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An analysis of the Right to work laws on wage dispersion in the United States

by

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Abstract

In this thesis, I investigate the effect of introducing Right-to-work laws on wages and the dispersion of wages in the United States, using a staggered Difference in Difference model pioneered by Callaway & Sant'Anna (2021) on wages and individual wage quantiles. Introducing Right-to-work laws appear to have a generally positive effect on wages and wage dispersion for all wages. The effects are heterogeneous by state and gender, however, most of the significant values for the lower wage levels appear to be increasing. There might be several plausible explanations for the effects observed, however, the notion that Right-to-work laws lower the threat effect significantly, or that this effect has a large and broad influence, is not observed.

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Introduction

1.1 introduction of the topic

Right-to-work laws are state laws in the United States; which give workers the right to individually determine whether or not to pay union fees in unionized workplaces (Moore, 1998). These laws form a free-riding problem for the unions since workers can attain union benefits without paying union membership fees (Fortin, Lemieux & Lloyd, 2022). Unions do not exist in a vacuum; powerful unions drive firms to hire relatively more high-wage workers who do not benefit from nor want unions to avoid unionization of the workplace; this compresses non-unionized wages and is commonly known as the threat effect (Taschereau-Dumouchel, 2020). Advocates argue that Right-to-work laws increase competition (Moore, 1998), which could increase total wages through, for instance, shifts in labor demand (Borjas, 2020). One notion is that the introduction of Right-to-work laws may push unions to bargain more aggressively; unions facing a threat to their survival from just a slight change in membership rates may arguably be more motivated by Right-to-work laws to campaign to attract new members by offering additional benefits and services, or higher wages (Chun, 2023), signaling an elevated threat to non-unionized firms. In contrast, opponents of Right-to-work laws argue that the laws undermine unions' barging power (Moore, 1998), which decreases non-unionized wages through a diminishing union threat effect (Fortin, Lemieux & Lloyd, 2022).

Through the threat effect, Right-to-work laws could also harm wage dispersion of non-unionized wages by changing non-unionized firms' hiring decisions (Taschereau-Dumouchel, 2020), an argument supported by findings from Fortin, Lemieux & Lloyd (2021), who demonstrate empirical evidence that threat effects compress non-unionized wages in times of falling unionization rates.

However, even though some evidence from Fortin, Lemieux & Lloyd (2022) and Fortin, Lemieux & Lloyd (2021) suggest that Right-to-work laws increase wage dispersion of non-unionized wages, based on the author's understanding of the literature, whether Right-to-work laws compress non-unionized wages or not remains relatively unexplored.

1.2 Research question and method

This thesis aims to estimate the average treatment on the treated effect of Right-to-work laws on wages and wage dispersion of all wages by using the staggered difference-in-difference model pioneered by Callaway & Sant'Anna (2021).

I provide separate estimates on wages and wage dispersion by gender to address the fact that men and women have different employment patterns in the sample. The wage dispersion effect was analyzed by applying the staggered difference in difference model on distinct sub-sample segmented based on different wage percentile levels.

The analysis subjects are Michigan and Indiana, which introduced legislation in 2012, followed by Wisconsin in 2015, West Virginia in 2016, and Kentucky in 2017 (NCSL, 2023). These states were compared to the control states, which never introduced legislation, while those who introduced legislation before 2012 were omitted from the analysis.

A data set from IPUMS between 2006 and 2019 was used to estimate the effect of wage dispersion and the impact on wages (IPUMS, 2023 A). It includes millions of observations (IPUMS, 2023 A), allowing for the sample to be stratified without reducing statistical power. In addition, the IPUMS data set contains many control variables (IPUMS, 2023 A) used to control for state-level endogeneity.

1.3 Literature Review and Contribution

In theory, free-riding from Righ-to-work laws should affect unions by decreasing unionization rates (Chun, 2023). Firstly, it raises the costs of union services, making joining the union a less compelling alternative for the worker (Chun, 2023). Secondly, it reduces union bargaining-power (Chun, 2023) and, consequently, their ability to increase union wages (Borjas, 2020).

Non-unionized wages could be affected by the threat effect (Fortin, Lemieux & Lloyd, 2022). In an analysis of the threat effect by Taschereau-Dumouchel (2020), he designs a model in which low-wage workers have incentives to unionize and need 50 % of workers' votes to form a union. If the firm suspects a high threat of unionization, they will adjust their hiring patterns, actively hiring relatively more skilled high-wage workers; who neither want nor benefit from unionization (Taschereau-Dumouchel, 2020). So, by over-hiring high-wage workers, the threat from strong unions compresses non-union wages (Taschereau-Dumouchel, 2020). These hiring decisions are neither profit nor output-maximizing; however, firms favor these over unionization (Taschereau-Dumouchel, 2020).

The existence of the threat effect aligns with empirical results by Fortin, Lemieux & Lloyd (2021) and Benmelech, Bergman & Kim (2018). Benmelech, Bergman & Kim (2018) show that unions significantly offset firms' capacity to dictate wage levels for low-wage workers in highly concentrated, low-mobility labor markets. Which arguably shows strong incentives from monopsonistic firms to keep unionization out of the workplace. Using distributional regressions, Fortin, Lemieux & Lloyd (2021) examine the effect of unionization rates and minimum wage changes on total wage dispersion. They found evidence that the fall in union membership rates since the late 1970s has significantly influenced wages by increasing wage dispersion for total wages, which they argue is evidence of the existence of a considerable threat effect (Fortin, Lemieux & Lloyd, 2021).

Building on results from Fortin, Lemieux & Lloyd (2021), Fortin, Lemieux & Lloyd (2022) argue that Right-to-work laws decrease total wages via a reduced threat effect. They use an event-study design, whereas they use the Right-to-work laws introduction as an instrument to isolate variation in the unionization rates to estimate the ATT effect on total wages and compare those to OLS estimates (Fortin, Lemieux & Lloyd, 2022). They find that introducing Right-to-Work laws decreases total wages and unionization rates (Fortin, Lemieux & Lloyd, 2022). When testing separately for men and women, they find heterogeneous effects on wages by gender (Fortin, Lemieux & Lloyd, 2022). This heterogeneous effect by gender, where women's wages depreciate significantly with the introduction of Right-to-work laws while men's wages show no significant change (Fortin, Lemieux & Lloyd, 2022), is also consistent with findings from Biasi & Sarsons (2022), whos' finding indicates that female teachers are more susceptible to changes in institutions ability to wage-bargain for them, from, for instance, unions, than their male counterparts. Although Fortin, Lemieux & Lloyd (2022) investigates the effect of Right-to-work laws on wages, they do not attempt to analyze wage dispersion.

Chun (2023) also finds that Right-to-work laws decrease unionization rates using a staggered difference in difference model. His results, contrary to results by Fortin, Lemieux & Lloyd (2022), imply that union wage increases (Chun, 2023). Chun (2023) also finds, by estimating individual quantities of the wage distribution, that Right-to-work laws have a wage-compressing effect on union wages. He argues that this finding could be explained by increasingly assertive union bargaining behavior (Chun, 2023). Unions balance increased wages and other benefits against reduced employment (Borjas, 2020). Suppose Right-to-work laws make membership rates fall slightly below a threshold that dissolves the union. In that case, the union might bargain more aggressively for higher wages to attract more members as a reaction to the introduction of Right-to-work laws (Chun, 2023). Even though results from Chun (2023) provide some insight into the wage distribution effects of Right-to-work laws, his analysis is ultimately restricted to union wages.

Building on results primarily from Fortin, Lemieux & Lloyd (2022), Fortin, Lemieux & Lloyd (2021), and Chun (2023), my contribution to the literature is firstly to estimate the effect of the Right-to-work law on total wage dispersion, which to the knowledge of the author has not been done before. Secondly, using a novel method, I estimate the effect of the Right-to-work law on total wages and total wage dispersion. Implementing the model by Callaway & Sant'Anna (2021) controls for additional biases arising from differences in treatment timing (Goodman-Bacon, 2021) which, to the author's knowledge, have not been controlled for before.

2

Institutional background

A sizeable group of primarily southern states began rapidly implementing Right-to-work legislation in the late 1940s, but after 1955, Right-to-work laws' expansion slowed (NCSL, 2023). The last state to introduce Right-to-work laws before Michigan and Indiana in 2012 was Oklahoma in 2001; before that, Idaho implemented it in 1985, Louisiana in 1976, and Wyoming in 1963 (NCSL, 2023). However, in only five years, between 2012 and 2017, five more states, mostly northern, started passing Right-to-work legislation (NCSL, 2023). As of January 2023, 26 states have adopted Right-to-work laws, most in the South or the Central continental United States, leaving 25 states which do not have Right Work laws (NCSL, 2023).

Between 1960 and 2017, there was a significant shift in the national unionization rates in the US(Borjas, 2020). Peaking at 25 % of all workers being unionized in the 1960s to the middle of the 1970s, the unionization rates fell to almost below 10 % in 2017 (Borjas, 2020). As of 2017, there are also significant differences in unionization rates between different industries, the national-level unionization rates range from 34 % in Government unions to 1.8% in agriculture, the *industrial unions* have a relatively high unionization rate with Transportation at 25%, construction at 15%, and manufacturing at 9% (Borjas, 2020).

Out of the five new states that adopted Right-to-work legislation between 2012 and 2017, the state of Michigan, but arguably also Wisconsin, sticks out as different (Kaminski, 2015). Unionization rates are lower in most Right-to-work states than in Michigan, and the law's introduction was unanticipated and quick (Kaminski, 2015). Considering that some argue that Right-to-work laws are only introduced as a manifestation of a preference(Moore, 1998). As Right-to-work states already are less unionized before the introduction of the law, it is also the reason they adopt it (Moore, 1998). And considering that lawmakers only took one week to form and pass the legislation in a state with higher unionization rates than most Right-to-work states (Kaminski, 2015), it is difficult to argue that at least Michigan follows the same pattern of adopting legislation as other Right-to-work states. Kaminski (2015) draws parallels to Wisconsin, as they followed a similar path of side-stepping unions to form and pass legislation quickly, and is also a union-dense state (Kaminski, 2015). However, as of March this year, Michigan is no longer a Right-to-work law state (NCSL, 2023).

As mentioned in Fortin, Lemieux & Lloyd (2021), minimum wage changes could play a major part in explaining changes in wage dispersion. As for the treatment states, both West Virginia (FRED, 2023 B) and Michigan (FRED, 2023 A) implemented state-level minimum wage increases between 2012 and 2019; however, only Michigan implemented changes after the treatment period (FRED, 2023 A). These type of state-level policy differences motivates the use of different group estimates to investigate the heterogeneity of treatment effect.

3

Data

3.1 IPUMS Source Material

Micro-level data was extracted from the IPUMS USA web page, a collection of extensive samples spanning several decades, including various control variables on both individual and household levels that are free of use (IPUMS, 2023 A). The data available to extract from the IPUMS web page consists of repeated one-year one percent probability samples from the American community survey samples (IPUMS, 2023 D). The primary outcome variable of interest is gross nominal wages and salaries, measured in US dollars (IPUMS, 2023 B). In addition to wages, IPUMS also provides information on self-reported average hours worked per week and many explanatory control variables, such as demographic variables, different labor types, industries, state-specific variables, and educational-specific variables(IPUMS, 2023 A).

IPUMS applies editing procedures to several variables. For instance, the outcome variable, gross wages and salaries, and self-reported average hours worked per week are top coded at $99999 and 99 hours per week, respectively (IPUMS, 2023 C). In addition, when variables are missing, IPUMS allocates values from individuals with similar values in other variables (IPUMS, 2023 C).

3.2 Data selection and processing

3.2.1 Sample selection

The sample selected for this analysis includes millions of observations per sample between 2006 and 2019, restricted to observations between the ages of 18 and 65 with positive non-zero income. By only observing working, wage-earning individuals, an industry code for every worker could be identified, which was not the case before the restriction. Furthermore, the states which introduced Right-to-work laws before 2012, the always treated, were omitted from the sample as the Difference in difference model by Callaway & Sant'Anna (2021) only uses treated and control states for their ATT estimates.

The analysis of this thesis exclusively addresses the intensive margin of labor, taking into account factors such as self-reported weekly hours worked, if workers are self-employed, and if workers have any cognitive impairment. This abstracts from selection into employment and might introduce selection bias into the estimates as the analysis restricts itself to workers within the labor market, who might not represent the general population.

The analysis of wages and wage dispersion uses two distinct sub-samples based on gender. The sample was divided by gender to address that men and women have different employment patterns. As presented in Table 1 and Table 2, the fraction of men and women within some industries differ significantly in the sample between treatment and control states. Men also earn a higher wage on average and work more hours per week.

To investigate wage dispersion, this thesis uses sub-samples based on percentile levels of wages for the total sample instead of the percentile level within each state. Five different sub-samples are used: 10th percentile, 20th percentile, 30th percentile, 50th percentile, and a top 50th percentile. The sub-samples are concentrated around the more low and middle-income levels, as there are higher incentives for unskilled workers to join unions than skilled workers, who have a higher competitive advantage within non-unionized workplaces (Taschereau-Dumouchel, 2020).

The wage dispersion measurement uses different percentile thresholds and looks at all the wages below or above the threshold. The assumption of rank preservation likely does not hold, and to account for threshold effects where, potentially, observations might exist just above or below a threshold, most of the percentile levels are overlapping. By using several overlapping percentiles, it is possible to observe if the estimator is consistent when the threshold is moved. However, the existence of thresholds may still introduce bias into the estimates.

3.2.2 Construction of the outcome variables

The analysis's outcome variable of interest is gross wages and salaries (IPUMS, 2023 B). Gross wages were logarithmized to get an interpretable ATT estimate expressed in percentages and were chosen over total gross income from all sources (IPUMS, 2023 E) as it is a more precise measurement and more related to the labor market.

The treatment variable was defined as zero for all observations in the control states and by the year of treatment introduction. For instance, observations in Michigan and Indiana, which introduced legislation in 2012, were coded 2012, Wisconsin 2015, West Virginia 2016, and Kentucky 2017.

Several control variables were aggregated. Metropolitan status was aggregated over all observations that were defined to be within the metropolitan area. All education levels below Grade 12 were joined together, and all the types of married dummy variables were combined into one dummy variable. Due to the large available quantities of different industries, the industry variables were aggregated two times. This thesis utilizes a recommended aggregation list provided by IPUMS called *Census 2017 Industry Code List with Crosswalk* (IPUMS, 2023 F). IPUMS recommends keeping fourteen different industries; however, the recommended aggregation still leaves significant discrepancies in industry size. Ultimately, three general industry types were created: industry, general services, and trade, while two remaining larger industries were left as recommended. Industrial comprises agriculture, forestry, fishing, hunting, mining, manufacturing, construction, and military professionals. Trade is the combination of wholesale trade and retail trade. Services include transportation warehousing, utilities, information, finance, insurance, real estate, rental, leasing, arts, entertainment, recreation, accommodation, food services, other services, and public administration services.

3.3 Descriptive statistics

Tables 1 and 2 provide descriptive statistics on the main outcome variable, and the control variables post aggregation by gender for the control and treatment state rounded to the nearest two-digit decimal.

The most significant difference between the genders exists in industrial composition between the genders, as the share of men in industrial industries, such as agriculture, forestry, fishing, hunting, mining, construction, and the military, is more than three times as large as the women's share. While on the other hand, the share of women who work in Educational Services, Health Care, and Social Assistance is approximately three times larger than that of men. This difference in industry belonging could also reflect the significant differences in the logarithmized gross wages and salaries between the genders and the average hours worked weekly.

Most other control variables between the genders show minor to no significant differences. Demographic variables, such as racial composition, cognitive impairment, and metropolitan status between men and women, appear comparatively similar. Women are more educated and less likely to be married; as indicated by the worker type dummy, women are also more likely to earn their wages through employment, as opposed to men, who are more likely to have their own businesses.

Table 3 displays the mean descriptive statistics by the two state-types. It shows that several variables show significant mean differences by state types, which could be an expression of time-invariant unobserved state-level endogenous variables.

Arguably the most crucial assumption in a difference-in-difference model is the parallel trend assumption (Angrist & Pischke, 2009), which likely would be violated if many state-level endogenous variables exist. The significant mean differences by state types observable in Table 3 highlight the importance of controlling for a large number of observed variables in the regression and exploiting the timing of the introduction of the treatment.

Table I

Descriptive statistics: Men in treated and never treated states with positive income between the ages of 18 & 65.

VARIABLES	Obs	Mean	Std. dev	Min	Max
Natural logarithmic income	6112401	10.39	1.24	1.39	13.51
Average hours worked weekly	6112401	41.735	12.00	1	99
Age	6112401	41.13	13.23	18	65
Worker type	6112401	0.94	0.23	0	1
Cognitive impairment	6112401	0.02	0.14	0	1
Metropolitan status: Not in Metropolitan area	6112401	0.13	0.33	0	1
Metropolitan status: In Metropolitan area	6112401	0.79	0.41	0	1
Metropolitan status: Unspecified	6112401	0.08	0.28	0	1
Industry: Industrial	6112401	0.29	0.46	0	1
Industry: Services	6112401	0.32	0.47	0	1
Industry: Trade	6112401	0.14	0.35	0	1
Industry: Education & Healthcare	6112401	0.12	0.32	0	1
Industry: Science, Admin & Management	6112401	0.11	0.33	0	1
Education: Less than Grade 12	6112401	0.07	0.26	0	1
Education: Grade 12	6112401	0.36	0.48	0	1
Education: 1 year of college	6112401	0.16	0.36	0	1
Education: 2 years of college	6112401	0.08	0.27	0	1
Education: 4 years of college	6112401	0.20	0.40	0	1
Education: 5+ years of college	6112401	0.12	0.33	0	1
Marriage status: Married	6112401	0.57	0.49	0	1
Marriage status: Separated	6112401	0.01	0.12	0	1
Marriage status: Divorced	6112401	0.08	0.28	0	1
Marriage status: Widowed	6112401	0.01	0.078	0	1
Marriage status: Never married/single	6112401	0.33	0.4688	0	1
Race: White	6112401	0.81	0.39	0	1
Race: Black	6112401	0.07	0.25	0	1
Race: Asian	6112401	0.07	0.26	0	1
Race: Native American	6112401	0.01	0.12	0	1
Race: Other	6112401	0.05	0.22	0	1
Race: Pacific Islander	6112401	0.004	0.07	0	1

Source: IPUMS A, (2023)

Table II

Descriptive statistics: Women in treated and never treated states with positive income between the ages of 18 & 65.

VARIABLES	Obs	Mean	Std. dev	Min	Max
Natural logarithmic income	5801478	10.01	1.24	1.39	13.51
Average hours worked weekly	5801478	35.98	12.00	1	99
Age	5801478	41.34	13.34	18	65
Worker type	5801478	0.97	0.17	0	1
Cognitive impairment	5801478	0.02	0.14	0	1
Metropolitan status: Not in Metropolitan area	5801478	0.13	0.33	0	1
Metropolitan status: In Metropolitan area	5801478	0.79	0.41	0	1
Metropolitan status: Unspecified	5801478	0.09	0.28	0	1
Industry: Industrial	5801478	0.09	0.29	0	1
Industry: Services	5801478	0.30	0.46	0	1
Industry: Trade	5801478	0.13	0.34	0	1
Industry: Education & Healthcare	5801478	0.37	0.48	0	1
Industry: Science, Admin & Management	5801478	0.09	0.29	0	1
Education: Less than Grade 12	5801478	0.05	0.21	0	1
Education: Grade 12	5801478	0.31	0.46	0	1
Education: 1 year of college	5801478	0.17	0.37	0	1
Education: 2 years of college	5801478	0.10	0.30	0	1
Education: 4 years of college	5801478	0.23	0.42	0	1
Education: 5+ years of college	5801478	0.14	0.35	0	1
Marriage status: Married	5801478	0.53	0.50	0	1
Marriage status: Separated	5801478	0.02	0.14	0	1
Marriage status: Divorced	5801478	0.12	0.33	0	1
Marriage status: Widowed	5801478	0.02	0.14	0	1
Marriage status: Never married/single	5801478	0.33	0.46	0	1
Race: White	5801478	0.80	0.40	0	1
Race: Black	5801478	0.09	0.28	0	1
Race: Asian	5801478	0.08	0.27	0	1
Race: Native American	5801478	0.01	0.12	0	1
Race: Other	5801478	0.04	0.21	0	1
Race: Pacific Islander	5801478	0.005	0.07	0	1

Source: IPUMS A (2023)

Table III

Descriptive statistics: Mean statistics, Women and Men by state type with positive income between the ages of 18 & 65.

	Treatment	control
VARIABLES	mean	mean
Natural logarithmic income	10.06	10.23
Average hours worked weekly	38.80	38.727
Age	41.42	41.19
Worker type	0.96	0.96
Cognitive impairment	0.02	0.02
Metropolitan status: Not in Metropolitan area	0.24	0.11
Metropolitan status: In Metropolitan area	0.57	0.83
Metropolitan status: Mixed	0.19	0.07
Industry: Industrial	0.26	0.19
Industry: Services	0.28	0.32
Industry: Trade	0.14	0.14
Industry: Education & Healthcare	0.24	0.25
Industry: Science, Admin & Management	0.08	0.11
Education: Less than Grade 12	0.05	0.06
Education: Grade 12	0.40	0.33
Education: 1 year of college	0.17	0.16
Education: 2 years of college	0.10	0.09
Education: 4 years of college	0.18	0.22
Education: 5+ years of college	0.097	0.14
Marriage status: Married	0.58	0.55
Marriage status: Separated	0.01	0.018
Marriage status: Divorced	0.12	0.10
Marriage status: Widowed	0.014	0.01
Marriage status: Never married/single	0.28	0.32
Race: White	0.91	0.79
Race: Black	0.06	0.08
Race: Asian	0.02	0.08
Race: Native American	0.01	0.01
Race: Other	0.01	0.05
Race: Pacific Islander	0.001	0.005

Source: IPUMS A (2023)

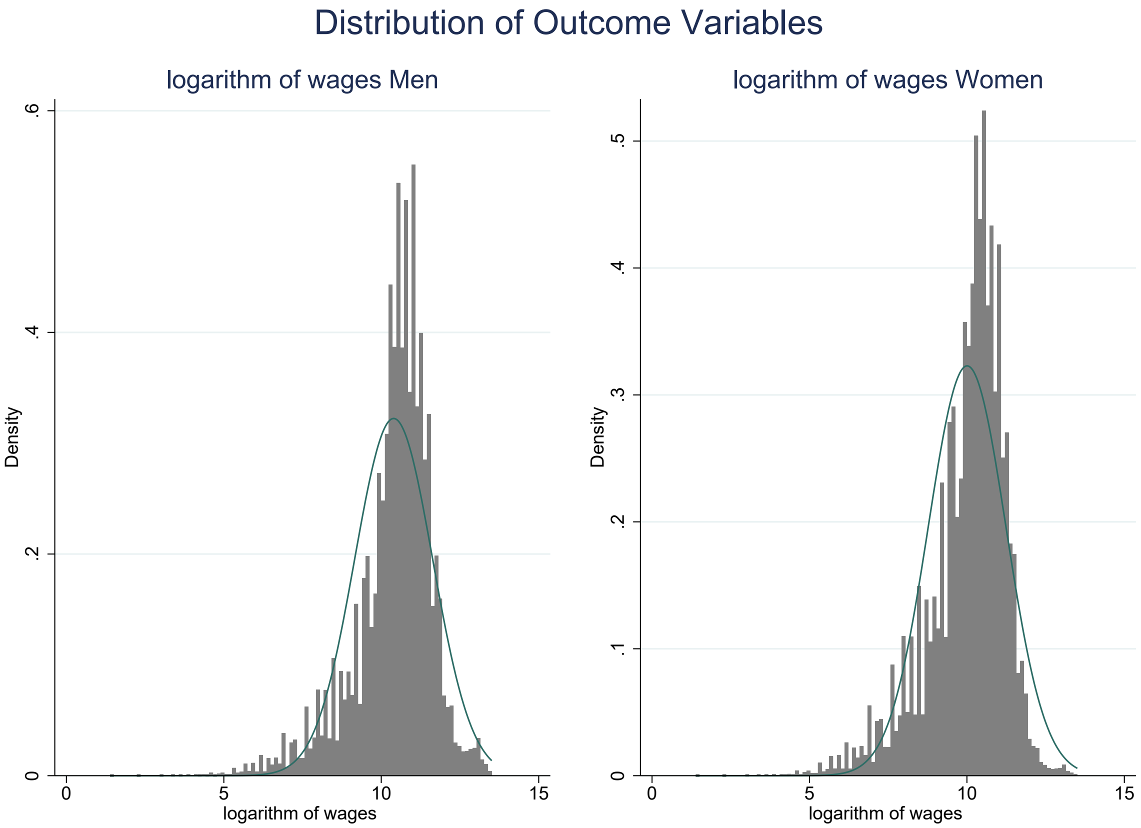

Figure 3.1: Distribution of wages for wage-earning men and women between the ages of 18 and 65

It is interesting to look further at distribution by gender as the wage distribution analysis relies on thresholds by looking for any jumps in the distribution that could impact the analysis. Figure 3.1 shows that the distribution of wages between men and women looks reasonably similar; men's wages are more rightwards shifted compared to the women's, with a slightly thicker right tail. Even though there are some jumps, the distributions appear relatively smooth, suggesting that they are suitable for the analysis.

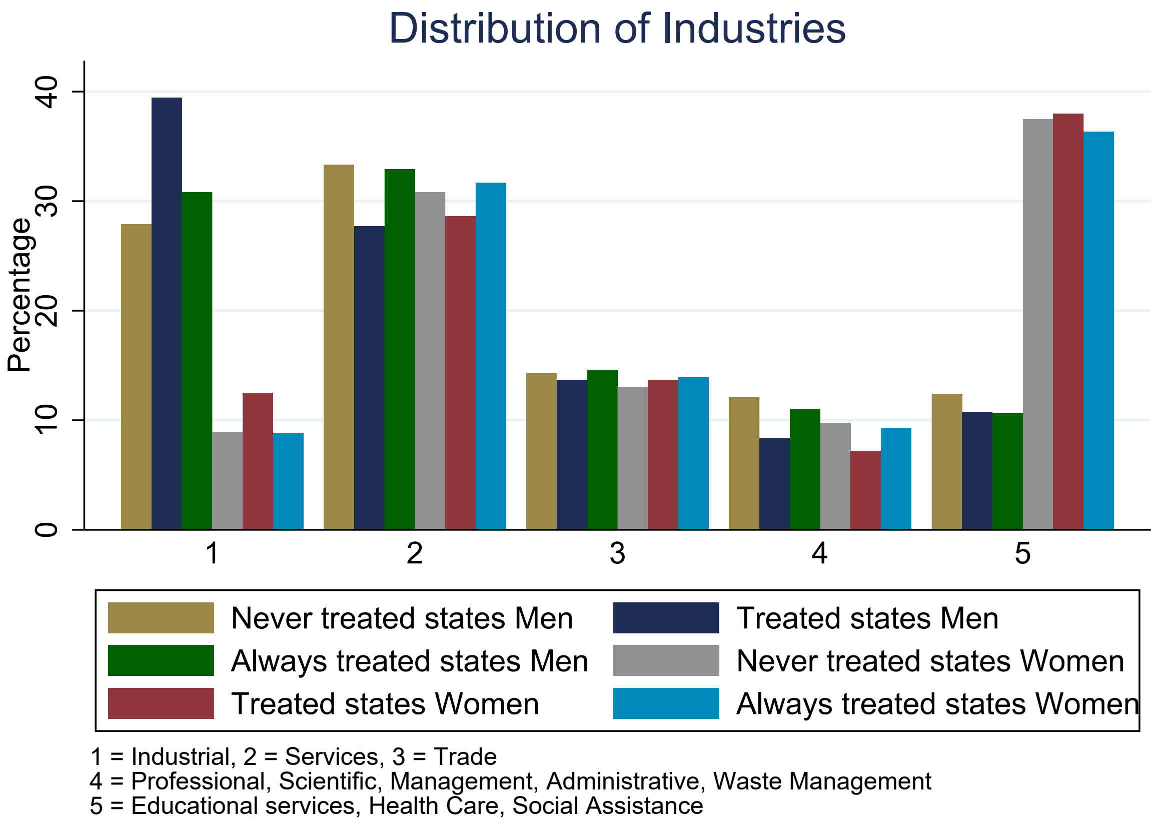

Figure 3.2: Distribution of industries by gender and type of state

Figure 3.2 shows the distribution of industries by gender and state type for all states, including the omitted always treated states. Figure 3.2 reveals some significant differences in industry composition between the state types; both genders are more likely to work within industrial industries and less likely to work in the service industry in the treated states than the control states *(Never treated)*. Aside from these differences, the industry composition appears similar in all types of states. In Figure 3.2 I have included the always-treated group that is omitted in any other inference or description of the data to underline that even though there are some differences in industry compositions, for most industries there are no or very little difference in the composition between any state group.

4

Empirical approach

4.1 Difference in Difference

To estimate the effect of introducing RTW laws on wages and wage dispersion this study makes use of a staggered Difference in Difference model, using the CSDID package in Stata, which is based on a paper by Callaway & Sant'Anna (2021). The difference in difference model, commonly referred to as a *DiD*, handles endogeneity on an aggregated level, such as a state or regional level (Angrist & Pischke, 2009). As clearly presented in Angrist & Pischke (2009) the simplest case of a standard Difference in Difference method isolates the effect of treatment by using a one pre-treatment period, one post-treatment period, one control group, and one treatment group setup:

$$Y_{ist} = \delta_s + \lambda_t + \sigma D_{st} + \varepsilon_{ist} \tag{4.1}$$

Where σ is the difference in difference estimator, the $\lambda_{t=1}$ is a trend-specific variable for the post-treatment period, $\lambda_{t=0}$ is a trend-specific variable for the pre-treatment period, and $\delta_{s=0}$ is a state-specific variable for the control state (Angrist & Pischke, 2009).

Following the notation from Angrist & Pischke (2009) the first difference in the control state would be:

$$E[y_{ist}|s = control, t = 1] - E[y_{ist}|s = control, t = 0] \tag{4.2}$$

$$\delta_{s=0} + \lambda_{t=1} - \delta_{s=0} - \lambda_{t=0}$$

$$= \lambda_{t=1} - \lambda_{t=0}$$

The first difference in the treatment state would be:

$$E[y_{ist}|s = treatment, t = 1] - E[y_{ist}|s = treatment, t = 0] \tag{4.3}$$

$$\delta_{s=1} + \lambda_{t=1} + \sigma - \delta_{s=1} - \lambda_{t=0}$$

$$= \lambda_{t=1} + \sigma - \lambda_{t=0}$$

Subtracting the difference in the treatment state from the difference in the control state gives the difference in difference estimator σ (Angrist & Pischke, 2009). The isolated effect remaining is the treatment on the treated TOT, sometimes referred to as the average treatment effect on the treated ATT (Angrist & Pischke, 2009). The DiD relies on the assumption that the trend-specific variables $\lambda_{t=1} - \lambda_{t=0}$ are equal in both the treatment and control state to estimate the effect of treatment (Angrist & Pischke, 2009). This is referred to as the parallel trend assumption, which, if true, states that the trends of the control and treatment groups would be parallel in the absence of treatment (Angrist & Pischke, 2009).

The staggered Difference in Difference model, using the CSDID package, controls for bias from when treatment is introduced or the timing of the treatment (Callaway & Sant'Anna, 2021), as explained in Goodman-Bacon (2021). The Callaway & Sant'Anna (2021) DiD model allows the treatment periods to vary, for multiple time periods to be included, and for the model to include a vector of covariates $\beta X_i'$. Similar to an event study design (Angrist & Pischke, 2009), the model includes several pre-treatment and post-treatment periods and a vector of covariates $\beta X_i'$ (Callaway & Sant'Anna, 2021), in addition when using the staggered DiD by Callaway & Sant'Anna, (2021), it controls for heterogeneous effects with a weighting scheme.

To achieve validity in the results, four assumptions must be satisfied, of which the first two can be investigated by examining the sample. Firstly, in assumption 1, *A1*, treatment has to be allowed to take place at different times for different states, and when treated, it is assumed that the treated state stays treated for all future periods (Callaway & Sant'Anna, 2021); secondly, *A2*, the sampling is random (Callaway & Sant'Anna, 2021). *A1* holds as no treated state ever reversed the treatment in the sample ones treated (NCSL, 2023), and *A2* holds the sampling is a collection of one percent random samples (IPUMS D, 2023).

The two latter assumptions need further inspection. For the third, *A3*, the model assumes that parallel trends hold conditionally, between the treated and the never treated group, after controlling for a vector of regressors (Callaway & Sant'Anna, 2021).

For the fourth, *A4*, the not treated yet but soon to be treated has to have limited knowledge of when treatment will happen (Callaway & Sant'Anna, 2021). This assumption underlines the importance of self-selection.

The CSDID package in stata provides several options for ATT estimators. This study first uses the simple ATT, which provides one ATT estimate across the four groups and the 14 periods. The groups are defined by when treatment was introduced, so Michigan and Indiana belong to the 2012 group, Wisconsin to the 2015 group, West Virginia to the 2016 group, and Kentucky to the 2017 group. A group-level ATT isolates each group ATT over all 14 periods, and a dynamic ATT utilizes all the pre-treatment periods from when the first group got treated, taking into account both time-specific and group-specific effects (Callaway & Sant'Anna, 2021).

4.2 Tests for identifying assumptions

The conditional parallel trend assumption, *A3*, is necessary to hold for the validity of the results, but it can never be confirmed with certainty as it includes counterfactuals (Angrist & Pischke, 2009). However, there are several ways to provide evidence of this assumption holding; a typical way to test the parallel trend assumption is to observe the outcome variable trends (Angrist & Pischke, 2009).

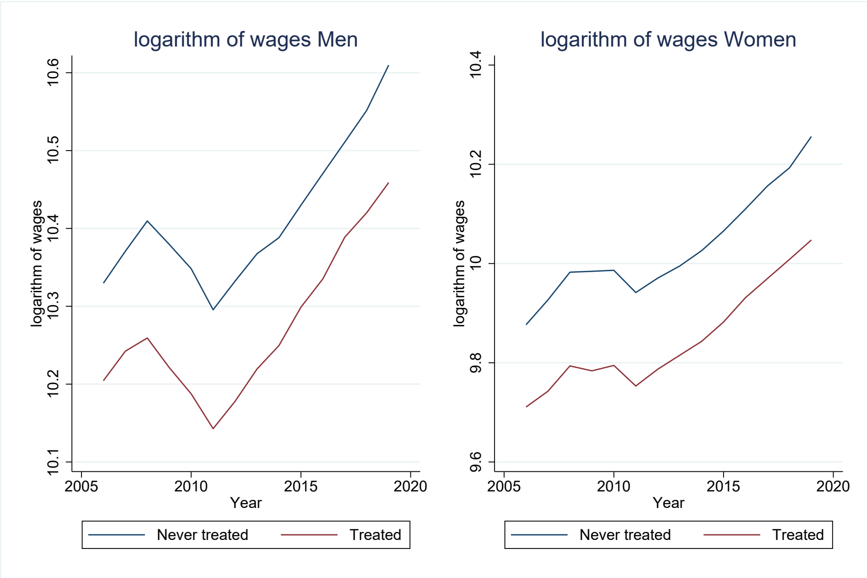

Figure 4.1: Mean logarithmized gross wages of wage-earning individuals between the ages of 18 and 65 by gender

Figure 4.1 would show if the parallel trends assumption is violated by looking at how parallel the trends are in the pre-treatment periods before treatment was gradually introduced in 2012. We cannot observe that the assumption of parallel trends is immediately rendered invalid, however, this test is fairly imprecise.

To further investigate the parallel trends assumption this study uses event study graphs from the different groups; the groups are defined by the first period when treatment was introduced. The event study design presented is based on the notation in Angrist & Pischke (2009), however not identical. The model contains several pre-treatment and post-treatment periods specified as:

$$y_{ist} = \delta_s + \lambda_t + \sum_{t=-\Omega}^{-1} \delta_t D_{st} + \sum_{t=0}^{m} \gamma_t D_{st} + \beta X_i' + \varepsilon_{ist} \tag{4.4}$$

Where λ_t is the time-variant effect, and δ_s is the state-specific time-invariant effect. The $\sum_{t=-\Omega}^{-1} \delta_t D_{st}$ is a sum of all pre-treatment periods relative to -1 which is used as a reference point (Angrist & Pischke, 2009). Similarly, $\sum_{t=0}^{m} \gamma_t D_{st}$ is a sum of all post-treatment periods where 0 indicates the time period treatment was introduced and $\beta X_i'$ is a vector of covariates (Angrist & Pischke, 2009).

As an example, Figure 4.2 shows the event study plot of the ATT effect on gross wages and salaries, using the whole sample, for the different groups. Figure 4.2 appears to show that the parallel trends hold in most of the pre-treatment time periods, however, it is not perfect, as some of the pre-treatment periods are statistically significantly different from zero at a 5 % level.

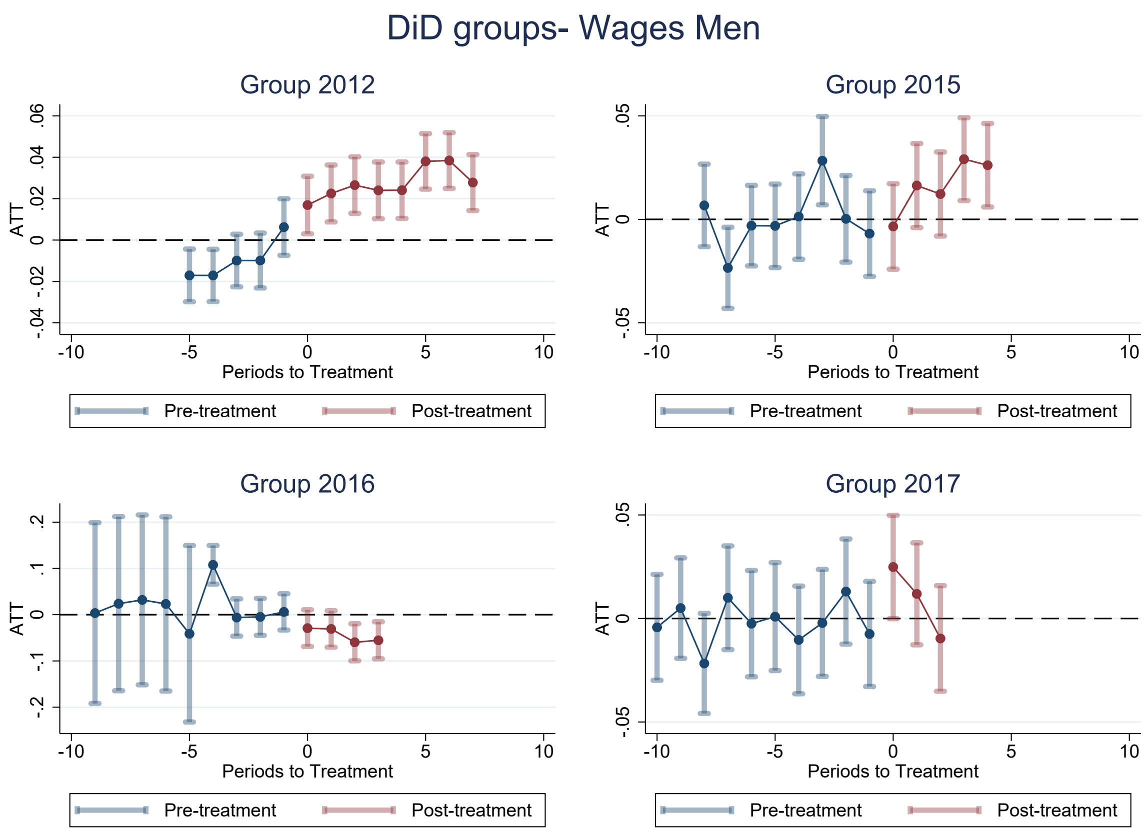

Figure 4.2: Event study wages for all wage-earning men between the ages of 18 and 65, with all controls

For a final test, the event study plots and table estimates of the dynamic ATT were used as a complement to the event study graphs. If a significant amount of the pre-treatment periods are statistically significantly different from zero in Figure 4.2 the pre-treatment periods in Figure A.13, the dynamic ATT plot, are also more likely to be statistically significantly different from zero. Although a less sensitive test, I provided table estimates for if the pre-treatment periods are statistically different from zero which provides a rough overview; however, to explore the parallel trend assumption with more confidence it is essential to primarily look at the event study graphs for the different groups.

There are potential threats to validity; in *A4*, if treated individuals select themselves into treatment, it could result in a biased estimator (Callaway & Sant'Anna, 2021). For this specific study, self-selection could be the case if treatment correlates with observable state-level endogenous variables, which make the treatment more or less likely such as political affiliation; or if individuals could select themselves into treatment by, for instance, moving to or from the treated states. To investigate this problem, I used several observable control variables and a robustness check where by introducing progressively more controls to the specification, I can investigate if the estimates change significantly, which would be the case if individuals can self-select into treatment. These tests can be found in Appendix B.

Finally, as this study measures the effect on unionized and ununionized wages by introducing RTW laws, the measurement is more susceptible to interactions with other state-level labor market policies, such as changes in the state-level minimum wage of the treatment group. To account for this, I have included group estimates to look for heterogeneity in the effect of treatment by groups. This does not control the problem of other policy effects interacting with the effect of the treatment. However, it allows us to observe if the treatment effect on the different groups is homogenous.

5

Empirical Analysis

5.1 Results

This study aims to estimate the Average treatment on the treated in the five states that introduced Right-to-work legislation between 2012 and 2017. The results are mixed. When looking at the dynamic ATT, the introduction of Right-to-work laws has a compressing effect on the wages of women and a generally positive effect on wages for men. By groups, I find heterogeneous effects by both state groups and gender. The 2017 group shows a significant wage compression effect for men, and the 2012 group shows a significant wage compression effect for women.

Table 4 shows ATT estimates and dynamic ATT estimates. When looking at the effect on wages (Full sample), the ATT and the dynamic ATT (post-treatment) are statistically significant for men and insignificant for women. The pre-treatment is insignificant for all specifications except for men's top 50th percentile level. When investigating the effect for different percentile levels for men, the ATT and the dynamic ATT are similar in significance and effect size. It shows a positive and significant effect between the 20th and the 50th percentile samples. Although largely positive in the lower percentiles, I find no evidence of a compression effect for men since the top 50th percentile is insignificant. For women, the results suggest that women's wages are compressed. All percentile levels between the 10th and 50th percentile show a positive effect, and the top 50th percentile shows a negative effect when looking at the dynamic ATT estimates. In contrast, the ATT shows significance only at the 10th, 30th, and top 50th percentile levels.

Table IV DiD results: ATT and Dynamic ATT with all regressors.

VARIABLES	10th percentile	20th percentile	30th percentile	50th percentile	Top 50th percentile	Full sample
Pre treatment Men	0.00574	0.00334	-0.000162	0.00243	-0.00302*	-0.00249
	(0.00902)	(0.00668)	(0.00546)	(0.00364)	(0.00183)	(0.00273)
Post treatment Men	0.0132	0.0219**	0.0273***	0.0257***	0.00332	0.0237***
	(0.0130)	(0.0103)	(0.00906)	(0.00681)	(0.00270)	(0.00432)
Pre treatment Women	-0.000596	0.000656	-0.00135	-0.00148	-0.00183	-0.00185
	(0.00724)	(0.00508)	(0.00398)	(0.00299)	(0.00237)	(0.00276)
Post treatment Women	0.0336***	0.0165*	0.0182**	0.0109**	-0.0123***	0.00390
	(0.0117)	(0.00873)	(0.00728)	(0.00544)	(0.00294)	(0.00427)
ATT Men	0.0130	0.0211**	0.0250***	0.0233***	0.00292	0.0216***
	(0.0126)	(0.0100)	(0.00880)	(0.00660)	(0.0126)	(0.00419)
ATT Women	0.0296***	0.0133	0.0150**	0.00792	-0.0105***	0.00271
	(0.0113)	(0.00847)	(0.00705)	(0.00526)	(0.00285)	(0.00412)

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The group effects in Table 5 of treatment within states appear to be heterogeneous between states. The 2012 group shows primarily positive effects on wages for men, although the lower percentile levels are insignificant. The 2017 men's group has experienced a wage compressing effect, while the 2015 and 2016 groups rarely show significant results; aside from for the whole sample, where the 2016 group shows a significant positive effect on wages, and the 2015 group has a significant negative effect. When looking at the average of the groups for men, the effect appears to be positively significant for all percentile levels except the top 50th percentile, where it is insignificant.

For women, the 2012 women's group shows an apparent compressing effect on wages, but the effect on wages is ultimately insignificant when looking at the whole sample. The 2015 women's group shows negative effects for the 20th, 30th, and 50th percentile, while 2016 has no significant results. The 2017 women's group shows mostly insignificant results, while it appears significant and negative when looking at the whole sample.

In conclusion, the different groups' estimates show both positive and negative significant results, although mostly positive. The effects from the 2012 group show the most consistency in its results between the genders, both in sign and significance. The magnitude of all the group estimators are roughly the same in size, except for the 2017 group for men, which shows a significant wage compression effect; for the women, however, it appears primarily insignificant.

Table V: Did group estimates with all covariates

VARIABLES	10th percentile	20th percentile	30th percentile	50th percentile	Top 50th percentile	Full sample
Average Men	0.0257**	0.0275***	0.0274***	0.0241***	0.000720	0.0181***
	(0.0123)	(0.00975)	(0.00851)	(0.00632)	(0.00254)	(0.00397)
Group 2012 Men	-0.00275	0.0190	0.0275**	0.0269***	0.00590*	0.0273***
	(0.0152)	(0.0122)	(0.0107)	(0.00815)	(0.00335)	(0.00531)
Group 2015 Men	0.0522*	-0.00272	-0.00699	-0.00406	0.000781	0.0161**
	(0.0285)	(0.0219)	(0.0192)	(0.0139)	(0.00513)	(0.00809)
Group 2016 Men	-0.0401	-0.0444	-0.0227	-0.0217	-0.00795	-0.0437***
	(0.0486)	(0.0387)	(0.0333)	(0.0239)	(0.0108)	(0.0158)
Group 2017 Men	0.153***	0.141***	0.0933***	0.0680***	-0.0149**	0.00904
	(0.0377)	(0.0299)	(0.0252)	(0.0176)	(0.00713)	(0.0106)
Average Women	0.0251**	0.00823	0.0119*	0.00359	-0.00909***	-0.00106
	(0.0108)	(0.00810)	(0.00674)	(0.00499)	(0.00274)	(0.00390)
Group 2012 Women	0.0371***	0.0239**	0.0238***	0.0169***	-0.0145***	0.00840
	(0.0138)	(0.0103)	(0.00866)	(0.00657)	(0.00369)	(0.00526)
Group 2015 Women	0.0112	-0.0323*	-0.0310**	-0.0227**	0.00267	-0.00601
	(0.0246)	(0.0179)	(0.0147)	(0.0104)	(0.00537)	(0.00776)
Group 2016 Women	-0.0269	0.00303	0.0173	-0.0148	-0.00803	-0.0182
	(0.0436)	(0.0342)	(0.0277)	(0.0198)	(0.0125)	(0.0159)
Group 2017 Women	0.00957	-0.00408	0.0163	-0.00699	-0.00956	-0.0235**
	(0.0305)	(0.0225)	(0.0187)	(0.0136)	(0.00719)	(0.0103)

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

5.2 Discussion

My results in Table 4 show a compression effect for women and a generally positive wage effect for men. These results contrast with findings by Fortin, Lemieux & Lloyd (2022), who found a negative effect on total wages for women and insignificant effects on wages for men. It also contrasts with findings by Fortin, Lemieux & Lloyd (2021), who argue that wage dispersion should increase when unionization rates decrease, which both Fortin, Lemieux & Lloyd (2022) and Chun (2023) show evidence of. In addition to mainly finding positive effects on wages in the group estimates, the dynamic ATT and ATT estimates are overwhelmingly positive in almost all the different percentile levels. In contrast, only the 2015 group (Wisconsin) for women experienced a significant adverse effect on wages in some percentile levels. It is essential to emphasize that my results from both tables show that the introduction of Right-to-work laws mainly affects wages in the lower and middle percentiles positively. Consequently, the idea that Right-to-work laws lower the threat effect through a reduction in unionization rates, as Fortin, Lemieux & Lloyd (2022) argued, or that its' impact is at the very least significantly influential, is not observable in my general results.

My general results align more with the result from Chun (2023), where he found significant positive effects on wages and wage compression for union wages. My ATT and dynamic ATT results support the notion that union bargaining behavior might have become increasingly assertive as a reaction to the Right-to-work law's introduction, as Chun (2023) argued. However, the group results reveal a broader mixture of effects and plausible explanations.

The group results show a broadly positive effect on wages in group 2012 for both genders (Michigan and Indiana). Since unionization rates in Michigan are higher than in most Right-to-work states and considering the rapid manner the law was introduced and how unexpected it was (Kaminski, 2015), changes in bargaining behavior in protest to the introduction of these laws is a plausible explanation of why wages have generally increased more prominently within the 2012 group. If the unions that are bargaining more assertively are connected to a highly unionized industry within a particular state, the bargaining effect on wages could arguably be more prominent. Even if unionization rates fall, if this results in a heightened effort to recruit new members or more actively demand higher compensations as a reaction, this could be perceived as an increased threat effect. If this threat or protests are particularly visible, as it was in the case of Michigan (Kaminski, 2015), the threat itself could spill over to other industries, highlighting the importance of the unionization rate before treatment and how it can impact the unionization threat.

Throughout this thesis, I also emphasized that within-state labor market policies could affect the estimates. As noted in Fortin, Lemieux & Lloyd (2021), it is essential not to exclude minimum wage changes from the analysis. Michigan's progressive increase in state minimum wage (FRED, 2023 A) also explains the compression effect observed in the 2012 group.

The group 2017 results (Kentucky) for men show estimates of between 7%-15%. These results are significantly larger than the effect sizes of other group ATT estimates, typically ranging from 1%-4%. The effect is distinctly an effect on men's wages, who arguably rely less on institutional collective bargaining agreements (Biasi & Sarsons, 2022). If these effects were a result of changes in the bargaining behaviors of unions, we would expect women to be at least relatively as affected as men. However, this is not supported by the results. Similarly, if group 2015 (Wisconsin) is so similar to Michigan as Kaminski (2015) suggests, how does it come that there are no wage-compressing effects visible in the results for the 2015 group? The results from Wisconsin appear to align more with the results from Fortin, Lemieux & Lloyd (2021), showcasing that there could be evidence of threat effects in the case of Wisconsin.

Finally, the introduction of Right-to-work laws encourages competition (Moore, 1998), which could increase total wages by increasing labor demand (Borjas, 2020). This is also a plausible explanation for increased wage levels. However, these effects could take time to show its effect and might not be captured by the estimates, especially not in the 2017 group.

Figures A.1 - A.12 in Appendix A provide evidence of the validity of the results by investigating if the parallel trend assumption holds. It is worth noting that the 2017 group tends to have one pre-treatment period right before treatment, which appears negative and significant in some of the different percentile levels, which could influence the validity of the results. Nevertheless, when evaluating these results, knowing that the parallel trend assumption generally holds well is essential. It is imperfect, as in several event-study graphs, pre-treatment periods exist that are statistically different from zero; however, the vast majority of pre-treatment periods are not statistically different from zero, showing that the parallel trend assumption appears to hold.

Appendix B, Table VI-XVII shows the robustness of the results. The tables indicate relatively robust results, as the estimates rarely change more than 0.01 between the specification without controls and with controls, and they rarely change sign. This indicates that treatment does not appear to change the composition of treatment and control groups through self-selection into treatment.

6

Conclusion

In this thesis, I estimate the ATT estimates of Right-to-work laws on wages and wage dispersion for all wages. Using the staggered difference-in-difference model pioneered by Callaway & Sant'Anna (2021) and analyzing different percentile levels, I have analyzed distributional effects and total effects on wages. These findings bring unique insights into the effect of introducing Right-to-work laws on wage dispersion and wages, as it shows significant effects on wages and a wage-compressing effect on the distribution of wages using a novel method.

My general results, supported by the ATT and dynamic ATT estimates, on the wage distribution, are comparable to results from Chun (2023), who used a similar method of analyzing distinct percentile levels and gets a similar result but for unionized wages. My group results, in contrast, display heterogeneous effects. The 2012 group results align with findings from Chun (2023) and I highlight the plausible explanation of a changed bargaining behavior from unions and the possibility that changes in state minimum wage explains the results. The 2017 group does not support this notion of changed bargaining behavior, as there are such large gender differences in the results. The 2015 group result aligns itself with findings from Fortin, Lemieux & Lloyd (2022) and points to a reduced threat effect as a plausible explanation.

Throughout this thesis, I have contributed evidence of how wages and compression of wage dispersion mostly increased with the introduction of Right-to-work laws by both gender and state groups. I have also thoroughly investigated the heterogeneous effect between state groups and arrived at the conclusion that Right-to-work laws might impact states differently, and there might be several plausible explanations for the effects observed.

However, the reader should be aware of the limitations, such as how introducing state-level labor market policies, such as raising the state minimum wage, might distort the results. The results could also be affected by time-invariant unobserved state-level endogenous variables, such as state-level union culture or differences in market structures or market densities, or if treatment is affected by political affiliation such that individuals select themselves into treatment. Yet, if the results were heavily influenced by time-invariant unobserved state-level endogenous variables or self-selection into treatment, it would likely have shown more clearly in the event study graphs or the robustness test; nevertheless, it cannot be excluded from the analysis.

In conclusion, introducing Right-to-work laws appear to have a generally positive effect on wages and wage dispersion for all wages. The effects are heterogeneous by state and gender, however, most of the significant values for the lower wage levels appear to be increasing. There might be several plausible explanations for the effects observed, however, the notion that Right-to-work laws lower the threat effect significantly, or that this effect has a large and broad influence, is not observed.

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Appendix A

Appendix A Event study graphs

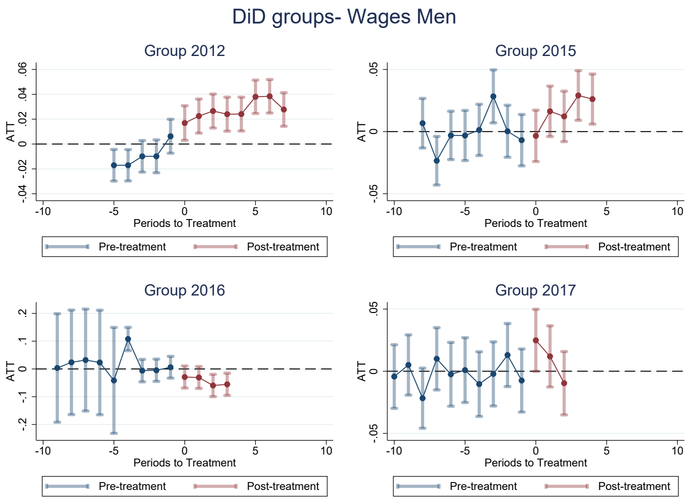

Figure A.1: Event study wages for all wage-earning men between the ages of 18 and 65 full sample all controls

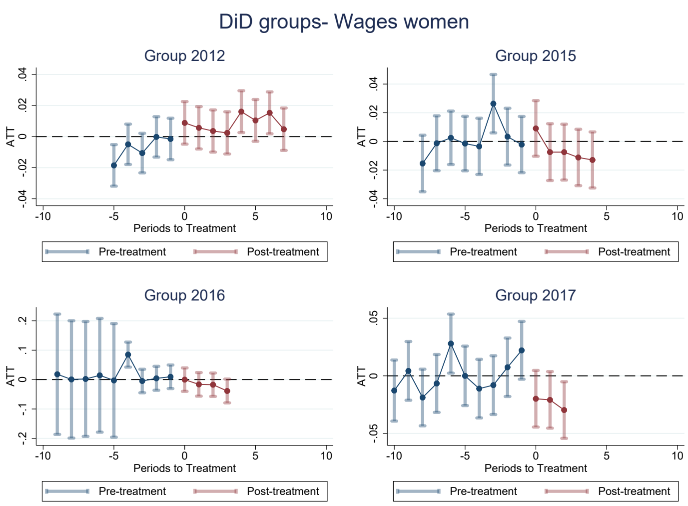

Figure A.2: Event study wages for wage-earning women between the ages of 18 and 65 full sample all controls

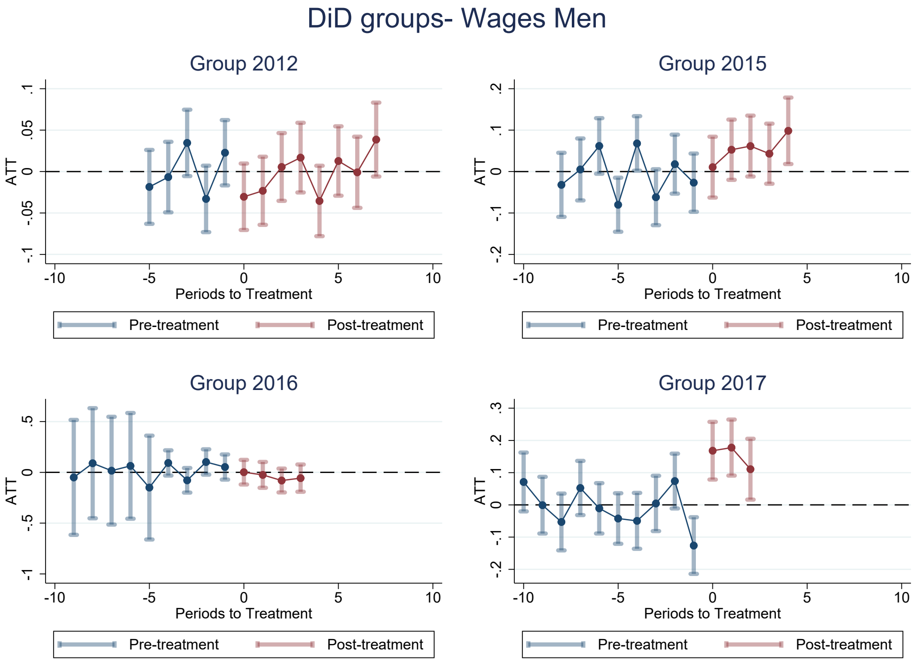

Figure A.3: Event study wages for bottom 10 percentile wage-earning men between the ages of 18 and 65, all controls

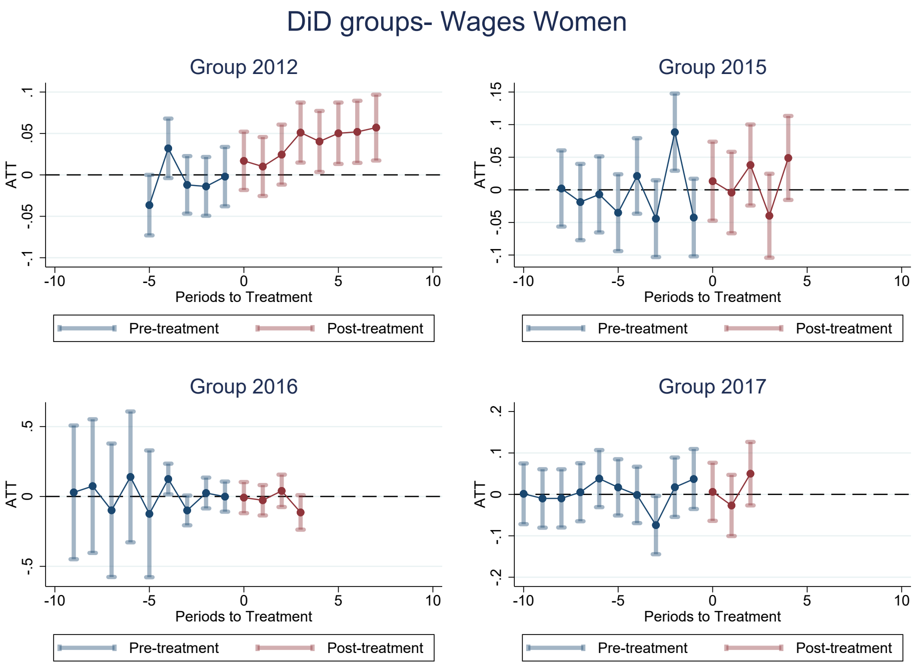

Figure A.4: Event study wages for bottom 10 percentile wage-earning women between the ages of 18 and 65, all controls

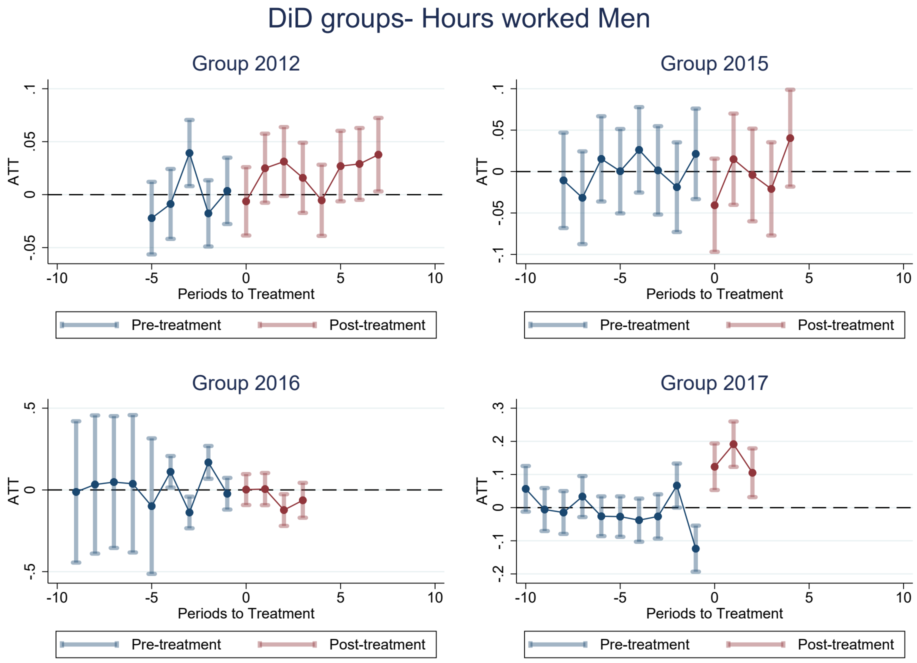

Figure A.5: Event study wages for the bottom 20 percentile of all wage-earning men between the ages of 18 and 65, all controls

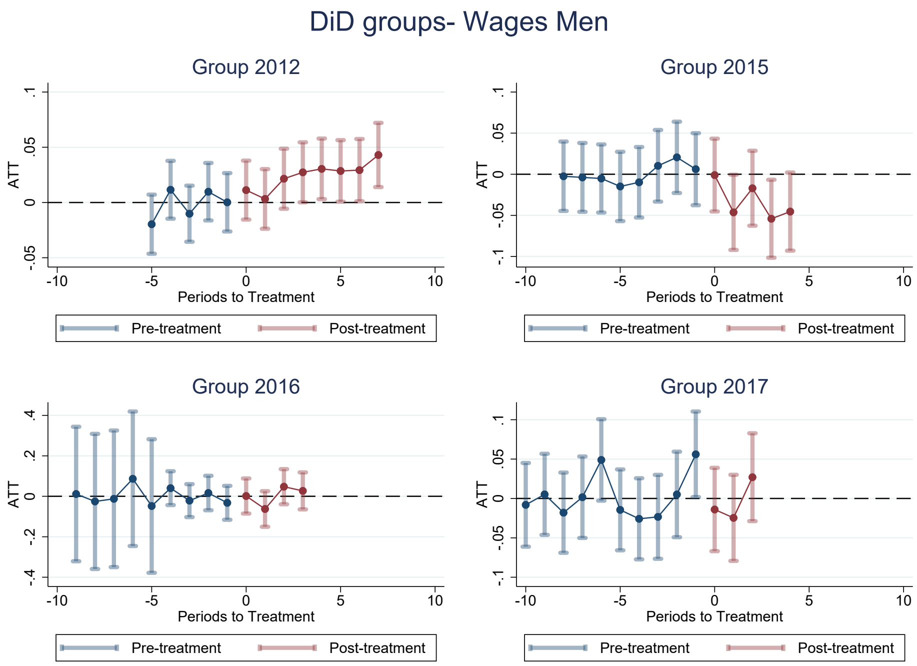

Figure A.6: Event study wages for bottom 20 percentile wage-earning women between the ages of 18 and 65, all controls

Figure A.7: Event study wages for the bottom 30 percentile of all wage-earning men between the ages of 18 and 65, all controls

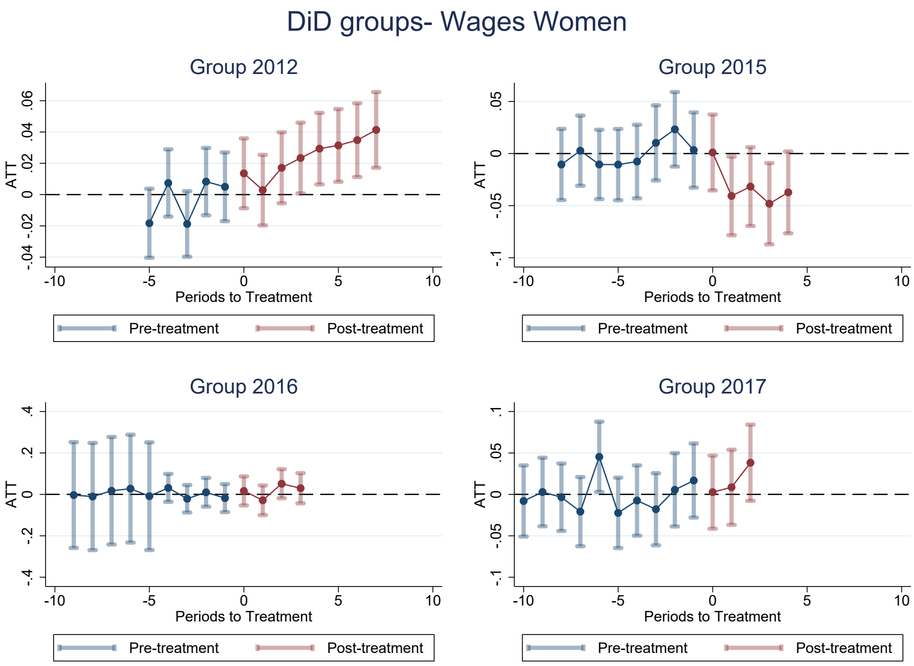

Figure A.8: Event study wages for bottom 30 percentile wage-earning women between the ages of 18 and 65, all controls

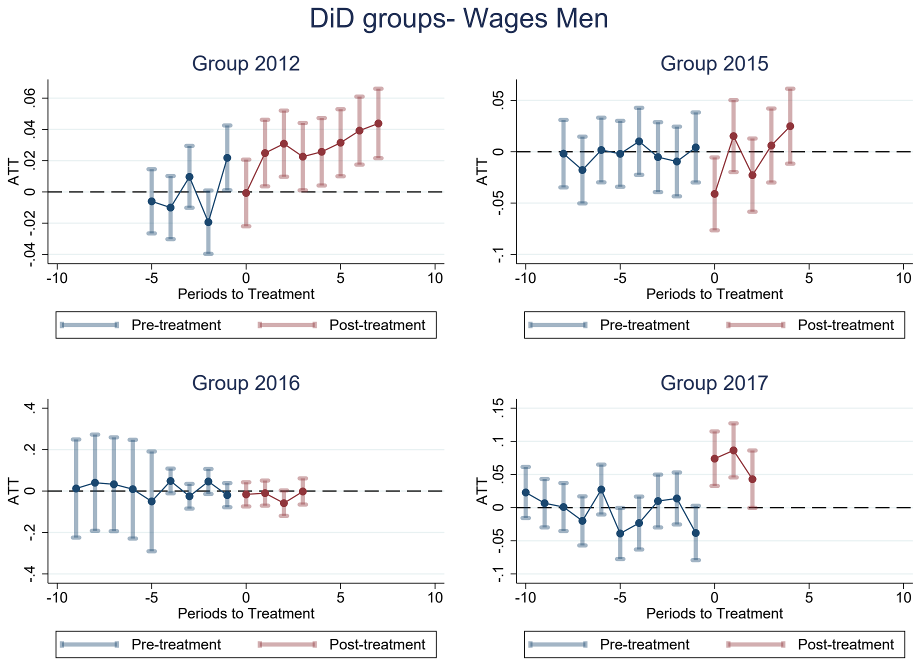

Figure A.9: Event study wages for the bottom 50 percentile of all wage-earning men between the ages of 18 and 65, all controls

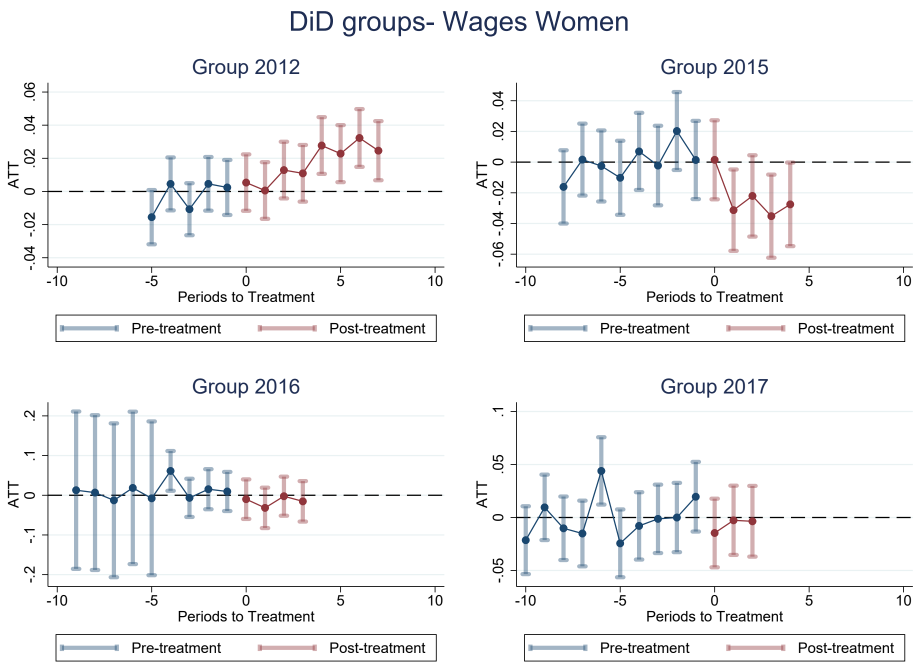

Figure A.10: Event study wages for bottom 50 percentile wage-earning women between the ages of 18 and 65, all controls

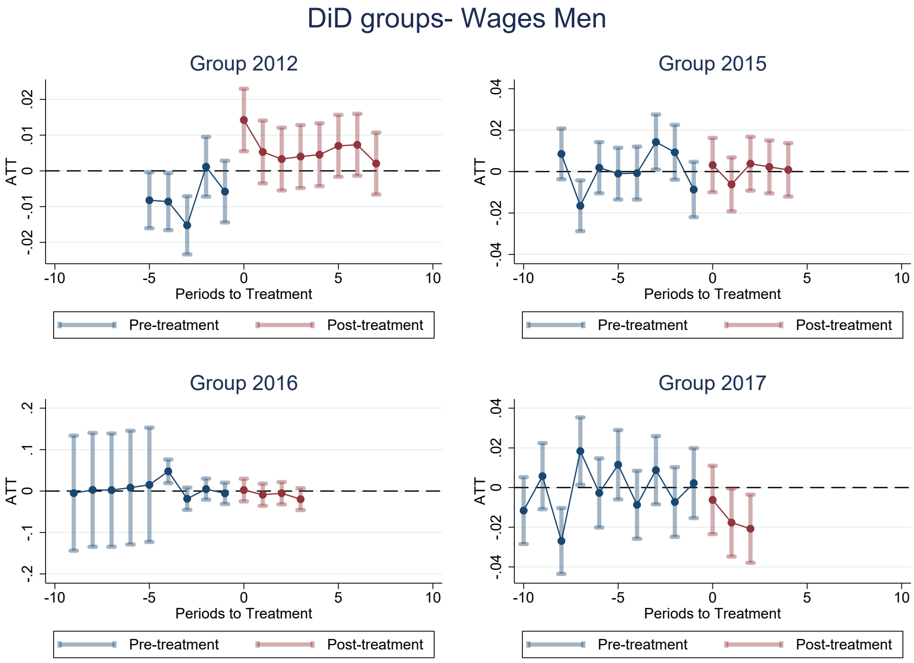

Figure A.11: Event study wages for top 50 percentile wage-earning men between the ages of 18 and 65, all controls

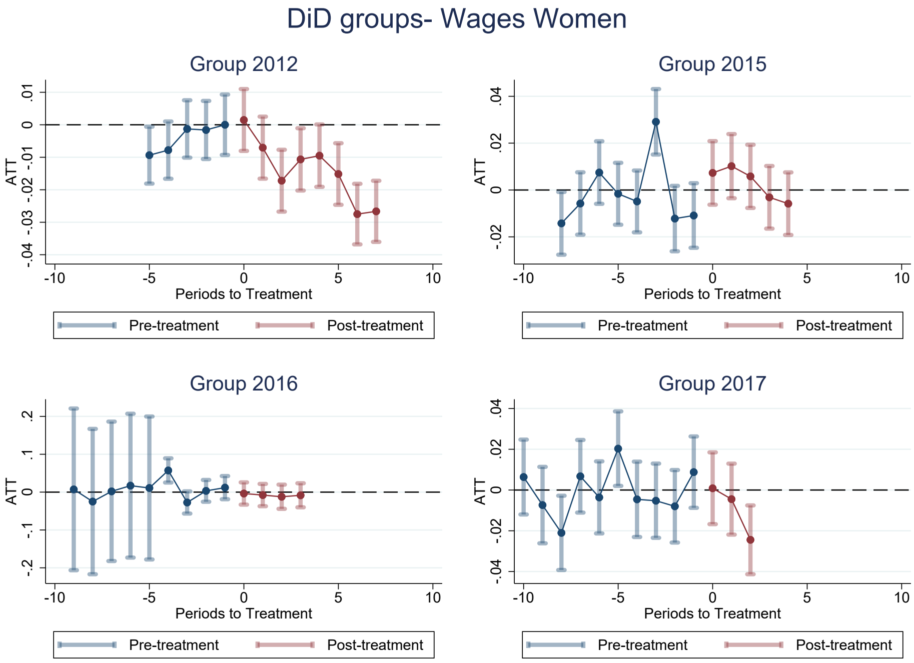

Figure A.12: Event study wages for top 50 percentile wage-earning women between the ages of 18 and 65, all controls

A.1 Dynamic and group estimates graphs

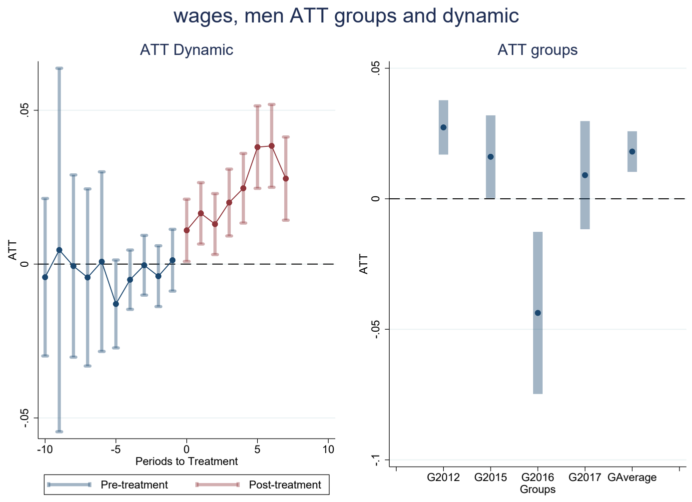

Figure A.13: Dynamic and group estimates graphs wages for all wage-earning men between the ages of 18 and 65 with all controls

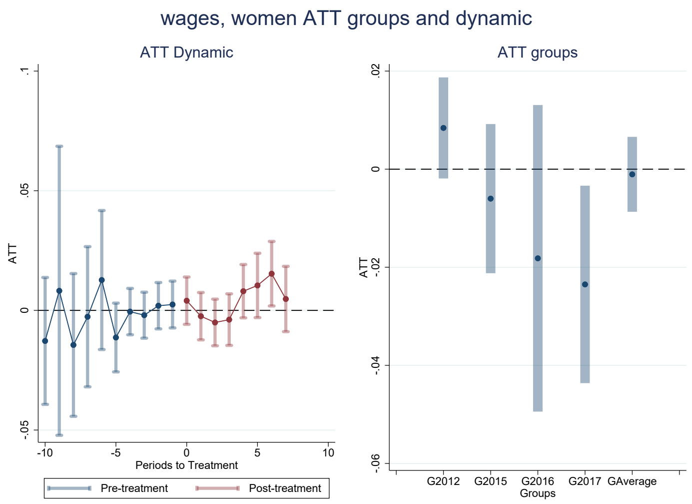

Figure A.14: Dynamic and group estimates graphs wages for all wage-earning women between the ages of 18 and 65, all controls

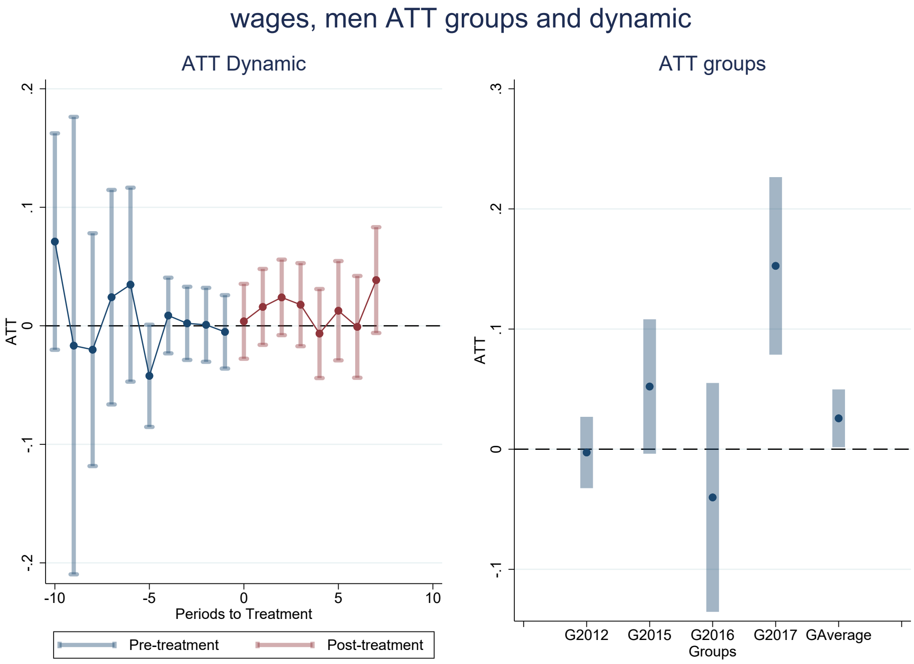

Figure A.15: Dynamic and group estimates graphs wages for the bottom 10 percentile wage-earning men between the ages of 18 and 65, all controls

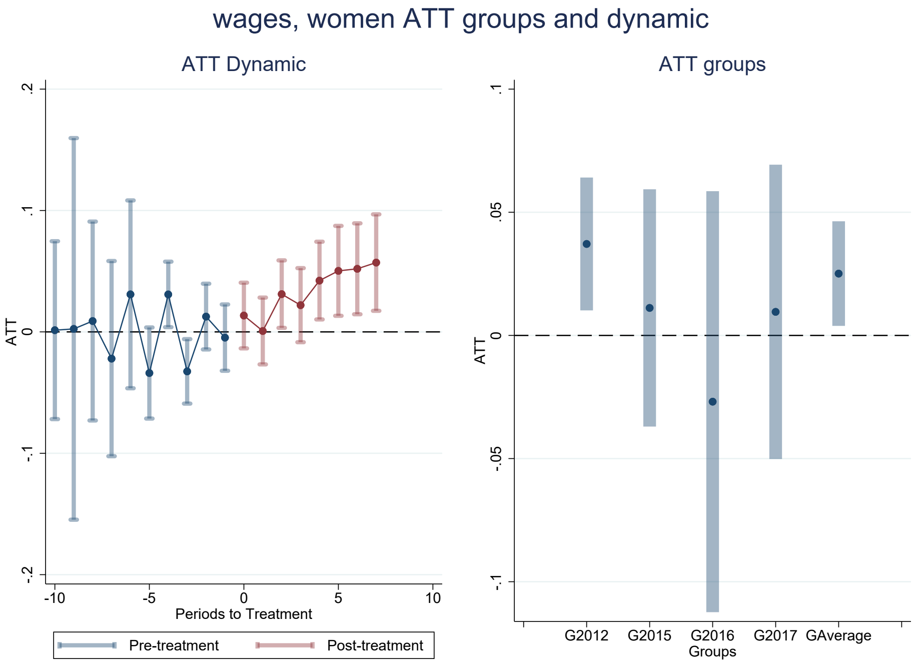

Figure A.16: Dynamic and group estimates graphs wages for the bottom 10 percentile wage-earning women between the ages of 18 and 65, all controls

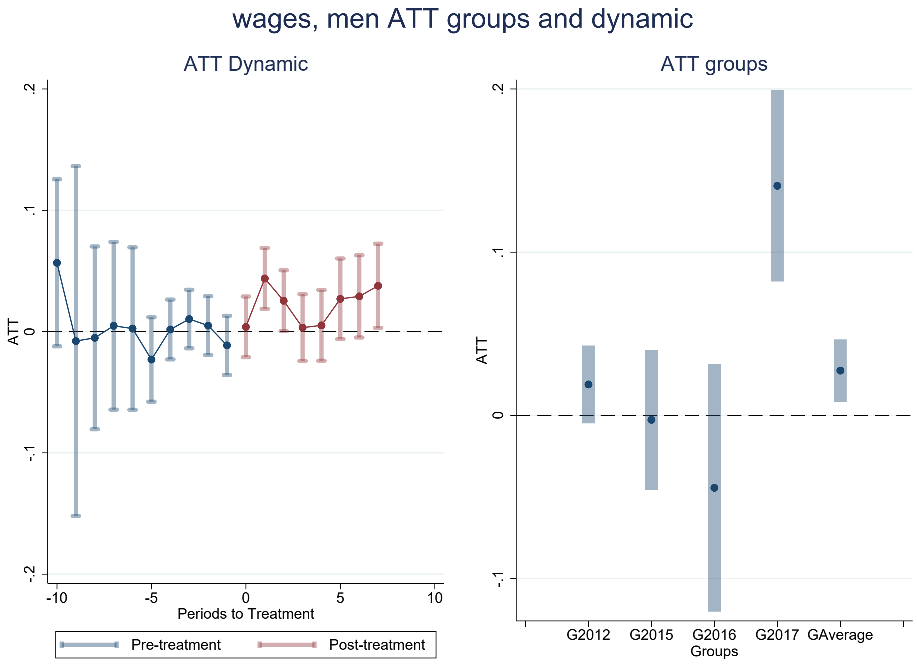

Figure A.17: Dynamic and group estimates graphs wages for bottom 20 percentile wage earning men between the ages of 18 and 65, all controls

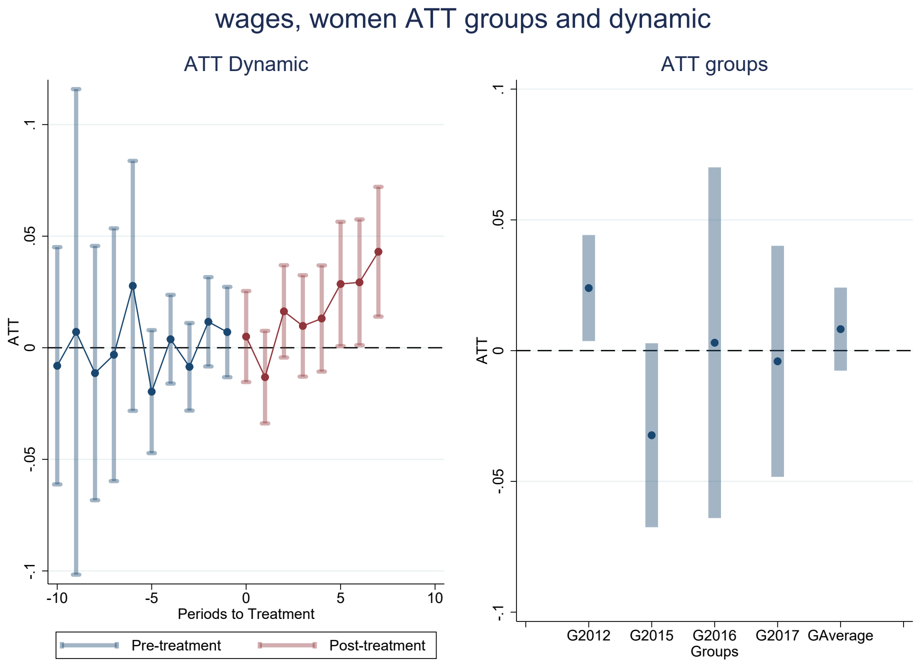

Figure A.18: Dynamic and group estimates graphs wages for the bottom 20 percentile wage-earning women between the ages of 18 and 65, all controls

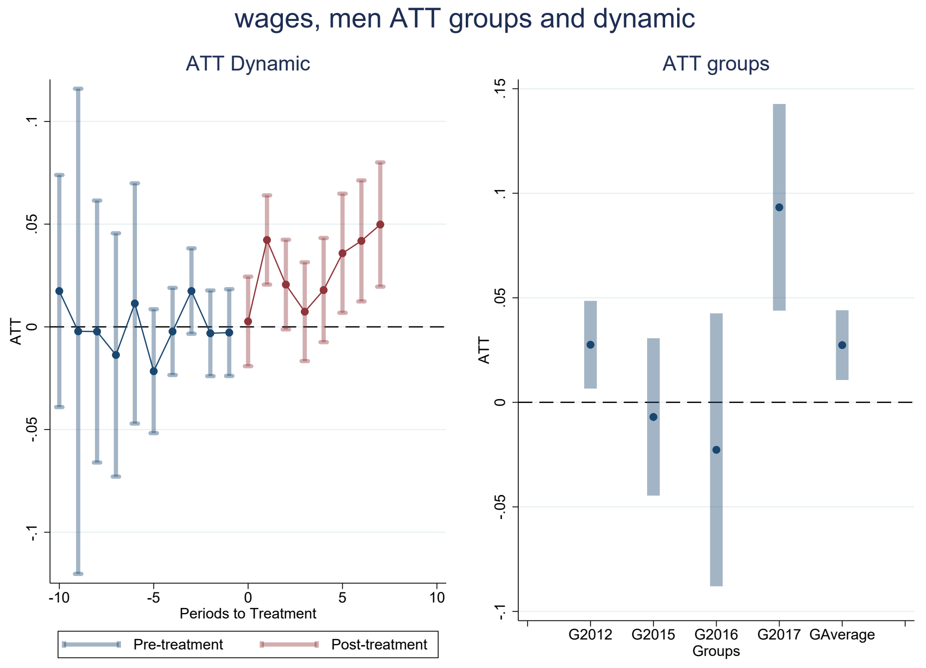

Figure A.19: Dynamic and group estimates graphs wages for bottom 30 percentile wage earning men between the ages of 18 and 65, all controls

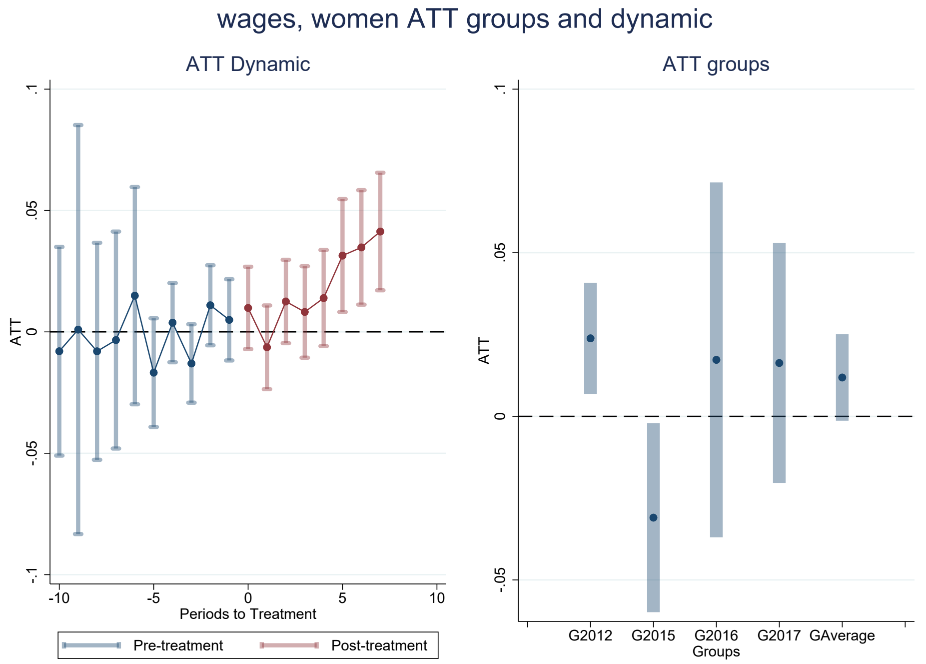

Figure A.20: Dynamic and group estimates graphs wages for the bottom 30 percentile wage-earning women between the ages of 18 and 65, all controls

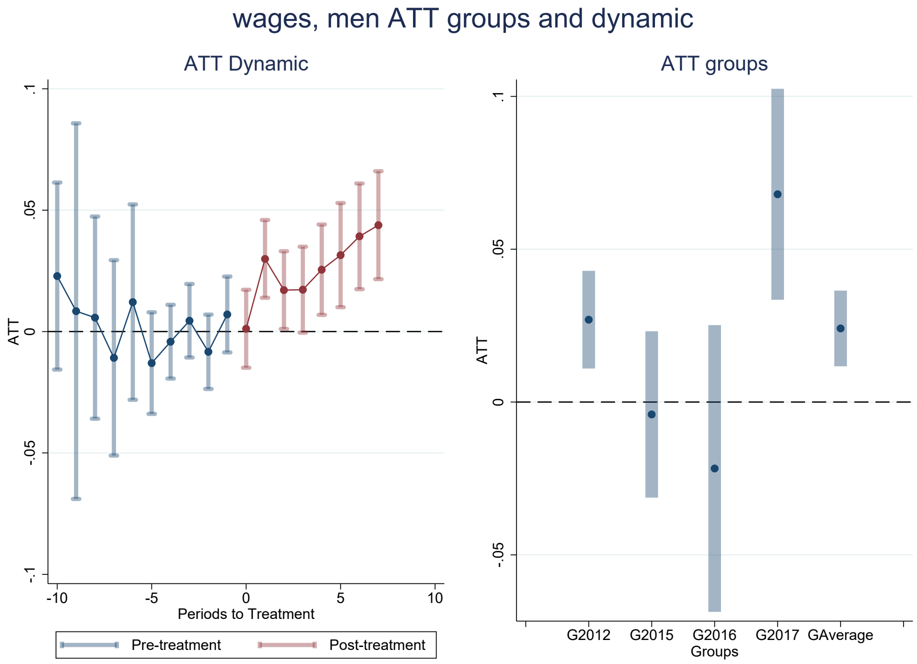

Figure A.21: Dynamic and group estimates graphs wages for the bottom 50 percentile wage-earning men between the ages of 18 and 65, all controls

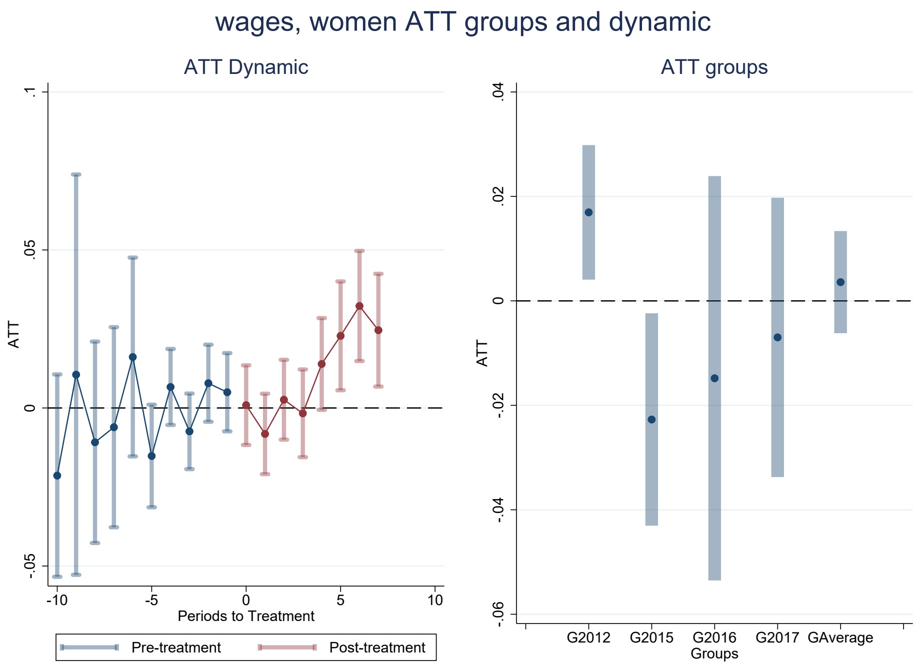

Figure A.22: Dynamic and group estimates graphs wages for bottom 50 percentile wage earning women between the ages of 18 and 65, all controls

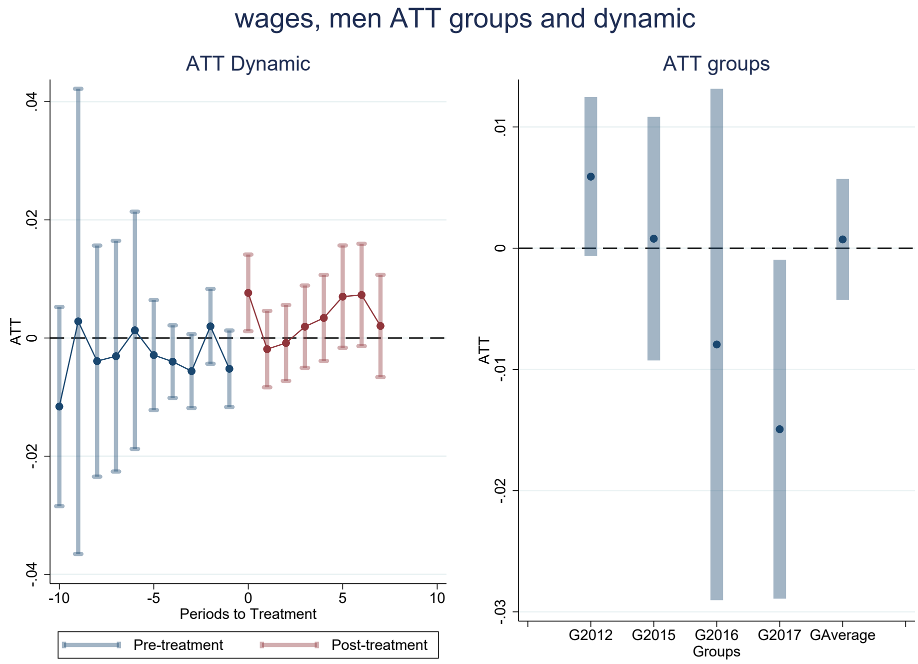

Figure A.23: Dynamic and group estimates graphs wages for top 50 percentile wage-earning men between the ages of 18 and 65, all controls

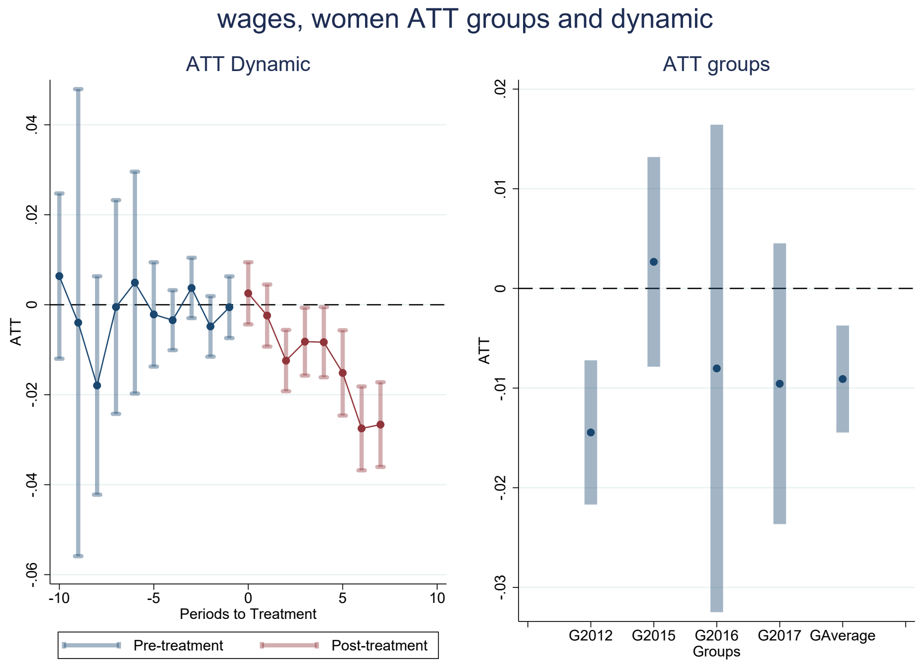

Figure A.24: Dynamic and group estimates graphs wages for top 50 percentile wage-earning women between the ages of 18 and 65, all controls

Appendix B

Appendix B Robustness tests

The reader will find a collection of 12 robustness tests in Appendix B. These tests provide information on the robustness of the estimators by showing if the estimators change dramatically when more controls are added to the specification, in order to investigate any selection into treatment that can affect the validity of the results.

Table VI DiD results: ATT and Dynamic ATT full sample.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre treatment Men	-0.000980	-0.00463***	-0.00303**	-0.00197	-0.00185	-0.000633	-0.00249
	(0.00177)	(0.00145)	(0.00145)	(0.00145)	(0.00138)	(0.00135)	(0.00273)
Post treatment Men	0.0171***	0.00166	0.00472	0.00662	0.0138***	0.0185***	0.0237***
	(0.00598)	(0.00461)	(0.00460)	(0.00460)	(0.00436)	(0.00427)	(0.00432)
Pre treatment Women	-0.00202	-0.00386***	-0.00278*	-0.00260*	-0.00171	-0.00115	-0.00185
	(0.00182)	(0.00144)	(0.00144)	(0.00143)	(0.00136)	(0.00136)	(0.00276)
Post treatment Women	-0.00677	-0.0120***	-0.0112**	-0.0103**	-0.00415	-0.00173	0.00390
	(0.00600)	(0.00443)	(0.00444)	(0.00442)	(0.00422)	(0.00420)	(0.00427)
ATT Women	-0.00726	-0.0113***	-0.0107**	-0.00974**	-0.00464	-0.00249	0.00271
	(0.00581)	(0.00429)	(0.00430)	(0.00427)	(0.00408)	(0.00406)	(0.00412)
ATT Men	0.0143**	0.00130	0.00413	0.00580	0.0124***	0.0165***	0.0216***
	(0.00579)	(0.00447)	(0.00446)	(0.00446)	(0.00422)	(0.00414)	(0.00419)
Hours worked	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table VII: Did group estimates full sample.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average Men	0.00816	-0.000626	0.00230	0.00393	0.0101**	0.0138***	0.0181***
	(0.00548)	(0.00426)	(0.00425)	(0.00424)	(0.00402)	(0.00393)	(0.00397)
Group 2012 Men	0.0237***	0.00543	0.00811	0.00980*	0.0161***	0.0212***	0.0273***
	(0.00737)	(0.00567)	(0.00566)	(0.00565)	(0.00536)	(0.00525)	(0.00531)
Group 2015 Men	0.00518	-0.00519	-0.00219	-0.000428	0.0110	0.0134*	0.0161**
	(0.0110)	(0.00872)	(0.00866)	(0.00865)	(0.00822)	(0.00805)	(0.00809)
Group 2016 Men	-0.0697***	-0.0552***	-0.0506***	-0.0498***	-0.0491***	-0.0498***	-0.0437***
	(0.0119)	(0.0116)	(0.0115)	(0.0114)	(0.0108)	(0.0107)	(0.0108)
Group 2017 Men	-0.0172	0.00361	0.00672	0.00828	0.00873	0.0102	0.00904
	(0.0145)	(0.0115)	(0.0115)	(0.0114)	(0.0107)	(0.0105)	(0.0106)
Average Women	-0.0116**	-0.0146***	-0.0134***	-0.0122***	-0.00696*	-0.00526	-0.00106
	(0.00549)	(0.00408)	(0.00409)	(0.00406)	(0.00387)	(0.00385)	(0.00390)
Group 2012 Women	-0.00210	-0.00691	-0.00707	-0.00624	-0.00147	0.00135	0.00840
	(0.00740)	(0.00545)	(0.00547)	(0.00544)	(0.00519)	(0.00517)	(0.00526)
Group 2015 Women	-0.00808	-0.0160**	-0.0141*	-0.0145*	-0.00844	-0.00706	-0.00601
	(0.0110)	(0.00812)	(0.00813)	(0.00808)	(0.00775)	(0.00768)	(0.00776)
Group 2016 Women	-0.0334	-0.0285*	-0.0269	-0.0172	-0.0123	-0.0147	-0.0182
	(0.0229)	(0.0172)	(0.0172)	(0.0169)	(0.0160)	(0.0159)	(0.0159)
Group 2017 Women	-0.0448***	-0.0366***	-0.0314***	-0.0299***	-0.0237**	-0.0243**	-0.0235**
	(0.0143)	(0.0110)	(0.0110)	(0.0109)	(0.0103)	(0.0102)	(0.0103)
Hours worked &Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table VIII DiD results: ATT and Dynamic ATT 10th percentile.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre treatment Men	0.0117**	0.00826*	0.0109**	0.0108**	0.00984**	0.00954**	0.00574
	(0.00486)	(0.00477)	(0.00480)	(0.00480)	(0.00479)	(0.00479)	(0.00902)
Post treatment Men	0.0118	0.0108	0.00984	0.00673	0.00755	0.00857	0.0132
	(0.0134)	(0.0128)	(0.0128)	(0.0127)	(0.0127)	(0.0127)	(0.0130)
Pre treatment Women	0.00354	0.000324	0.00123	0.00138	0.000442	-9.79e-05	-0.000596
	(0.00393)	(0.00382)	(0.00384)	(0.00385)	(0.00385)	(0.00386)	(0.00724)
Post treatment Women	0.0238**	0.0292**	0.0283**	0.0281**	0.0299***	0.0303***	0.0336***
	(0.0119)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0117)
ATT Women	0.0205*	0.0257**	0.0249**	0.0247**	0.0264**	0.0268**	0.0296***
	(0.0116)	(0.0111)	(0.0112)	(0.0111)	(0.0111)	(0.0112)	(0.0113)
ATT Men	0.0107	0.0106	0.00962	0.00668	0.00737	0.00848	0.0130
	(0.0130)	(0.0125)	(0.0125)	(0.0124)	(0.0124)	(0.0124)	(0.0126)
Hours worked	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table IX: Did group estimates 10th percentile

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average Men	0.0227*	0.0230*	0.0219*	0.0197	0.0200*	0.0212*	0.0257**
	(0.0128)	(0.0122)	(0.0122)	(0.0121)	(0.0121)	(0.0121)	(0.0123)
Group 2012 Men	-0.00436	-0.00485	-0.00524	-0.00909	-0.00831	-0.00759	-0.00275
	(0.0156)	(0.0150)	(0.0149)	(0.0149)	(0.0148)	(0.0148)	(0.0152)
Group 2015 Men	0.0515*	0.0491*	0.0443	0.0420	0.0454	0.0485*	0.0522*
	(0.0301)	(0.0291)	(0.0287)	(0.0286)	(0.0285)	(0.0284)	(0.0285)
Group 2016 Men	-0.0531	-0.0375	-0.0388	-0.0328	-0.0351	-0.0319	-0.0401
	(0.0515)	(0.0483)	(0.0481)	(0.0479)	(0.0474)	(0.0476)	(0.0486)
Group 2017 Men	0.144***	0.145***	0.146***	0.148***	0.143***	0.144***	0.153***
	(0.0396)	(0.0381)	(0.0380)	(0.0376)	(0.0374)	(0.0374)	(0.0377)
Average Women	0.0144	0.0206*	0.0204*	0.0206*	0.0225**	0.0228**	0.0251**
	(0.0111)	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0108)
Group 2012 Women	0.0296**	0.0339**	0.0323**	0.0314**	0.0332**	0.0337**	0.0371***
	(0.0141)	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0138)
Group 2015 Women	-0.00350	0.00628	0.00684	0.00827	0.00895	0.00752	0.0112
	(0.0257)	(0.0247)	(0.0246)	(0.0245)	(0.0244)	(0.0244)	(0.0246)
Group 2016 Women	-0.00691	-0.0261	-0.0289	-0.0243	-0.0265	-0.0216	-0.0269
	(0.0451)	(0.0431)	(0.0430)	(0.0432)	(0.0432)	(0.0434)	(0.0436)
Group 2017 Women	-0.0231	-0.00275	0.00393	0.00562	0.0113	0.0113	0.00957
	(0.0306)	(0.0299)	(0.0299)	(0.0299)	(0.0298)	(0.0299)	(0.0305)
Hours worked &Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table X DiD results: ATT and Dynamic ATT 20th percentile.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre treatment Men	0.00734*	0.00394	0.00482	0.00475	0.00457	0.00522	0.00334
	(0.00376)	(0.00359)	(0.00359)	(0.00359)	(0.00357)	(0.00358)	(0.00668)
Post treatment Men	0.0247**	0.0166	0.0165	0.0143	0.0144	0.0162	0.0219**
	(0.0109)	(0.0102)	(0.0102)	(0.0102)	(0.0101)	(0.0101)	(0.0103)
Pre treatment Women	0.00114	0.00114	0.00160	0.00131	0.00117	0.00132	0.000656
	(0.00277)	(0.00277)	(0.00279)	(0.00278)	(0.00278)	(0.00278)	(0.00508)
Post treatment Women	0.0125	0.0125	0.0132	0.0134	0.0130	0.0143*	0.0165*
	(0.00857)	(0.00857)	(0.00860)	(0.00858)	(0.00856)	(0.00857)	(0.00873)
ATT Women	0.00974	0.00974	0.0103	0.0105	0.0102	0.0114	0.0133
	(0.00832)	(0.00832)	(0.00835)	(0.00833)	(0.00831)	(0.00832)	(0.00847)
ATT Men	0.0227**	0.0158	0.0159	0.0138	0.0139	0.0156	0.0211**
	(0.0106)	(0.00993)	(0.00994)	(0.00989)	(0.00985)	(0.00985)	(0.0100)
Hours worked	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table XI: Did group estimates 20th percentile

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average Men	0.0304***	0.0238**	0.0238**	0.0222**	0.0223**	0.0239**	0.0275***
	(0.0103)	(0.00969)	(0.00968)	(0.00963)	(0.00960)	(0.00960)	(0.00975)
Group 2012 Men	0.0174	0.0111	0.0116	0.00894	0.00871	0.0106	0.0190
	(0.0129)	(0.0120)	(0.0120)	(0.0120)	(0.0119)	(0.0119)	(0.0122)
Group 2015 Men	0.0158	-0.00143	-0.00160	-0.00367	-0.00164	-0.00112	-0.00272
	(0.0232)	(0.0221)	(0.0219)	(0.0218)	(0.0217)	(0.0217)	(0.0219)
Group 2016 Men	-0.0437	-0.0411	-0.0429	-0.0442	-0.0438	-0.0427	-0.0444
	(0.0422)	(0.0388)	(0.0385)	(0.0384)	(0.0382)	(0.0382)	(0.0387)
Group 2017 Men	0.143***	0.147***	0.145***	0.149***	0.148***	0.150***	0.141***
	(0.0316)	(0.0298)	(0.0298)	(0.0296)	(0.0296)	(0.0296)	(0.0299)
Average Women	0.00387	0.00387	0.00540	0.00576	0.00572	0.00647	0.00823
	(0.00798)	(0.00798)	(0.00800)	(0.00798)	(0.00797)	(0.00797)	(0.00810)
Group 2012 Women	0.0211**	0.0211**	0.0205**	0.0204**	0.0199**	0.0219**	0.0239**
	(0.0101)	(0.0101)	(0.0102)	(0.0102)	(0.0101)	(0.0102)	(0.0103)
Group 2015 Women	-0.0356**	-0.0356**	-0.0326*	-0.0313*	-0.0320*	-0.0336*	-0.0323*
	(0.0178)	(0.0178)	(0.0178)	(0.0178)	(0.0178)	(0.0178)	(0.0179)
Group 2016 Women	0.00549	0.00549	0.00777	0.00687	0.00568	0.00686	0.00303
	(0.0342)	(0.0342)	(0.0342)	(0.0342)	(0.0340)	(0.0341)	(0.0342)
Group 2017 Women	-0.0194	-0.0194	-0.0106	-0.00922	-0.00584	-0.00727	-0.00408
	(0.0222)	(0.0222)	(0.0223)	(0.0222)	(0.0222)	(0.0222)	(0.0225)
Hours worked &Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table XII DiD results: ATT and Dynamic ATT 30th percentile.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre treatment Men	0.00469	0.000618	0.000836	0.00114	0.000568	0.00183	-0.000162
	(0.00319)	(0.00294)	(0.00296)	(0.00295)	(0.00294)	(0.00294)	(0.00546)
Post treatment Men	0.0335***	0.0224**	0.0210**	0.0200**	0.0196**	0.0219**	0.0273***
	(0.00991)	(0.00893)	(0.00896)	(0.00892)	(0.00889)	(0.00889)	(0.00906)
Pre treatment Women	0.00183	-0.00155	-0.00152	-0.00183	-0.00180	-0.00141	-0.00135
	(0.00254)	(0.00224)	(0.00226)	(0.00226)	(0.00225)	(0.00225)	(0.00398)
Post treatment Women	0.0154*	0.0137*	0.0155**	0.0154**	0.0140*	0.0163**	0.0182**
	(0.00824)	(0.00716)	(0.00719)	(0.00717)	(0.00715)	(0.00716)	(0.00728)
ATT Women	0.0126	0.0111	0.0127*	0.0127*	0.0114	0.0134*	0.0150**
	(0.00799)	(0.00694)	(0.00697)	(0.00695)	(0.00694)	(0.00694)	(0.00705)
ATT Men	0.0291***	0.0201**	0.0191**	0.0182**	0.0178**	0.0199**	0.0250***
	(0.00964)	(0.00869)	(0.00871)	(0.00867)	(0.00864)	(0.00864)	(0.00880)
Hours worked	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table XIII: Did group estimates 30th percentile.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average Men	0.0319***	0.0247***	0.0235***	0.0229***	0.0227***	0.0247***	0.0274***
	(0.00932)	(0.00844)	(0.00845)	(0.00841)	(0.00839)	(0.00839)	(0.00851)
Group 2012 Men	0.0297**	0.0195*	0.0188*	0.0178*	0.0168	0.0193*	0.0275**
	(0.0117)	(0.0105)	(0.0106)	(0.0105)	(0.0105)	(0.0105)	(0.0107)
Group 2015 Men	0.0114	-0.00659	-0.00708	-0.00922	-0.00603	-0.00606	-0.00699
	(0.0209)	(0.0193)	(0.0192)	(0.0191)	(0.0191)	(0.0191)	(0.0192)
Group 2016 Men	-0.0293	-0.0198	-0.0222	-0.0257	-0.0235	-0.0225	-0.0227
	(0.0378)	(0.0332)	(0.0331)	(0.0329)	(0.0329)	(0.0329)	(0.0333)
Group 2017 Men	0.0944***	0.108***	0.105***	0.108***	0.107***	0.109***	0.0933***
	(0.0274)	(0.0251)	(0.0251)	(0.0251)	(0.0250)	(0.0250)	(0.0252)
Average Women	0.00862	0.00742	0.00971	0.00980	0.00871	0.0103	0.0119*
	(0.00762)	(0.00665)	(0.00668)	(0.00666)	(0.00664)	(0.00664)	(0.00674)
Group 2012 Women	0.0218**	0.0201**	0.0209**	0.0205**	0.0192**	0.0220***	0.0238***
	(0.00982)	(0.00851)	(0.00854)	(0.00852)	(0.00850)	(0.00851)	(0.00866)
Group 2015 Women	-0.0297*	-0.0330**	-0.0300**	-0.0295**	-0.0315**	-0.0323**	-0.0310**
	(0.0166)	(0.0147)	(0.0147)	(0.0147)	(0.0146)	(0.0146)	(0.0147)
Group 2016 Women	0.00887	0.0195	0.0228	0.0241	0.0211	0.0224	0.0173
	(0.0327)	(0.0279)	(0.0279)	(0.0278)	(0.0276)	(0.0276)	(0.0277)
Group 2017 Women	0.00361	0.00274	0.0103	0.0113	0.0134	0.0129	0.0163
	(0.0208)	(0.0185)	(0.0186)	(0.0185)	(0.0185)	(0.0185)	(0.0187)
Hours worked &Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table XIV DiD results: ATT and Dynamic ATT 50th percentile.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre treatment Men	0.00382	-0.000114	0.000935	0.00172	0.00148	0.00346*	0.00243
	(0.00237)	(0.00207)	(0.00208)	(0.00207)	(0.00206)	(0.00204)	(0.00364)
Post treatment Men	0.0279***	0.0155**	0.0189***	0.0176***	0.0169**	0.0228***	0.0257***
	(0.00806)	(0.00674)	(0.00677)	(0.00675)	(0.00671)	(0.00670)	(0.00681)
Pre treatment Women	0.00114	-0.00230	-0.00179	-0.00140	-0.00159	-0.000696	-0.00148
	(0.00204)	(0.00168)	(0.00169)	(0.00169)	(0.00166)	(0.00166)	(0.00299)
Post treatment Women	0.0131*	0.00743	0.00869	0.00810	0.00614	0.00939*	0.0109**
	(0.00679)	(0.00538)	(0.00540)	(0.00539)	(0.00535)	(0.00534)	(0.00544)
ATT Women	0.00922	0.00498	0.00603	0.00559	0.00373	0.00667	0.00792
	(0.00658)	(0.00521)	(0.00523)	(0.00522)	(0.00518)	(0.00517)	(0.00526)
ATT Men	0.0243***	0.0139**	0.0170***	0.0158**	0.0152**	0.0204***	0.0233***
	(0.00783)	(0.00654)	(0.00657)	(0.00654)	(0.00651)	(0.00649)	(0.00660)
Hours worked	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table XV: Did group estimates 50th percentile.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average Men	0.0241***	0.0159**	0.0186***	0.0177***	0.0169***	0.0219***	0.0241***
	(0.00750)	(0.00629)	(0.00631)	(0.00629)	(0.00626)	(0.00624)	(0.00632)
Group 2012 Men	0.0296***	0.0167**	0.0199**	0.0185**	0.0177**	0.0235***	0.0269***
	(0.00967)	(0.00807)	(0.00811)	(0.00808)	(0.00803)	(0.00801)	(0.00815)
Group 2015 Men	-0.00598	-0.0161	-0.0123	-0.0140	-0.0111	-0.00847	-0.00406
	(0.0165)	(0.0140)	(0.0140)	(0.0139)	(0.0139)	(0.0138)	(0.0139)
Group 2016 Men	-0.0391	-0.0272	-0.0246	-0.0267	-0.0286	-0.0262	-0.0217
	(0.0295)	(0.0239)	(0.0239)	(0.0238)	(0.0238)	(0.0237)	(0.0239)
Group 2017 Men	0.0668***	0.0723***	0.0717***	0.0742***	0.0691***	0.0749***	0.0680***
	(0.0207)	(0.0176)	(0.0177)	(0.0176)	(0.0176)	(0.0175)	(0.0176)
Average Women	0.00350	0.000470	0.00215	0.00185	0.000252	0.00276	0.00359
	(0.00624)	(0.00496)	(0.00498)	(0.00497)	(0.00493)	(0.00492)	(0.00499)
Group 2012 Women	0.0206**	0.0142**	0.0144**	0.0138**	0.0115*	0.0150**	0.0169***
	(0.00821)	(0.00650)	(0.00653)	(0.00651)	(0.00646)	(0.00645)	(0.00657)
Group 2015 Women	-0.0260**	-0.0265**	-0.0240**	-0.0253**	-0.0253**	-0.0235**	-0.0227**
	(0.0131)	(0.0104)	(0.0104)	(0.0104)	(0.0103)	(0.0103)	(0.0104)
Group 2016 Women	-0.0280	-0.0114	-0.00976	-0.00618	-0.00911	-0.00840	-0.0148
	(0.0257)	(0.0201)	(0.0201)	(0.0200)	(0.0197)	(0.0197)	(0.0198)
Group 2017 Women	-0.0127	-0.0132	-0.00651	-0.00593	-0.00609	-0.00633	-0.00699
	(0.0168)	(0.0137)	(0.0137)	(0.0137)	(0.0136)	(0.0135)	(0.0136)
Hours worked &Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table XVI DiD results: ATT and Dynamic ATT top 50th percentile.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre treatment Men	-0.00299***	0.00442***	0.00381***	-0.00334***	-0.00307***	-0.00339***	-0.00302*
	(0.000980)	(0.000955)	(0.000956)	(0.000946)	(0.000877)	(0.000876)	(0.00183)
Post treatment Men	-0.00784**	0.00962***	0.00911***	-0.00475	-0.000969	-0.00178	0.00332
	(0.00314)	(0.00303)	(0.00303)	(0.00300)	(0.00271)	(0.00270)	(0.00270)
Pre treatment Women	-0.00333***	0.00389***	0.00358***	-0.00379***	-0.00264***	-0.00276***	-0.00183
	(0.000981)	(0.000960)	(0.000966)	(0.000964)	(0.000920)	(0.000922)	(0.00237)
Post treatment Women	-0.0257***	-0.0261***	-0.0253***	-0.0227***	-0.0161***	-0.0169***	-0.0123***
	(0.00322)	(0.00314)	(0.00314)	(0.00315)	(0.00293)	(0.00293)	(0.00294)
ATT Women	-0.0225***	-0.0229***	-0.0221***	-0.0198***	-0.0140***	-0.0148***	-0.0105***
	(0.00312)	(0.00304)	(0.00304)	(0.00305)	(0.00284)	(0.00283)	(0.00285)
ATT Men	-0.00762**	0.00917***	0.00860***	-0.00475	-0.00110	-0.00188	0.00292
	(0.0130)	(0.0125)	(0.0125)	(0.0124)	(0.0124)	(0.0124)	(0.0126)
Hours worked	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table XVII: Did group estimates top 50th percentile.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average Men	0.00939***	-0.0106***	-0.00979***	-0.00634**	-0.00259	-0.00346	0.000720
	(0.00294)	(0.00283)	(0.00283)	(0.00280)	(0.00255)	(0.00253)	(0.00254)
Group 2012 Men	-0.00562	-0.00750**	-0.00717*	-0.00276	0.000316	-0.000441	0.00590*
	(0.00390)	(0.00377)	(0.00376)	(0.00373)	(0.00336)	(0.00334)	(0.00335)
Group 2015 Men	-0.00867	-0.0104*	-0.00964*	-0.00620	0.000726	0.000645	0.000781
	(0.00584)	(0.00564)	(0.00564)	(0.00557)	(0.00511)	(0.00507)	(0.00513)
Group 2016 Men	-0.00338	-0.00806	-0.00612	-0.00568	-0.00721	-0.00983	-0.00795
	(0.0119)	(0.0116)	(0.0115)	(0.0114)	(0.0108)	(0.0107)	(0.0108)
Group 2017 Men	-0.0263***	-0.0228***	-0.0208***	-0.0197**	-0.0166**	-0.0184***	-0.0149**
	(0.00826)	(0.00788)	(0.00786)	(0.00780)	(0.00715)	(0.00712)	(0.00713)
Average Women	-0.0199***	-0.0205***	-0.0196***	-0.0174***	-0.0119***	-0.0126***	-0.00909***
	(0.00300)	(0.00292)	(0.00293)	(0.00293)	(0.00273)	(0.00273)	(0.00274)
Group 2012 Women	-0.0285***	-0.0287***	-0.0283***	-0.0260***	-0.0196***	-0.0204***	-0.0145***
	(0.00404)	(0.00395)	(0.00395)	(0.00396)	(0.00368)	(0.00368)	(0.00369)
Group 2015 Women	-0.00638	-0.00651	-0.00462	-0.00197	0.00265	0.00235	0.00267
	(0.00588)	(0.00570)	(0.00571)	(0.00570)	(0.00534)	(0.00533)	(0.00537)
Group 2016 Women	-0.0101	-0.0159	-0.0130	-0.0103	-0.00553	-0.00818	-0.00803
	(0.0135)	(0.0133)	(0.0132)	(0.0131)	(0.0125)	(0.0125)	(0.0125)
Group 2017 Women	-0.0149*	-0.0163**	-0.0157**	-0.0148*	-0.0107	-0.0111	-0.00956
	(0.00789)	(0.00768)	(0.00769)	(0.00767)	(0.00717)	(0.00716)	(0.00719)
Hours worked &Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes
Education dummies	No	No	No	No	Yes	Yes	Yes
Marriage dummies	No	No	No	No	No	Yes	Yes
Metropolitan status	No	No	No	No	No	No	Yes
Worker type dummy	No	No	No	No	No	No	Yes
Cognitive impairment	No	No	No	No	No	No	Yes

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix C

Appendix C compositional descriptive statistics

In this appendix, I provide additional descriptive statistics on some of the explanatory variables; here, I look for changes in trends to investigate if individuals can act on the treatment. Figure C.1 and Figure C.2 reveal no significant shifts in the trends for the industrial and service industries. There is a decrease in the fraction of both men and women working in the trade industry, although these changes are homogeneous among states. Figure C.3 and Figure C.4 reveals some compositional changes in the two remaining industries; the professional, scientific, and management industry shows a rapid expansion of the educational, healthcare, and social assistance industry. In the treated states, the men in this industry are more similar to the always treated than the never treated, while the women in the treated states are more similar to the never treated. Even though there is a rapid increase in both men and women working in this industry, the trends appear relatively parallel between the different state types. In summary, even though some difference exists in the industry compositions between the treated and the never treated in some industries, there does not appear to be any significant changes in the compositions, nor more similarities between the treated and the never treated than the treated and the always treated.

As for years of education, figures C.5 and C.6 show that the treated states are, in most cases, more similar to the always treated than the never treated. The treated states have fewer women and men with four or more years of college than the never treated states, with similar levels to the always-treated states. Similarly, a higher fraction of women and men completed Grade 12. The education level is increasing, and there are also some compositional changes for men and women with two years of college, where the fraction in the never treated states decreases while in the treated states, it increases.

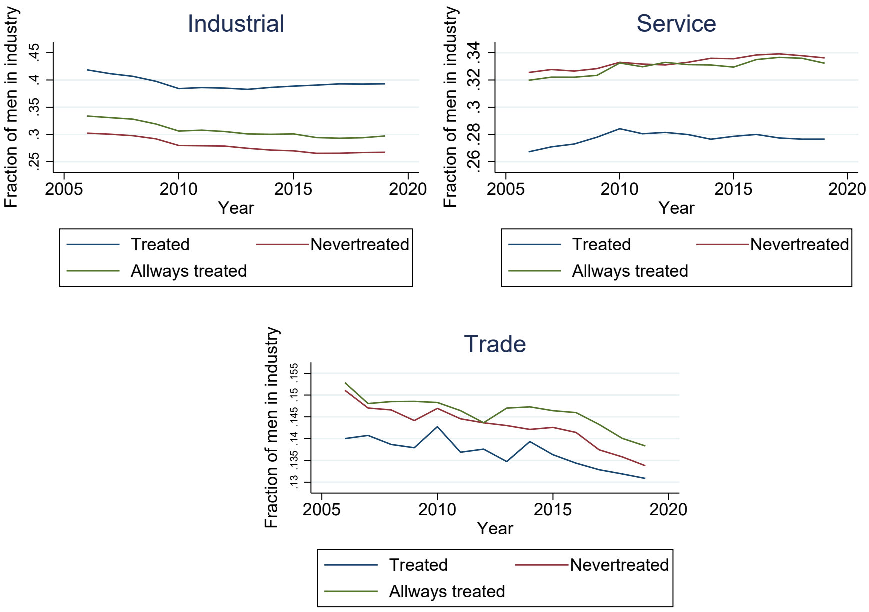

Figure C.1: Fraction in Industry 1-3; for wage-earning men between the ages of 18 and 65.

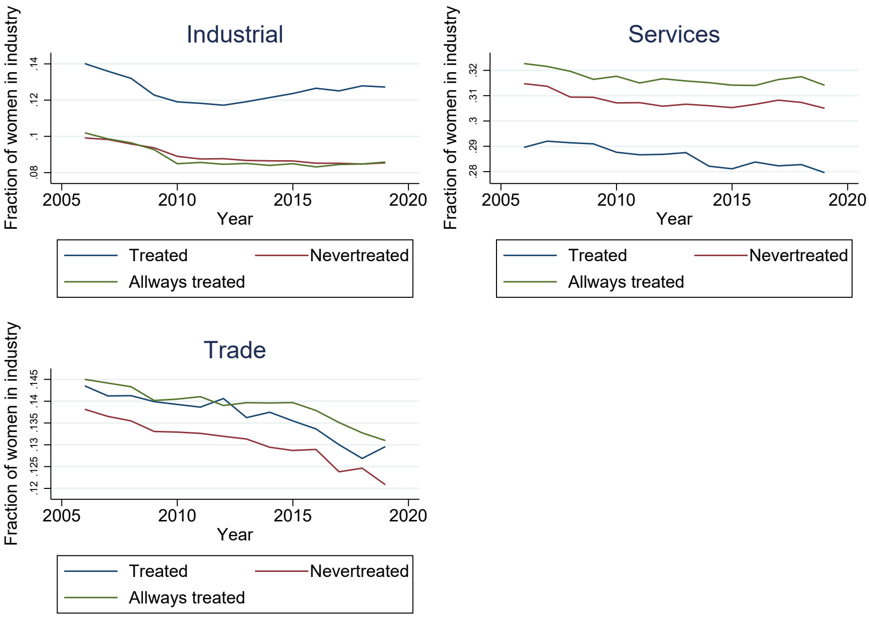

Figure C.2: Fraction in Industry 1-3; for wage-earning men between the ages of 18 and 65.

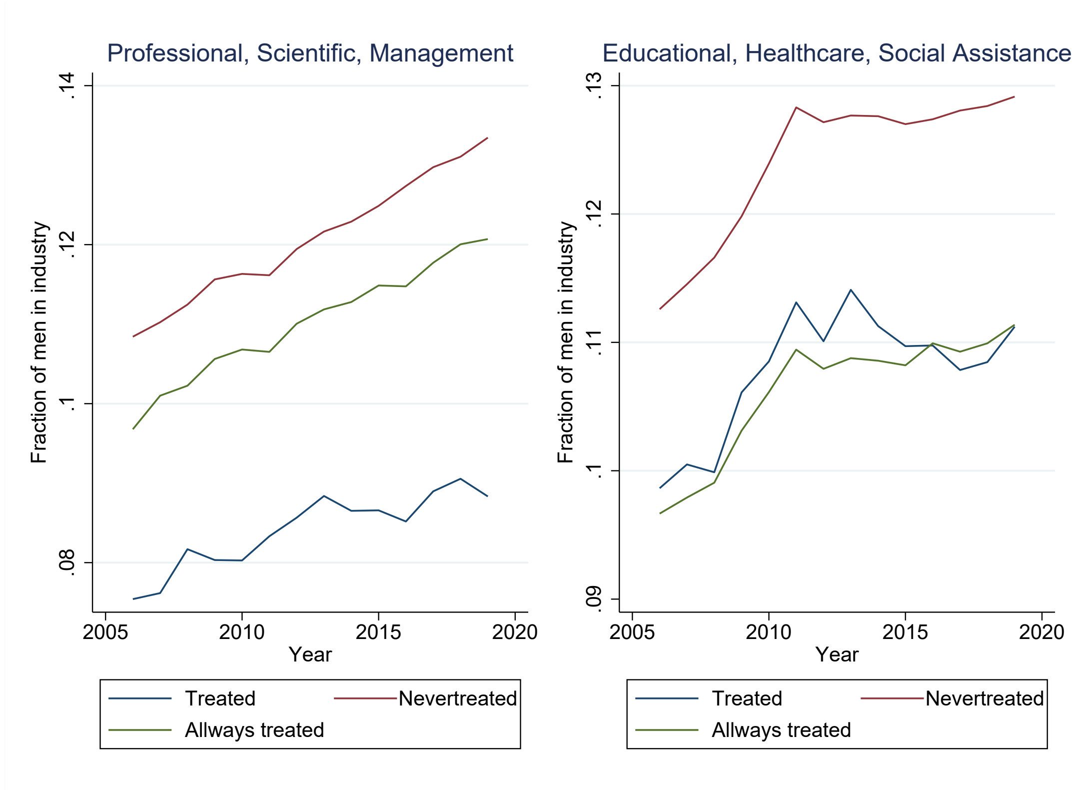

Figure C.3: Fraction in Industry 4-5; for wage-earning men between the ages of 18 and 65.

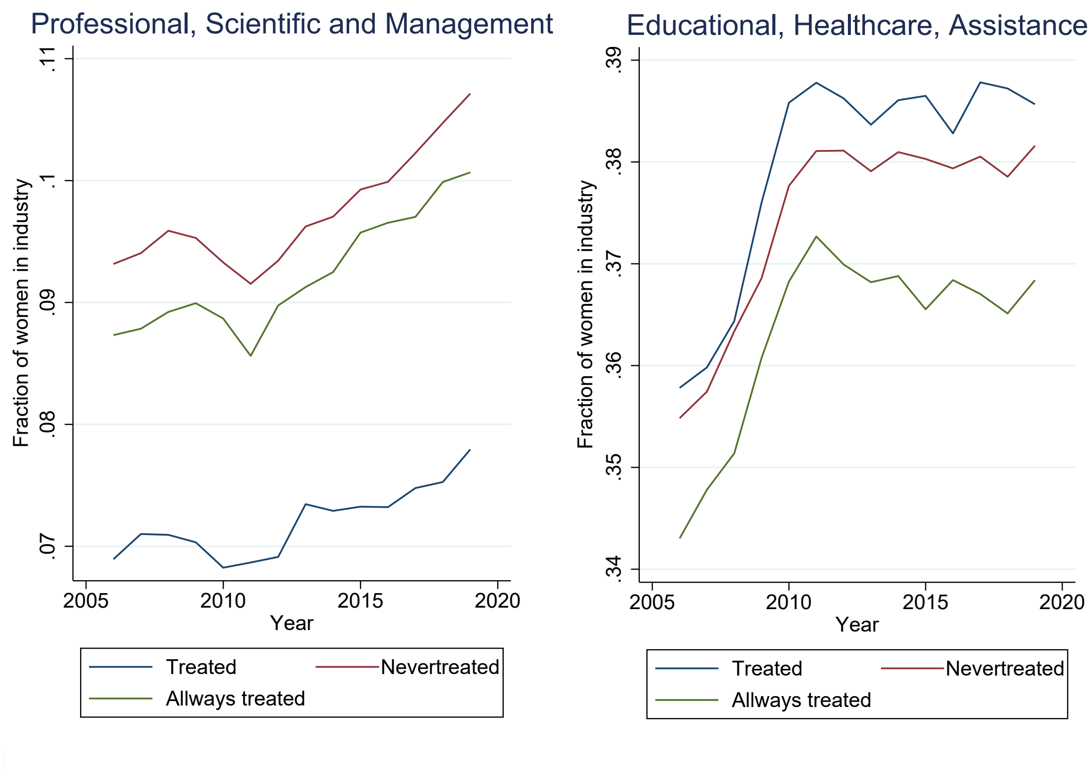

Figure C.4: Fraction in Industry 4-5; for wage earning women between the ages of 18 and 65.

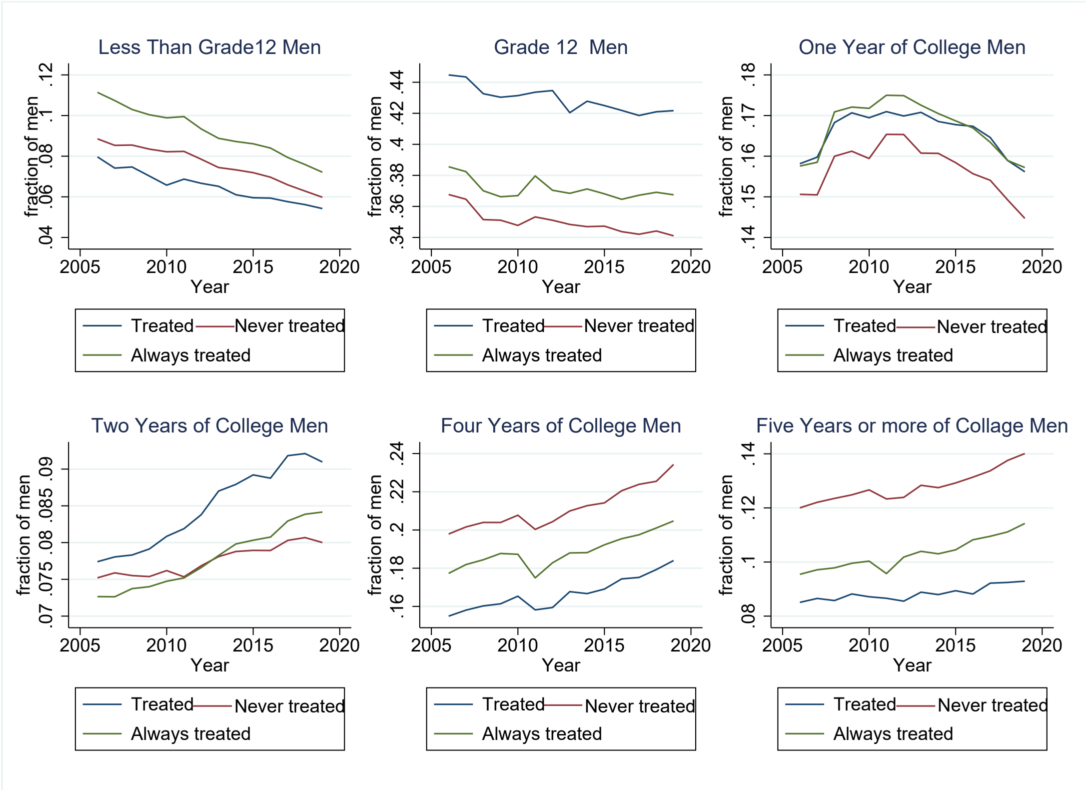

Figure C.5: Fraction of different education levels for wage-earning women between the ages of 18 and 65.

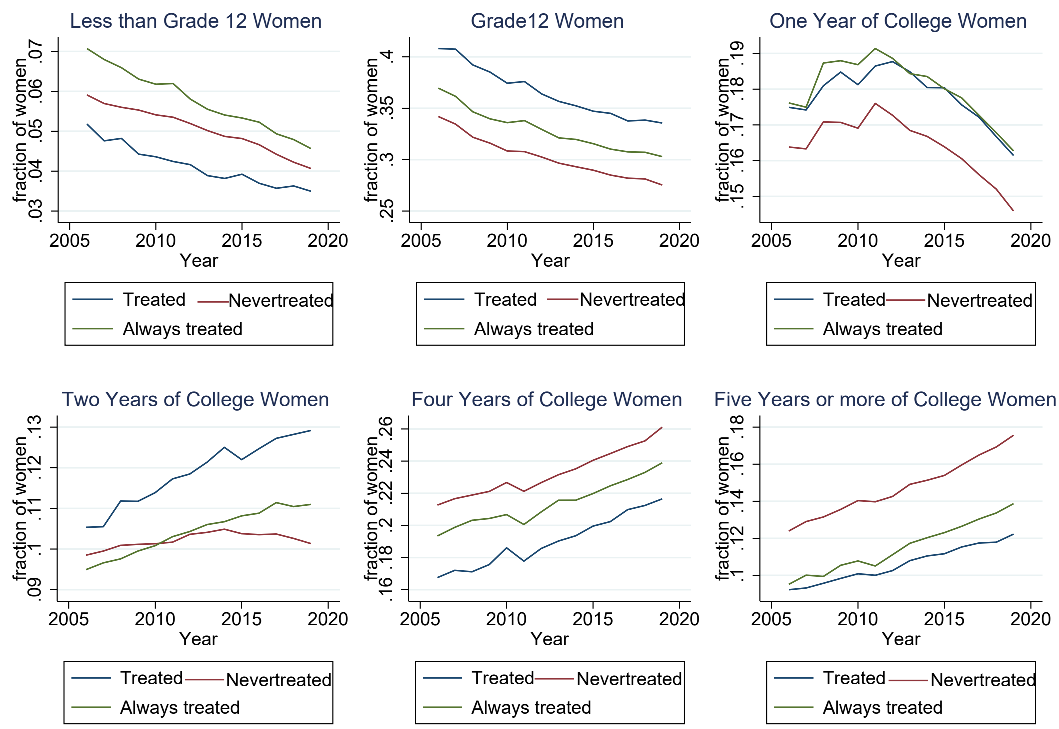

Figure C.6: Fraction of different education levels for wage-earning women between the ages of 18 and 65.