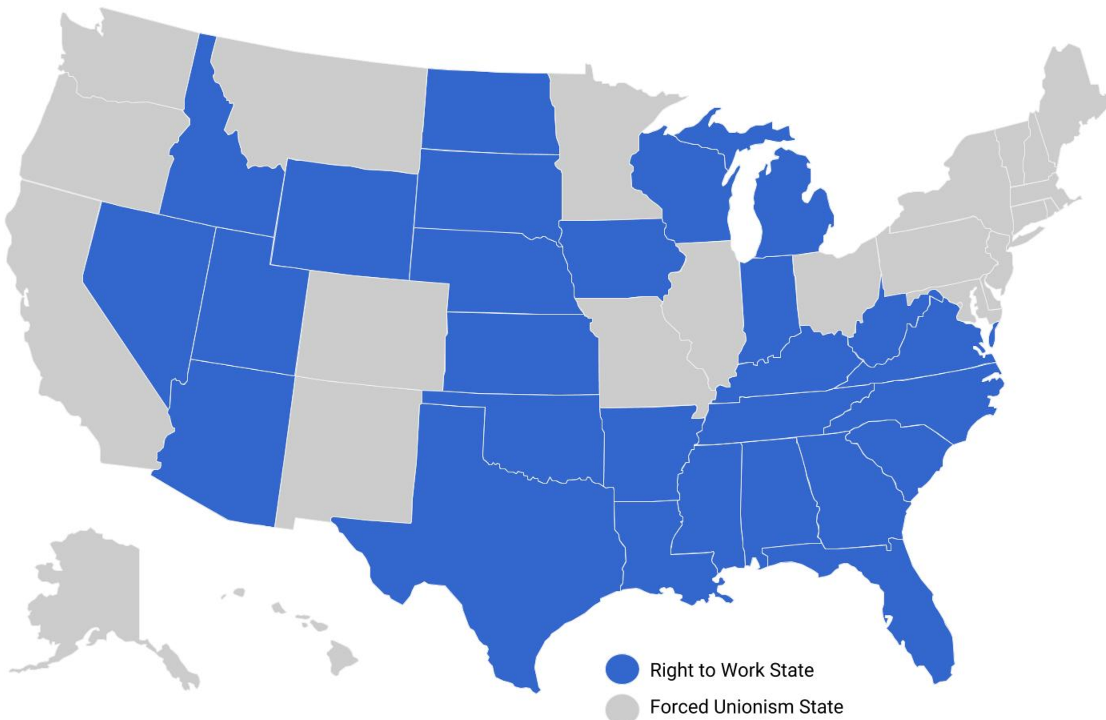
# A Appendix

## A.1 Right-to-Work States as of 2022



## A.2 Union Membership and Coverage and Relationship to RTW

Table A.1: Union Coverage/Membership and RTW

| | Union Coverage | | Union Membership | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| RTW | -7.5107*** | -1.7243*** | -7.5171*** | -1.8823*** |
| | (0.2515) | (0.5069) | (0.2526) | (0.4304) |
| $N$ | 672 | 672 | 672 | 672 |
| Fixed Effects | No | Yes | No | Yes |

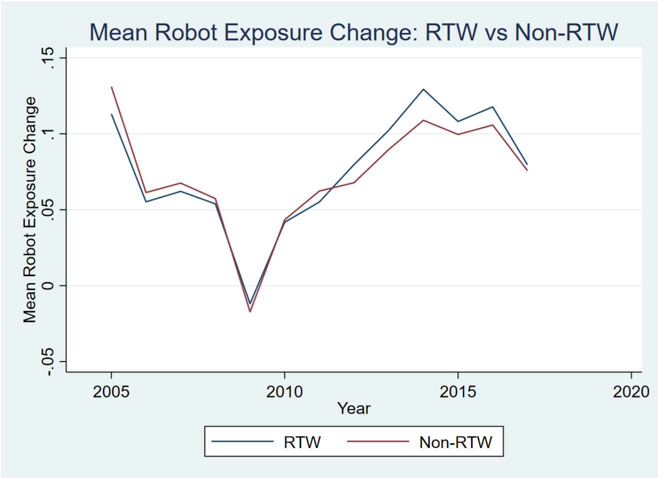
Note: *** p<0.01, ** p<0.05, * p<0.10. Regression specification is the same as equation (2) except with union coverage and union membership as outcome variables and this regression includes all 48 states in our data, not just the Midwest states.

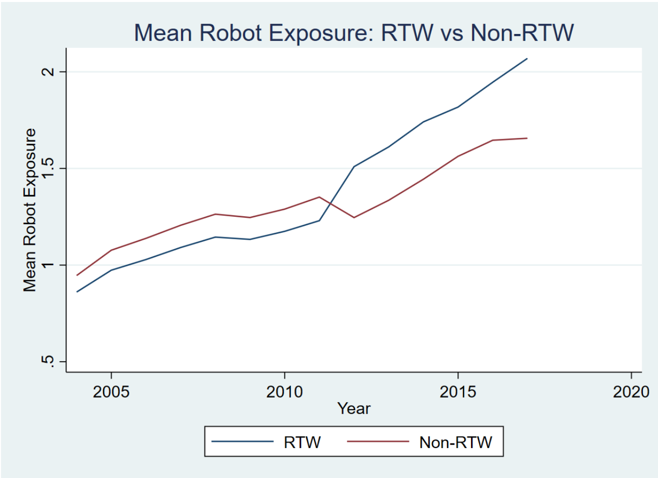
## A.3 RTW and Robot Exposure (Over all 48 States in Dataset)

Table A.2: Robot Exposure and Right-to-Work

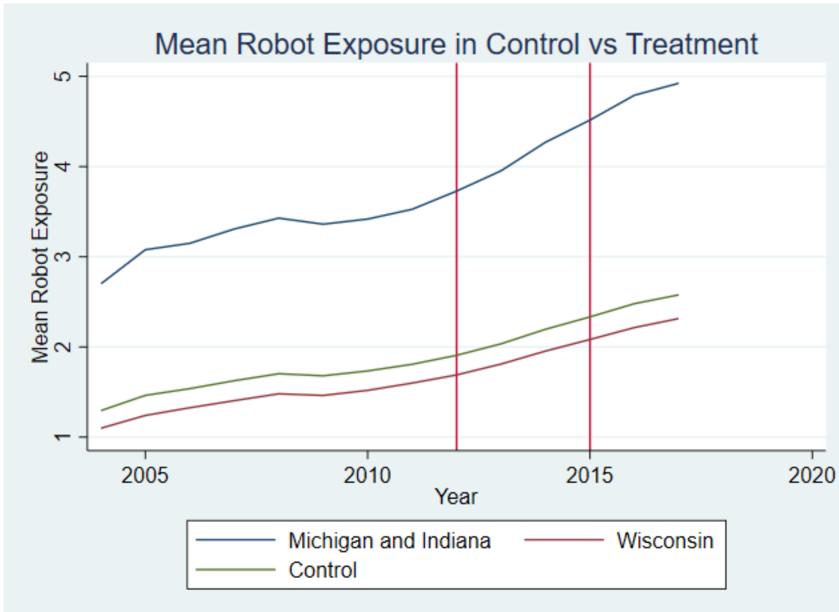
| | Robot Exposure | | Robot Exposure Change | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| RTW | 0.1039 | 0.3643*** | 0.0050 | 0.0365* |
| | (0.0664) | (0.0874) | (0.0046) | (0.0188) |
| $N$ | 672 | 672 | 624 | 624 |
| Fixed Effects | No | Yes | No | Yes |

Note: *** p<0.01, ** p<0.05, * p<0.10.



## A.4 Midwest States: Robot Exposure Trends Over Time




Note: Control is Illinois, Minnesota, Missouri, Nebraska, and Ohio. Vertical line at 2012 mark Michigan and Indiana swap to RTW and line at 2015 marks Wisconsin swap to RTW.