THE EFFECT OF RIGHT-TO-WORK LAWS ON SUBJECTIVE WELL-BEING: A CASE STUDY OF OKLAHOMA

by

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The following individuals read and discussed the thesis submitted by student Tyler Qualls, and they evaluated the student's presentation and response to questions during the final oral examination. They found that the student passed the final oral examination.

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DEDICATION

I would like to dedicate this thesis to my friends and family. A special thanks to my mother and grandparents who helped put me through college and for putting up with me this long lifetime. Additionally, I would like to thank my friends for all of the good times that made college enjoyable, be it through a hobby or conversations on the semantics of economics.

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I would like to express my deepest appreciation to my committee for providing a profound belief in my ability and valuable advice on the most effective methods for tackling this problem. More specifically, I would also like to extend my deepest gratitude to Dr. Samia Islam and Dr. Kelly Chen for providing me with a Research Assistant position, and allowing me to assist in their research (Chen & Islam, 2021). Finally, my success would be significantly inhibited had I not had the support of my friends and family through their faith in my ability and helpful insights.

ABSTRACT

Using Oklahoma as a case study, this thesis applies a synthetic controls model to investigate the causal effect of right-to-work (RTW) laws on the well-being of the total population with a particular focus on the most affected subset, blue-collar workers and the less educated. The effect of RTW laws leads to a significant decrease in the happiness of blue-collar workers. To be specific, while results show a possible increase in unhappiness in the total population immediately following the adoption of the RTW law, for the more vulnerable blue-collar workers, the statistically significant negative effect of the law on happiness is observed not only immediately after adoption but remains persistent for a decade after.

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LIST OF ABBREVIATIONS

BLS United States Bureau of Labor Statistics

CES Current Employment Statistics Surveys

CPI Consumer Price Index

CPS Current Population Survey

DiD Difference in Difference

GSS General Social Survey

ISSP International Social Survey Program

NBER National Bureau of Economic Research

NIRA National Industrial Recovery Act

NLRB National Labor Relations Board

NORC National Opinion Research Center

OLS Ordinary Least Squares

ORG Outgoing Rotation Group

RMSE Root Mean Squared Error

RMSPE Root Mean Squared Prediction Error

RTW right-to-work

SCM Synthetic Controls Method

SD Standard Deviation

SUTVA Stable Unit Treatment Value Assumption

SWB subjective well-being

U.S United States of America

UMWA United Mine Workers of America

CHAPTER 1:

INTRODUCTION

"In our glorious fight for civil rights, we must guard against being fooled by false slogans, such as 'right to work.' It is a law to rob us of our civil rights and job rights. Its purpose is to destroy labor unions and the freedom of collective bargaining by which unions have improved wages and working conditions of everyone... Wherever these laws have been passed, wages are lower, job opportunities are fewer and there are no civil rights. We do not intend to let them do this to us. We demand this fraud be stopped. Our weapon is our vote."

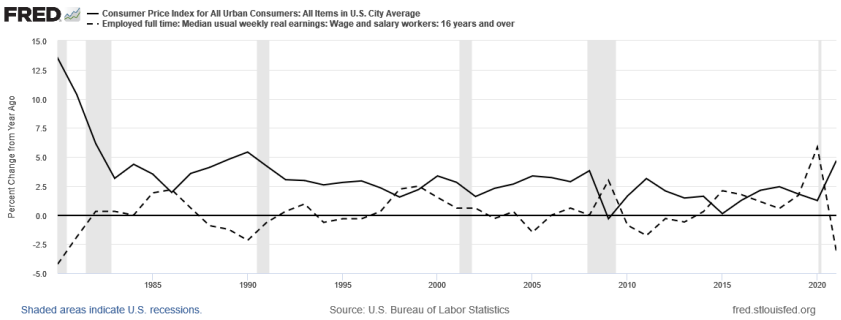
Martin Luther King, Jr. (1961)

The Covid 19 pandemic has had a substantial effect on the daily life of people in the United States. Preventative health measures temporarily limited the economic stability of many families through loss of income and led to many businesses moving to fully remote or hybrid workplaces in an attempt to limit the spread of this disease. These shifts to hybrid and remote working conditions have relaunched the conversations regarding working conditions and workers' rights, especially pertaining to the rights and responsibilities of "essential workers"[1]. The increased work expec-

[1]"Essential workers" as those who conduct a range of operations and services in industries that

tations imposed upon those classified as essential workers during the pandemic led to a number of strikes against large companies such as Amazon and Nabisco, or the general strike of 2020, which covered "essential workers" across many industries and companies[2] (Gurley, 2021).

Figure 1.1: Percentage Change Comparison of CPI and Weekly Wage



(U.S. Bureau of Labor Statistics, 2022)

These recent challenges regarding worker rights and work conditions are exacerbated in the U.S, where inflation has increased more than wages since the 1980's. Figure 1.1 demonstrates the percentage change from the previous years for the full-time employees' weekly wage and the Consumer Price Index (CPI) for all items in the U.S city average (U.S. Bureau of Labor Statistics, 2022). This plot shows that with minimal exceptions, the purchasing power of income decreased from 1980 to 2008 as the percent change in wages stays between 2.5 and -2.5 percent. The percent change in inflation is almost always 2.5 percent or higher demonstrating, that the cost of living increased substantially across the time-frame. Although during the

are essential to ensure the continuity of critical functions in the United States of America (U.S) (CDC, 2021)

[2]The companies that were part of this general strike were Amazon, Instacart, Target, Walmart, and Whole Foods (Neuman, 2020)

2008 recession and the economic shutdown due to the Covid-19 pandemic, wages grew more than inflation, between 2009 and 2021, wage growth outpaced inflation in just three instances. These increases are likely due to the high unemployment primarily affecting lower-income individuals raising the overall averages as they coincide with the recessions of the time. These plots also don't fully demonstrate the increasing costs of obtaining higher education or housing. Between 1990 and 2020, higher education costs have increased 130 percent after accounting for inflation (Hanson, 2022). Additionally, Covid-19 has caused housing prices to skyrocket, with housing costs increasing by 18.6 percent between September 2020 and September 2021 (Bernstein *et al.*, 2021). Such discrepancies between wages and living costs can make it harder for individuals to achieve life goals successfully. This failure to achieve life goals negatively affects subjective well-being (SWB) (Headey, 2008).

Historically, unions have been one of the primary driving forces for wage increases and improving working conditions for workers. However, unions are at the weakest they've ever been in part due to 27 states having RTW laws. RTW laws make it illegal to require union membership for employment. The full effects of RTW laws are a continually debated topic, but there have still been concurrent attempts to install national RTW laws in 2017, 2019 and 2021 by Senator Rand Paul (King, 2017; Paul, 2019, 2021). These attempts as well as the aforementioned economic challenges affecting employees have prompted further investigation into what the actual effects of RTW laws are due to a history of mixed results regarding the law's economic implications. There is, however, limited research into the impact that these laws have on the SWB [3] of individuals both directly or indirectly affected by these laws.

[3] subjective well-being (SWB) refers to how people experience and evaluate their lives and specific domains and activities in their lives (Stone *et al.*, 2013).

This paper uses the General Social Survey (GSS) conducted by the National Opinion Research Center (NORC) at the University of Chicago, which is a large-scale national survey with 64,814 interviews from 1972 to 2018. These surveys also provide in-depth responses with each interview taking a median of 1.5 hours. Also, the GSS is the only International Social Survey Program (ISSP)[4] organization in the U.S collecting the survey data through rigorous methodological specifications, all of which are publicly available.

The second problem researchers have encountered regarding finding the effects of RTW laws is controlling for the unobserved differences across states. This paper looks to resolve this problem through the use of the Synthetic Controls Method (SCM). SCM allows us to create a 'synthetic' version of our investigated state, called the treated unit, before the adoption of the RTW law so that it is possible to generate a version of the geographic unit under study that is similar to the post-RTW treated unit in all respects except for the adoption of the law itself. This synthetic unit allows for the direct apples-to-apples comparison between the pre-treatment state and the post-treatment state.

This study aims to add to the research on the impact of RTW laws by being the first to utilize a SCM to investigate the psychological effects of RTW laws on subjective well-being through the case study of Oklahoma. The remainder of this report will proceed as follows: Chapter 2 will provide background and justification for this study, Chapter 3 provides a summary of the existing relevant literature on RTW laws, subjective well being and Oklahoma's history with unions, Chapter 4 provides details on the data utilized in the study, Chapter 5 presents the empirical model,

[4] "The ISSP is a cross-national collaboration programme conducting annual surveys on diverse topics relevant to social sciences" (ISSP, n.d.)

Chapter 6 reports the results and examines reliability through robustness checks, Chapter 7 discusses the implications of these findings as well as possible avenues of future research, Chapter 8 provides concluding comments.

CHAPTER 2:

BACKGROUND AND JUSTIFICATION

2.1 Background

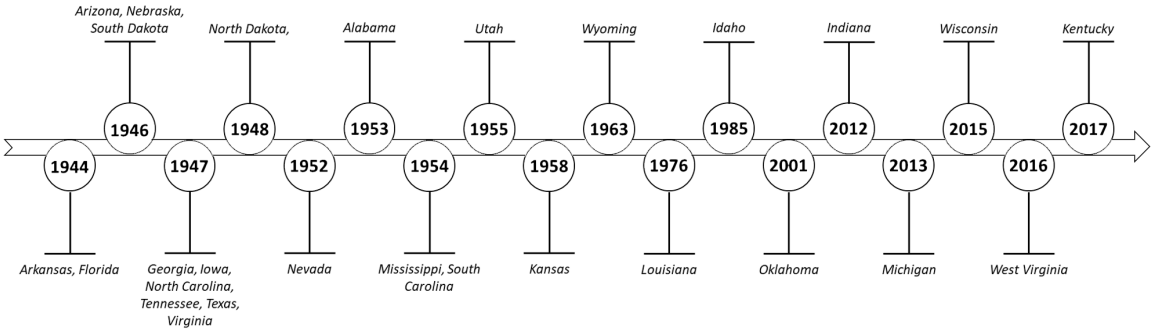
During the Great Depression in 1933, President Franklin D. Roosevelt enacted the National Industrial Recovery Act (NIRA), which while having some other effects such as suspending antitrust laws, gave employees the right to organize and bargain collectively. The NIRA also included a RTW clause that banned the requirement to join or refrain from joining a labor organization (Doughton, 1933). This clause, however was removed along with the similarly created National Recovery Administration on the grounds that they improperly delegated legislative powers to the executive branch in 1934.

While the NIRA was the first effort to implement RTW laws in the U.S, the true origin of RTW laws emerged in retaliation to the National Labor Relations Act (1935 Wagner Act), which created the National Labor Relations Board (NLRB), who has the job of enforcing workers rights (The Editors of Encyclopaedia Britannica, n.d.c). This act also gave rights to the employee to unionize, and it required that the employer collectively bargain[1] with unions (The Editors of Encyclopaedia Britannica, n.d.c). Many union agreements with companies included a requirement for employees

[1]Collective bargaining is the negotiation of wages and other conditions of employment by an organized body of employees

to join the union or be either fired or not hired, depending on the situation. This led to four states contesting this act with their constitutional amendments, codifying that employees cannot be penalized for not joining a union. The states were Arkansas and Florida in 1944 and Arizona and Nebraska in 1946. These states also pushed for the Labor Management Relations Act (1947 Taft-Hartley Act), which made six amendments to the previous 1935 Wagner Act. The most important aspect of this act was that it explicitly allowed states to prohibit the mandatory inclusion of employees into unions which eventually led to the modern RTW laws (The Editors of Encyclopaedia Britannica, n.d.b). The 1947 Taft-Hartley Act combined with the Lincoln Federal Labor Union No 19129 v. Northwestern Iron and Metal Co. et al. Supreme Court Case found that these RTW laws and amendments were constitutional, sealing the validity of this legislation (The Editors of Encyclopaedia Britannica, n.d.b; noa, 1949). Figure 2.1 below demonstrates the adoption timeline over time.

Figure 2.1: Right-to-Work Adoption Timeline



This figure demonstrates the timeline of states adopting RTW laws (Ballotpedia, 2021).

Moving from historical context to today, the most recently inducted RTW states are Kentucky in 2017 and West Virginia in 2016, bringing the total number of RTW states to 27 – a majority across the nation. There have been three attempts to

institute a National Right to Work Act in 2017, 2019, and 2021 however, it has stalled in all cases (King, 2017; Paul, 2019, 2021). It also seems that union support may be changing in recent years as union petitions have increased by 57% during the first six fiscal months of 2022[2] according to the NLRB (Office of Public Affairs, n.d.). This is up from the 14% increase in the same 2021 time-frame.

2.2 Justification

In the U.S, the average working individual worked 7.7 hours per working day in 2019, with an additional commute time of 1.2 hours, i.e., slightly more than one-third of an individual's day is dedicated towards working or performing a job (Bureau of Labor Statistics, 2021). Thus it is fair to assume that any changes in the workplace will have a significant impact on the rest of an employee's quality of life. Additionally, in the U.S, the majority of people get access to healthcare through their place of employment, intrinsically linking an employee's health and well-being to their place of work and thus making any positive or negative changes in the workplace that much more influential beyond the impact expected through the wage channel alone. These connections between employees and employers put employees in a situation where the work environment can impact the sense of well-being and happiness of employees either directly through workplace quality or indirectly through injuries or health outcomes.

Traditionally, unions would be the institution providing a voice to employees so that workers' rights and safety can be discussed on a level playing field without the employer having a substantial power advantage over the employee through collective bargaining (Freeman, 1976; Freeman & Kleiner, 1990). However, under RTW laws,

[2]The fiscal year begins in October.

this 'voice' of the union may weaken over time. This weakening of unions can then further reduce the already large power gap that the majority of employees feel (Kochan *et al.*, 2019).

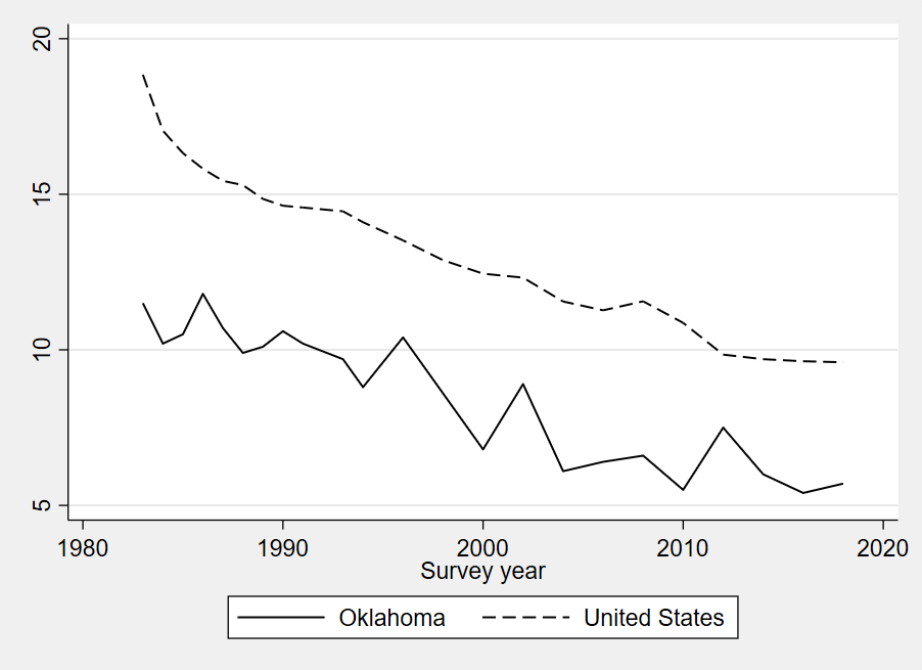
One reason why employers may not have a favorable view of unions is that unions have been shown to increase wages for the employees they cover as compared to non-union jobs (Freeman, 1982; Card, 1996). Thus, unions can negatively affect employers either through the undertaking of more debt as a way to increase bargaining power or by decreasing a firm's market value (Klasa *et al.*, 2009; Matsa, 2010; Lee & Mas, 2009).

Some scholars have argued that when businesses spend less money/energy fighting unions, they may redistribute the increased revenue back to the employees, thereby counteracting the well-being effect of reduced union power. This, however would be disputed by the fact that unions have historically helped to reduce income inequality by distributing more benefits and income to blue-collar workers (Card, 1996; Farber *et al.*, 2021). Given that the primary objective of businesses is to maximize net profits, it is more likely that companies will have less of a financial incentive to remedy workers' problems.

While these changes primarily affect the blue-collar workers' quality of life, differences are likely to ripple out to society through spillover effects. These spillover effects could be caused directly through the decreased income of families under a weakened union presence and, consequently, lower disposable income, which could potentially go into the community as reduced consumption and investments. These income changes could also cause indirect effects through taxes and directly through purchases. This decrease in the dissemination of funds could lead to fewer resources

being distributed to public goods such as education or transportation, decreasing the quality of life for everyone that uses these services. Likewise, increasing the benefits to blue-collar sectors will also lead to better compensation for all industries through competition. Due to increases in income and better benefits, blue-collar positions become more desirable to the average individual. Increased competition in other sectors leads to better compensation packages to retain employees.

Figure 2.2: US vs. OK Unionization Rate



This paper specifically looks at the state of Oklahoma for a couple of reasons. Firstly, Oklahoma's position between other states' adoption of RTW policies means it can have a consistent comparison set of non-RTW states. There is a 16-year span before the adoption of Oklahoma's RTW amendment and 11 years after, bounded by Idaho's RTW law in 1985 and Indiana's RTW law in 2012. Secondly, Oklahoma is selected as its unionization rate is lower than that of the mean for the U.S by

a relatively consistent 3-4%, as can be seen in Figure 2.2. This means that the institution of RTW laws should have a reduced effect on the population. This means that any statistically significant effect demonstrated in Oklahoma should translate to an underestimation of the effect in another state or across the whole of the U.S, thereby improving the external validity of the model[3].

[3]"External validity captures the extent to which inferences drawn from a given study's sample apply to a broader population or other target populations." (Findley *et al.*, 2021)

CHAPTER 3:

LITERATURE REVIEW

3.1 Effects of Right to Work

The effects of RTW laws are challenging to estimate convincingly as many other factors tend to change along with RTW laws, not the least of which is other government policies. This, however hasn't stopped the assessment of these laws through various methods.

Ozkan Eren and Serkan Ozbeklik (2011) used SCM to investigate the effect of RTW on economic factors such as private union membership, union coverage rates, foreign direct investment, manufacturing employment rate, per capita income, and average wage rates and found that RTW laws reduced private union membership by 14.5 percent and union coverage rates decreased by 13.8 percent (Eren & Ozbeklik, 2011). The authors also found that while there was a statistically significant decrease in the average wage rate by 0.8 percent, in Idaho, RTW laws increased manufacturing employment by 14.4 percent (Eren & Ozbeklik, 2011). In 2016 Eren and Ozbelik extended their research to more thoroughly investigate Oklahoma and found that private sector unionization decreased by 30.6 percent and manufacturing sector unionization fell 21.8 percent with the adoption of the RTW law (Eren & Ozbeklik, 2016). The authors also found that average wages for both the private sector and

the manufacturing sector had insignificant changes (Eren & Ozbeklik, 2016). These estimated effects provide necessary information regarding the indirect effects of RTW laws.

Makridis (2019) examined the effect of RTW on well-being and economic sentiment utilizing a Difference in Difference (DiD)[1] methodology. He found that RTW laws caused a 0.025 Standard Deviation (SD) increase in well-being and a 0.04 SD increase in economic sentiment (Makridis, 2019) in the total population of the U.S. However, when applying a border county method to comparing counties along state borders to control for heterogeneity he found that the actual differences were not significantly different from 0. Chen and Islam (2021) expand on this research through the usage of Instrumental Variables (IV)[2], as well as through the usage of a longer time frame as compared to Makridis (2019). They specifically utilize IV-DiD on border counties, where they find that adoption of RTW laws causes a net negative decrease of .12 SD. Some of the primary differences between these reports are that Chen and Islam (2021) look at a smaller and more homogeneous collection of people through border counties resulting in these differing results. These papers provide different methods and time-frames from this report demonstrating a baseline to which the results of this study will be compared (Makridis, 2019; Chen & Islam, 2021).

3.2 Oklahoma

Oklahoma has a long history of organized labor, with the first official union appearing in August 1882 when miners were organized at Midway by the Knights

[1]Difference in Difference (DiD) looks to find the effects of a treatment through the comparison between a treated unit and another homogeneous group

[2]IVs are a two stage ordinary least squares process which can be used to control for some types of bias

of Labor[3]. While the Knights of Labor were the first national union to help the miners in Oklahoma, it was far from the most influential, the United Mine Workers of America (UMWA) was the labor union that took over for the Knights of Labor after they collapsed and in February 1899 the UMWA led a strike of coal miners that lasted until 1903 which led to the agreement that miners would have an 8 hour work day and payment of wages twice a month (O'Dell, n.d.; Dunbar, n.d.).

Other industries were quick to unionize as well; however there were no distinctly significant strikes. In chronological order, the Brotherhood of Locomotive Engineers was brought into Oklahoma in 1883 as the railroads entered the Oklahoma area. The first trade union followed within the next ten years with the Bricklayers of Oklahoma, but the first agricultural union wasn't started until 1902 (O'Dell, n.d.).

Oklahoma experienced similar trends in unionization as the rest of the U.S, with unionization dropping in the 1920s but rapidly increasing with the Great Depression in the 1930s (O'Dell, n.d.). Specifically, the NIRA ushered in a wave of union membership, with the number of current members tripling from 1932 to 1939 (O'Dell, n.d.). While the NIRA wasn't the sole reason for this influx, the additional powers it gave unions provided union members job security in a time where having a job was a luxury (O'Dell, n.d.). After World War 2, there was an era of prosperity such that in the 1950s and 1960s the middle class was getting substantial increases to wages and benefits. This led to few strikes as the traditional demands were already being fulfilled.

During the prosperity of the 1960s was Oklahoma's first attempt to pass a RTW amendment; it occurred as an amendment to the state constitution. This attempt

[3]The Knights of Labor were the first significant national labor organization in the United States, founded in 1869 (The Editors of Encyclopaedia Britannica, n.d.a)

failed with 51.66 percent voting against it (Creel, n.d.). Between the 1960s and 2001, there were no notable union-related policies in Oklahoma. In 2001 this amendment was attempted again; however this time the vote went the other way with 54.15 percent of people voting for the change (Creel, n.d.). In the 2001 instance, the amendment had bipartisan support from the at the time incumbent Republican Governor Frank Keating, as well as former Governors David Boren and George Nigh, both being Democrats. After the passing of this amendment, a lawsuit was filed challenging its validity. After going through both federal and state courts, three of the amendments changes as well as the penalty were found to be preempted by federal law. However, the RTW portion was declared effective and constituted the law in Oklahoma (Creel, n.d.). This led to Oklahoma being the 22nd right-to-work (RTW) state.

3.3 Subjective Well-being

Subjective well-being has extensive literature due to its deep roots in psychology, philosophy, and economics. This literature has found approximately seven broad categories of determinants of SWB (Dolan *et al.*, 2008; Das *et al.*, 2020). These categories are; demographics, socioeconomic status, health, personality, social support, religion and culture, geography and infrastructure. Each of these categories can be broken down in numerous ways, with many of the specific determinants having contradictory impacts even within the same categories. Since RTW laws have no direct implication on the demographics, personality, or the religion and culture of individuals, these categories won't be discussed in this paper. Additionally, the determinants covered in this section are not all-inclusive and only include determinants that are most likely to be impacted by these policies. [4]

[4] A more thorough discussion of the literature on determinants of SWB can be found in Das et

Examples of socioeconomic status would be income and employment. Income as a determinant for SWB has been found to have a positive relationship with SWB however, the specifics behind the magnitude continue to be discussed (Kaliterna Lipovčan *et al.*, 2007; Cramm *et al.*, 2010; Clark *et al.*, 2017). Some papers find that there is a diminishing effect of income. One explanation is that additional income decreases worry rather than directly increasing SWB. However, since income directly affects many aspects of life, these increases in SWB could also be representative of the income effect elsewhere. Unemployment as a determinant has been found to have a negative impact on SWB through many avenues, such as financial difficulties and its impact on stress and health (Di Tella *et al.*, 2001; Stutzer, 2004; Lamu & Olsen, 2016).

When considering the determinants of health, there is agreement within the literature that the worse someone's health is, the lower their SWB. Additionally, specific conditions have been found to have a greater effect on SWB such as heart attacks and strokes being more harmful to SWB (Zautra & Hempel, 1984; Lamu & Olsen, 2016; Lee & Browne, 2008; George & Landerman, 1984; Shields & Wheatley Price, 2005). The stresses caused by health problems can impact SWB through several avenues – from hurting the ability to generate income to driving high medical costs.

Social support as a set of determinants has been consistently found to correlate with SWB positively. Specifically, when an individual feels that they get support from their friends, family, or community, it positively influences their SWB (Cramm *et al.*, 2010; Khan & Husain, 2010; Kutek *et al.*, 2011). It has also been found that various characteristics of a social group also contribute positively to SWB; examples

al.(2020) and Dolan, Peasgood, and White (2008).

of these traits would be quality of relationships, size, or rate of interaction (Olsson *et al.*, 2014; Pinquart & Sörensen, 2000; Sandstrom & Dunn, 2014; Chou, 1999).

While RTW laws and unions won't directly affect the actual geography of an area, they can affect the policies that lead to better infrastructure or better safety conditions for employees. Studies have demonstrated that better infrastructure improves SWB (Winters & Li, 2017). Additionally, negative externalities from businesses, such as pollution, can lead to decreased SWB (Moro *et al.*, 2008; Węziak-Białowolska, 2016). Regional characteristics also factor into the SWB of individuals, such as whether a region is urban or rural. While RTW laws and unions cannot affect whether a region is urban or rural, it is relevant when looking at the DiD methodology, which looks at border counties. This is because border counties are generally more rural than the cores of a state. This is important as rural areas tend to demonstrate higher SWB than urban areas (Winters & Li, 2017; Hudson, 2006; Dockery, 2003).

Studies that solely focus on the economic impact of RTW laws overlook the findings of this substantial stream of literature that has established the critical connection between employment quality and well-being.

CHAPTER 4:

DATA

4.1 Data Sources

This data was acquired and compiled through previous research on the effects of RTW laws on SWB performed by Dr. Samia Islam, and Dr. Kelly Chen (Chen & Islam, 2021).

4.1.1 General Social Survey

This paper utilizes the GSS as performed by the NORC at the University of Chicago. This data contains an extensive set of survey responses utilized as covariates for this report. This report also provides the SWB measure, unhappiness. The GSS gets its data explicitly through interviews that are administered to NORC national samples using a standardized set of questions, some of which rotate every three years. In 1988 however, rotating questions were removed and instead were split amongst the given surveys in order to provide more consistent results. Through the invariance of verbiage over time, this study provides comparable results across time. Spatially, the GSS breaks into census county divisions while temporally it is yearly from 1972 till 1991 then goes to 1993 to 1994 continuing from then every other year. A full breakdown of the variables as well as the methodologies can be found in the GSS Codebook (Smith *et al.*, 2019).

The subjective well-being measure used for this report is obtained from the GSS (Smith *et al.*, 2019). This measure is found using the specific survey question, "Taken all together, how would you say things are these days – would you say that you are very happy, pretty happy, or not too happy?". Each response is given a value between one and three with one being very happy and three being not too happy,

For the final dataset, some indicator variables were also created in order to provide more predictors. The relevant predictors for this report are as follows: *GFPHealth* which uses the survey question for self rated health[1], it is equal to one in the case that individual rated their health something other than excellent and zero otherwise. *inLF* is an indicator for if the individual surveyed would be considered part of the labor force it was derived from the employment questions, it is equal to one if the individual was working full-time, working part-time, temporarily not working, or unemployed due to being laid off with it being zero otherwise. *Lower_ quartile* is an indicator for if the individual falls within the lower quartile of equivalised household income[2]. *Secondary* is an indicator for if an individual works in the secondary sector which includes the manufacturing of both durable and non-durable goods, this is found based on industry code so if the individual works in codes between 1070 and 3990 they get a one and all other industries get a zero. Three age and race interaction terms were made with them being indicators of individuals that are both white and within the age ranges; 45 to 65, 25 to 45 or under 25 years of age. Finally one additional interaction term was made which looked at the interaction between white individuals that also had a child that was under six years of age.

[1]The question asked by the GSS is "Would you say your own health , in general, is excellent, good, fair, or poor?" with one being excellent and four being poor (Smith *et al.*, 2019).

[2]Equivalised household income is household income divided by the square root of household size

4.1.2 Current Population Survey Outgoing Rotation Group

This report supplements the covariates from the GSS using the Current Population Survey (CPS) Outgoing Rotation Group (ORG) earnings files in order to obtain estimates for union membership and union coverage at a state level. This dataset covers the years from 1983 to 2018 and is collected at the household level. Individual households are interviewed for four months followed by an eight month break with this pattern continuing until either the household moves away or is no longer participating in the CPS. Additionally the households that are interviewed are rotated in order to gather information throughout the year and for a variety of sub-samples of the overarching CPS. These results are then gathered and merged by the National Bureau of Economic Research (NBER) to be distributed to the public in the Merged Outgoing Rotation Group file. Further details regarding the specific questions and methodologies of this can be found (Bureau, n.d.).

A couple of indicators were also generated using the CPS however only *other_service* is relevant to this report. *Other_service* was generated so that any individual who worked in the industry codes 6470 and 9870 would get a one and any other industry would get a 0.

4.1.3 Bureau of Labor Statistics

This report also supplements the GSS with the United States Bureau of Labor Statistics (BLS) state-level employment and unemployment statistics. The BLS gets its estimates from the Current Employment Statistics Surveys (CES), which surveys approximately 131,000 business and government agencies monthly. The actual variables used from the BLS are limited to the estimates for each state of unemployed individuals, employed individuals, and the total labor force. This series covers the

years from 1983 to 2018 following the CPS

4.1.4 Final Dataset

The combined dataset for this thesis is at the state level and covers the time from 1988 to 2018. We chose to restrict the start date of the dataset to 1988 as the GSS stopped rotating questions for the 1988 survey and beyond, meaning there would be consistent observations for our model. Within our model, the end date is also restricted because in 2012, Indiana implemented the RTW law. Since states that have been or switched to RTW laws in the time-frame cannot be used in the construction of the counterfactual, it was decided that the increased donor pool of states was a higher priority than the one additional post-treatment observation.

Right to Work VS. Non Right to Work States

Looking at the specific values comparing RTW to non-RTW states may also provide some perspective on the effects of RTW laws more broadly than just for Oklahoma. Covering only variables with significant differences, the equalized household income for non-RTW states is 5,578 dollars higher. This is also evident in Figure A.1e which demonstrates a significant gap between RTW and non-RTW states. Wage indicates a similar change with a 1.23 dollar per hour difference between RTW states and those without. On the mean non-RTW states have a higher SWB of 0.02, which is significant due to its low SD of 0.04 in RTW or 0.02 in non-RTW. Unsurprisingly union membership is also much higher in non-RTW states, with around a 10% difference. From Figure A.2a it appears that non-RTW states also work fewer weekly hours on average. From Figure A.3d RTW states look to have a higher percentage of people in utility, transportation, and information industries. Finally, Figure A.2b looks to

Table 4.1: Summary Statistics for RTW Vs. non-RTW

	RTW		Non-RTW	
Variable	Mean	SD	Mean	SD
ehhincome	28750.64	5531.69	34328.18	6358.115
hourly_wage	14.87076	2.555111	16.10078	2.384484
hs	0.5228479	0.020702	0.5158156	0.027241
college	0.152791	0.0210627	0.1663424	0.0272522
unhappy_current	1.805684	0.0462278	1.829724	0.0286389
GFPHealth	0.7217584	0.0421004	0.7025366	0.0270974
lower_quartile	0.484387	0.0041365	0.4842314	0.0332377
Mem	7.21951	0.1466045	17.94136	2.306864
secondary	0.1466045	0.028057	0.161037	0.0339622
other_service_c	0.4110987	0.0350908	0.433308	0.0396768
weekly_hours	42.24791	0.5800153	41.13498	0.6379512
inLF	0.6578772	0.0348151	0.6717573	0.0231477
white	0.7541445	0.0542328	0.8089485	0.048409
lower_class	2.575473	0.0544141	2.53507	0.0332377
utility_trans_info_c	0.06937	0.0020743	0.0667413	0.0014733
white _age_45to65	0.2407023	0.0337649	0.247789	0.0313657
white_age_25to45	0.2885348	0.0452147	0.3313038	0.2396925
white_age_25under	0.079924	0.0194487	0.0847795	0.0504841
white_cld_under6	0.1331476	0.0314497	0.1559568	0.0899582

have some interesting trends over time with RTW states having a relatively consistent rate of individuals with high school diplomas however non-RTW demonstrates a drop in high school graduates from 2000 to 2010.

CHAPTER 5:

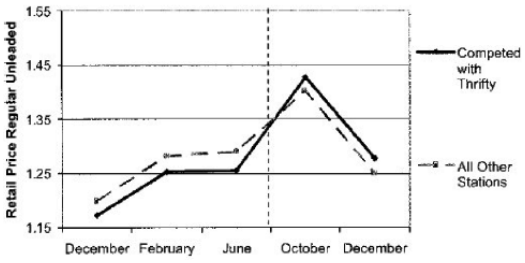
ECONOMETRIC MODELING

There are several natural experiment methods to determine the effect of an event. The most common methodology is the Difference in Difference (DiD) estimation which can be done with an Ordinary Least Squares (OLS) estimation implementing a binary variable for the event to isolate any immediate shock that may have occurred. Additionally, the inclusion of an interaction term between the event and time is included to determine any longer term effect caused by the event. This newly fitted model is compared with a collection of controls that didn't experience the event in order to find if there is any actual shift due to this event. DiD modeling thrives in situations with a large number of controls to compare against. For interpretable results, DiD modeling requires a parallel trend assumption meaning that the treated group and the control group have a consistent difference between them, Figure 5.1a demonstrates this assumption (Columbia Public Health, n.d.). Figure 5.1b then shows how Oklahoma doesn't fulfill this assumption as Oklahoma doesn't follow the trends of non-RTW states. DiD must also assume the Stable Unit Treatment Value Assumption (SUTVA)[1] (Columbia Public Health, n.d.). With these assumptions met the DiD estimator will provide interpretable and causal effects of the investigated event.

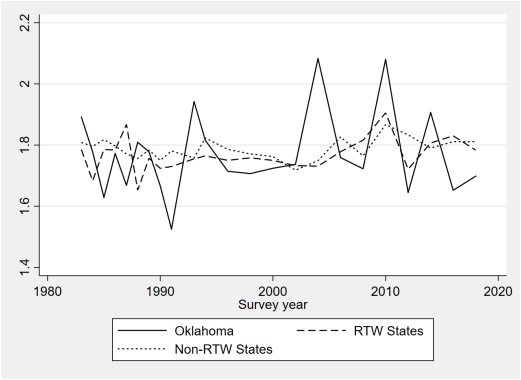
[1]This assumption, firstly, means that the composition of treated units and the control group must be consistent. Secondly, there must be no unmodeled spillover effects between the treated unit and the control group.

Figure 5.1: Parallel Trend Assumption

(a) Parallel Trend Demonstration (Columbia Public Health, n.d.)



(b) Plot of Unhappiness



For state-wise policy implications the assumptions required for DiD modeling become difficult with nearly all aspects of states being heterogeneous across the U.S. This heterogeneity violates the SUTVA as the control groups as well as the treatment group won't stay consistent over time. Normally the solution to this problem is to compare only regions that are along state lines in order to minimize the differences between the control and treatment group. This solution while fixing the SUTVA requires the now strong assumption that there is no spillover effect between regions that bound each other. This assumption is easily violated looking at the case where one state increases wages whereas another does not.

It is likely that the majority of people within a state will work locally due to the cost of going to a different state increasing the further the distance from the treated state. This means that when looking at the state as a whole the number of people crossing borders to take advantage of the difference in wage is negligible. However on boundary regions where the cost to work across state borders is relatively low there

is the likelihood that the increased wages will also increase the income for individuals in the untreated state therefore violating the spillover assumption.

In order to avoid the violation of these assumptions this paper utilizes a variation upon the DiD method which looks to estimate the treated unit through a panel of the control group in order to remove the SUTVA as this synthetic unit will be theoretically the same as the treated unit before the treatment allowing for a direct comparison after the treatment. The specific methodology and it's requisite assumptions are described in the remainder of this section.

5.1 Synthetic Controls Method

This report uses an expansion on Difference in Difference (DiD) modeling called Synthetic Controls Method (SCM). SCM was put forward first in the paper Abadie and Gardeazabal (2003) and expanded on in Abadie, Diamond, and Hainmueller(2010) and Abadie (2021) (Abadie & Gardeazabal, 2003; Abadie *et al.*, 2010; Abadie, 2021). Following their work SCM looks to create a synthetic counterfactual from non-treatment entities in order to provide more accurate results as compared to DiD.

Mathematically this begins with a set of units or for this report, states, of size S+1 such that only one state has experienced the treatment.It also needs a set of time t of size T. Within T there is a T_0 such that $1 \leq T_0 \leq T$, T_0 represents when the investigated state becomes affected by the treatment. This leads to two time frames $[1, T_0) and (T_0, T]$. The first time frame is the pre-intervention period where none of the states have experienced the treatment resulting in

$$Y_{it}^{pre} = Y_{it}^{N} \tag{5.1}$$

where Y_{it}^{pre} is the output during the pre-intervention period and Y_{it}^{N} is the output without intervention. The second time frame is the post-intervention period where the state of interest has been effected by the treatment, this means:

$$\begin{gathered} Y_{it}^{post} = Y_{it}^{N} + \beta_{it} D_{it}, \\ i \in (1, S+1),\, t \in (T_0, T). \end{gathered} \tag{5.2}$$

Where D is a binary variable that is 1 if i has been effected by the treatment at time t and 0 otherwise. Since we assume only one state is affected by the treatment, let this treated state be i=1 we can then clarify that D=1 if and only if i=1 and $T_0 \leq t \leq T$. β_{it} is the corresponding effect of D. From 5.2 it is clear that $\beta_{it} = Y_{it}^{post} - Y_{it}^{N}$. Additionally, by our definition of D we can rewrite β as $\beta_{1t} = Y_{1t}^{post} - Y_{1t}^{N}$. Since Y_{1t}^{post} has already been observed estimating the counterfactual (Y_{1t}^{N}) is all that is required to find the affect of the treatment(β_{1t}). We assume that Y_{it}^{N} can be written with the factor model (Abadie & Gardeazabal, 2003; Abadie *et al.*, 2010; Abadie, 2021);

$$Y_{1t}^{N} = \delta_t + \theta_t Z_i + \varphi_t u_i + \epsilon_{it} \tag{5.3}$$

Let δ_t be an unknown common factor with constant factor loadings, Z_i is a vector of independent variables which are known. They have a corresponding vector of parameters θ_t which are unknown. φ_t is a vector of unknown parameters that correspond to the θ_t's. Lastly ϵ_{it} contains unobserved temporary shocks with a mean of 0. In order to begin to construct the estimation of Y_{1t}^{N} first imagine a vector of weights W = (ω_2, ... ω_{S+1}) where $\omega_s \geq 0$ such that s $\in$ [2,S+1]. Then imagine that there is a

vector $\omega^* = (\omega_2^*, \ldots \omega_{S+1}^*)$ which forms the synthetic control;

$$\sum_{s=2}^{S+1} \omega_s^* Y_{s1} = Y_{11}, ..., \sum_{s=2}^{S+1} \omega_s^* Y_{sT_0} = Y_{1T_0}, \; and \sum_{s=2}^{S+1} \omega_s^* Z_s = Z_s \tag{5.4}$$

Abadie, Diamond, and Hainmueller (2010) found that as long as there is a large enough number of observations in the pre-intervention time frame to control for transitory shocks while assuming that errors are independent across time and unit (Abadie & Gardeazabal, 2003; Abadie *et al.*, 2010; Abadie, 2021);

$$Y_{1t}^N - \sum_{s=2}^{S+1} \omega_s^* Y_{st} \approx 0 \tag{5.5}$$

So our estimate on the effect of the treatment on the output can be estimated by;

$$\beta_{1t} = Y_{1t}^{post} - \sum_{s=2}^{S+1} \omega_s^* Y_{st} \, where \, t \in [T_0 + 1, ..., T] \tag{5.6}$$

This results in the interpretable coefficient used in the analysis of the treatment.

5.2 Synthetic Control Model Assumptions

5.2.1 Existence of Weights

The first assumption required for SCM is that there is a set of weights that successfully replicate the unobserved factors behind the variable of interest. The function to find the set of weights is found in equation 5.6 when rewritten regarding the pre-intervention time period.

$$\beta_{0t} = Y_{1t}^{pre} - \sum_{s=2}^{S+1} \omega_s^* Y_{st} \, where \, t \in [1, ..., T_0] \tag{5.7}$$

Since, β_{0t} should be 0 for our weights to be correct this can be written as a minimization problem finding the ω^* which minimizes the $||Y_{1t}^{pre} - \sum_{s=2}^{S+1} \omega_s^* Y_{st}||$ with a perfect vector of weights resulting in a $\beta_{0t} = 0$. This minimization can be done with any number of minimization techniques all of which should give similar if not identical results (Abadie & Gardeazabal, 2003; Abadie *et al.*, 2010; Abadie, 2021; Lu, 2021).

5.2.2 Stationarity

The second assumption behind SCM is that the variable of interest is weakly stationarity and second moment ergodic. These two traits combine in order to make the series stationary. The weakly stationary part of stationarity requires that the mean is constant over time e.g;

$$\mu_x = E[X(t)] \tag{5.8}$$

The second moment ergodic requirement states that the variance must be able to be deduced from a single sufficiently long random sample. This essentially means that there is some consistent process that leads to any given variance, so in the case that our variable of interest were to be predicted randomly across time it would violate this ergodic requirement (Abadie & Gardeazabal, 2003; Abadie *et al.*, 2010; Abadie, 2021; Lu, 2021).

5.3 Potential Bias

Availability Bias [2] is one of the most common sources of bias in using survey data as asking what policy they prefer whichever they previously discussed is likely the

[2] Availability bias is the fact that whatever someone thinks of first is the option they'll prefer, for example if someone just saw Jaws and then went to beach they would likely prioritize the "threat" of a shark-bite over other potential problems as it's the first thing that comes into their mind.

option they'll prefer. This research however is protected from availability bias by not directly asking about the subjective impact of RTW laws but instead looking at how SWB changes from before and after the law's implementation.

Another common type of bias from survey data is reporting bias as there is a tendency for individuals to either omit information or under-report information. This bias while inevitable from surveys is also limited by the fact that the variable being investigated is an aggregate so all observations should theoretically be equally biased making the interpretations still consistent and reliable.

CHAPTER 6:

RESULTS

6.1 Total Population

In the pre-treatment model, the synthetic control specification for the entire population of Oklahoma includes the lagged values of unhappiness, specifically 1993 and 1989, the average of unhappiness across all pre-treatment years, the GFPHealth of 1993, the lower quartile of income of 1994, the MeanMem of unions for the state in 1996, the Secondary sectors for the year 1988, the mean weekly hours for 1993, and the number of people in the labor force for the year 2000. This vector of predictors used to find the weights are presented in Table 6.1. Utilizing the methodology described in 5.1, the optimal synthetic for the whole population of Oklahoma is developed using four states: Colorado (30.8 percent), Indiana (10.8 percent), Washington (25.4 percent), and Wisconsin (33 percent). The remaining non-RTW states having a weight of zero percent.

Table 6.1 compares the actual Oklahoma values to the synthetic Oklahoma and the average of the 18-state donor pool. Most of the synthetic versions of the predictors are very similar except for MeanMem, which is over-predicted by 50 percent. The significant difference between the synthetic and the treated unit actually demonstrates

Table 6.1: Unhappiness Predictor Means Total Population

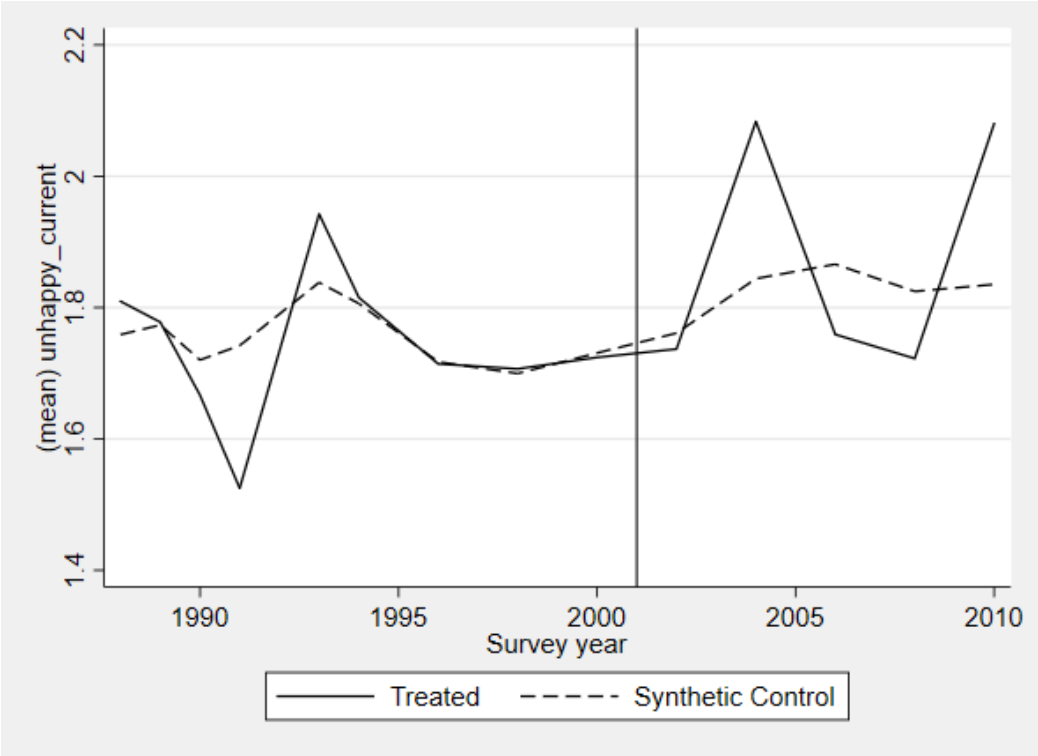
	Oklahoma		Average of 18
Variable	Observed	Synthetic	Control States
unhappy_current (1993)	1.942308	1.838153	1.774157
unhappy_current (1989)	1.777772	1.773414	1.745793
unhappy_current	1.742416	1.754065	1.787519
std_unhappy_current (1989)	0.0572063	0.0640403	0.1073558
GFPHealth (1993)	0.6785685	0.6789941	0.6999478
lower_quartile (1994)	0.5454582	0.511305	0.4965075
Mem (1996)	10.4	15.83	18.00588
secondary (1988)	0.2631621	0.2260679	0.1795774
other_service_c (1996)	0.3955436	0.400389	0.4139045
weekly_hours (1993)	43.6499	42.58121	40.34162
inLF (2000)	0.7586198	0.7447919	0.7032868

a valuable trait of SCM which is protection from extreme counterfactuals[1], this is due to the minimization process which prioritizes certain variables over others through a matrix of weights V. The matrices V for each model can be found in Appendix B, but the value for MeanMem is .01 explaining the 4.4 difference between the observed and the synthetic. Comparing then the observed values with the average values of the donor pools in Table 6.2 it is clear that the SCM method provides substantially better estimates. This can be seen through how average other non-RTW states have been more unhappy than Oklahoma by a relatively significant margin. Interestingly, Oklahoma tends to have around 3.3 lower weekly work hours on average than the donor pool.

In Figure 6.1, we see that the synthetic follows the original trend very well; however, the synthetic fails to predict the full effect of shocks to unhappiness, as seen

[1]Extreme counterfactuals are defined as "that is, those counterfactuals that fall far outside the convex hull of the data" (King & Zeng, 2006)

Figure 6.1: Synthetic vs. Observed Total Population



in 1992 and 1993. The overall fit of the line is very good with a pre-intervention Root Mean Squared Error (RMSE) of .0841 [2].The post-treatment synthetic, however, shows some large divergences from the real Oklahoma with the synthetic not fully predicting the large spikes in unhappiness in 2004 and 2010, nor fully predicting the drop in unhappiness between those two spikes in 2006 or 2008. Instead, the synthetic seems to indicate the middle ground between these spikes and shows that unhappiness appears to be higher than the pre-intervention time period.

Numerically, the post-treatment predictions of the effect in Table 6.2 show that there will be little to no effect on unhappiness in the immediate time frame, with

[2]The pre-intervention RMSE is the root mean error for all of the time periods before the treatment.

Table 6.2: Estimated Effects on the Total Population

Year	Estimated Effects	p-value
2002	-0.0242677	1
2004	0.2392934	0.111111111
2006	-0.1069141	0.222222222
2008	-0.1021193	0.611111111
2010	0.2448134	0

only 2010 demonstrating a statistically significant prediction at the 5 percent level[3]. Combining Figure 6.1 and Table 6.2, the difference that appears to grow over time demonstrates that there is a long-term positive effect on unhappiness after the implementation of RTW laws.

6.1.1 Inferential Capabilities

Since we are not using a standard regression model here, the p-value reported for the specific estimate above is computed differently from the traditional t-test. The interpretation is, however, similar. This p-value is found through the computation of the "in-place" placebo test (Abadie *et al.*, 2015; Galiani & Quistorff, n.d.). The "in-place" placebo test is done by performing the above SCM specification on the other states in the donor pool, which can be seen in Figure 6.2a. Since there was no real treatment on the placebos, the weights should still accurately predict the time frame after this pseudo treatment, These estimates are then used to compute the two-sided p-value through the function:

[3]The P-values given are not the same as from a traditional regression however, the interpretation is equivalent. A full description is given in section 6.1.1 (Galiani & Quistorff, n.d.)

$$
\begin{aligned}
p\text{–}value &= Pr(|\hat{\alpha}_{1t}^{PL}| \geq |\hat{\alpha}_{1t}|) \\
&= \frac{\sum_{j \neq 1} 1(|\hat{\alpha}_{jt}| \geq |\hat{\alpha}_{1t}|)}{J}
\end{aligned}
\tag{6.1}
$$

where $\hat{\alpha}_{1t}$ is the estimated effect for a specific post-treatment period and $\hat{\alpha}_{1t}^{PL} = \{\hat{\alpha}_{jt} : j \neq 1\}$ is the set of "in-place" placebo effects, which doesn't include j = 1 because that represents the unit that is being investigated. J is number of units that are included. This p-value provides a similar interpretation as the equivalent value from a standard regression, so ideally, the results will be significant at the 5 percent confidence interval or better.

Returning to the above estimates, while the 2010 estimate demonstrates statistical significance, the reliability of the entire prediction can be further investigated utilizing these "in-place" placebos through the ratio of $\frac{post-treatment\,RMSPE}{pre-treatment\,RMSPE}$. The goal for this proportion is for the actual treated unit to have the largest value compared to the placebos. An assessment of the "in-place" placebo test is the proportion of placebos that are at least as large as the treated unit. This measure is then standardized based on the pre-treatment quality of fit and is denoted as the joint p-value. This joint p-value can be interpreted approximately in the same way as a traditional p-value.

This model looking at the total population of Oklahoma, has a joint p-value of $0.1\bar{1}$. While this p-value falls outside of the standard bounds of significance, since the joint p-value incorporates the quality of fit in the pre-treatment time period in its computation, while the overall trend is accurate, the specific values should be taken with a grain of salt. The estimated effects can be reinforced by looking at Figure 6.2a as this joint p-value also shows that our counterfactual falls within the convex

hull of placebos meaning that our treated unit doesn't leave the bounds of the other placebos. However, Figure 6.2a also shows that in 1991 the synthetic Oklahoma fell outside of the bounds of the other placebos.

Since the SCM is a non-traditional time series model, the actual quality of fit provided by the pre-treatment Root Mean Squared Prediction Error (RMSPE) needs to be compared against the pre-treatment RMSPEs of the "in-place" placebos with ideally, the one treated unit having the best pre-treatment RMSPE. This paper looks at this ranking through the average pre-treatment RMSPE, which states that the proportion of placebos has a pre-treatment RMSPE at least as large as the treated unit. This model has an average pre-treatment RMSPE of $.9\bar{4}\bar{4}$ stating that the synthetic Oklahoma has a better pre-treatment RMSPE than 94 percent of the placebos.

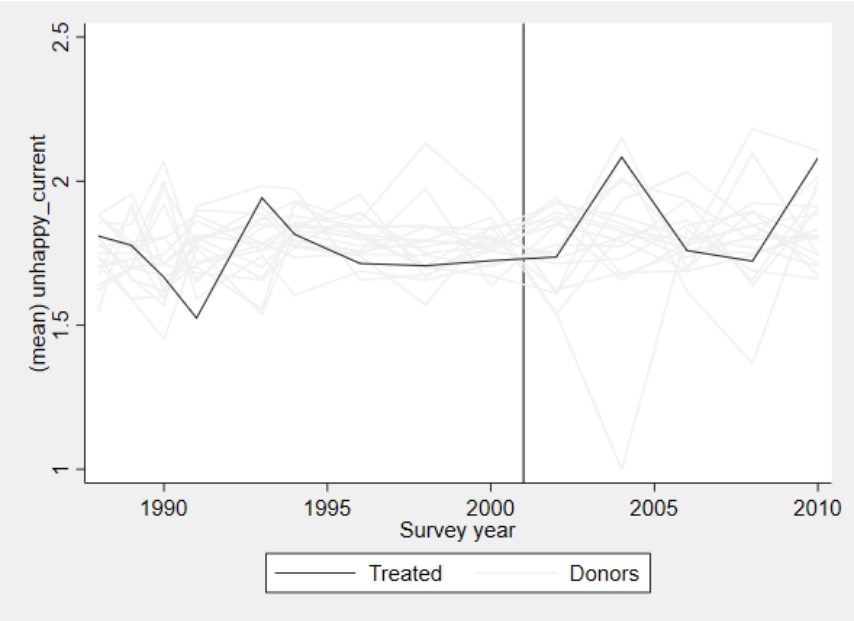
The second type of placebo test is the "in-time" placebo test, which looks at the model's reliability by pretending that the treatment occurred before the actual treatment (Abadie *et al.*, 2015; Abadie, 2021). Precisely, for this test, cutting the pre-treatment time frame in half is required. In this test, the time frame between the fictitious treatment date and the proper treatment date is important because if the model either matches or over predicts unhappiness in this time frame then the effect post-treatment should be attributable to the treatment. The results of this test can be seen in Figure 6.2b, where it is evident that between 1994 and 2002, this model matches the true value very well, showing that the effect between the model and the post-treatment time frame should be attributable to the implementation of RTW laws.

6.2 Blue-Collar or Non-College Educated

Due to the borderline significance of the model investigating the total population,

Figure 6.2: Placebo Tests for the Total Population

(a) "in-Place" Placebo



(b) "in-Time" Placebo

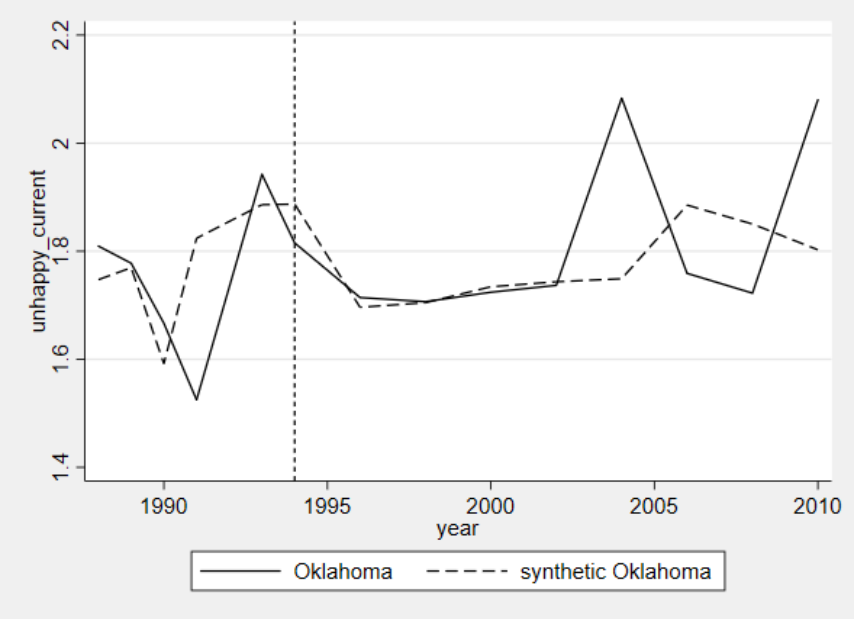


Table 6.3: Unhappiness Predictor Means Blue-Collar Population

	Oklahoma		Average of 18
Variable	Observed	Synthetic	Control States
unhappy_current (1996)	1.819446	1.834586	1.833423
unhappy_current (1994)	1.774996	1.797338	1.845164
unhappy_current (1993)	1.925001	1.846044	1.798525
unhappy_current (1991)	1.681825	1.676793	1.776116
unhappy_current (1989)	1.709672	1.745531	1.748856
unhappy_current	1.780435	1.783779	1.818869
white (1993)	0.9499988	0.9526609	0.8850959
lower_class (1990)	3	2.723144	2.568927
utility_trans_info_c (1990)	0.0627356	0.0667504	0.0654129
white _age_45to65 (1994)	0.3500051	0.2562185	0.2564197
white_age_25to45 (1989)	0.2580592	0.4809297	0.3938059
white_age_25under (1990)	0.2	0.1280182	0.1365963
weekly_hours (1988)	46.24999	43.68615	40.26095
white_cld_under6 (2000)	0.1951181	0.1642786	0.1493407

subsetting the population into a demographic that is theoretically more impacted by these RTW laws will provide some additional credence to the above model as it successfully passed the other inference tests. For this model, the sample population only includes individuals who are either currently working as a blue-collar employee or is not college-educated.

Table 6.3 demonstrates the vector of predictors as compared to their synthetic counterpoint and the average for RTW states. These predictors found that the optimal synthetic was made of five states, specifically; Maryland (1.7 percent), Massachusetts (37.7 percent), Missouri (17.4 percent), Washington (36.2 percent), and Wisconsin (7 percent), with the remaining non-RTW states are assigned a weight of zero percent. Comparing the synthetic and the actual values, the estimates for the percentage of white people in various age demographics are 0.094, 0.222, and 0.072,

respectively; however the matrix V in Appendix B helps explain that these are so far off due to their low prioritization in the minimization process having weights of 0.013, 0.006, and 0.025. In this demographic, it is clear that Oklahoma had a significantly higher number of weekly hours in 1988 compared to the average for non-RTW states.

Figure 6.3: Synthetic vs. Observed Blue-Collar Population

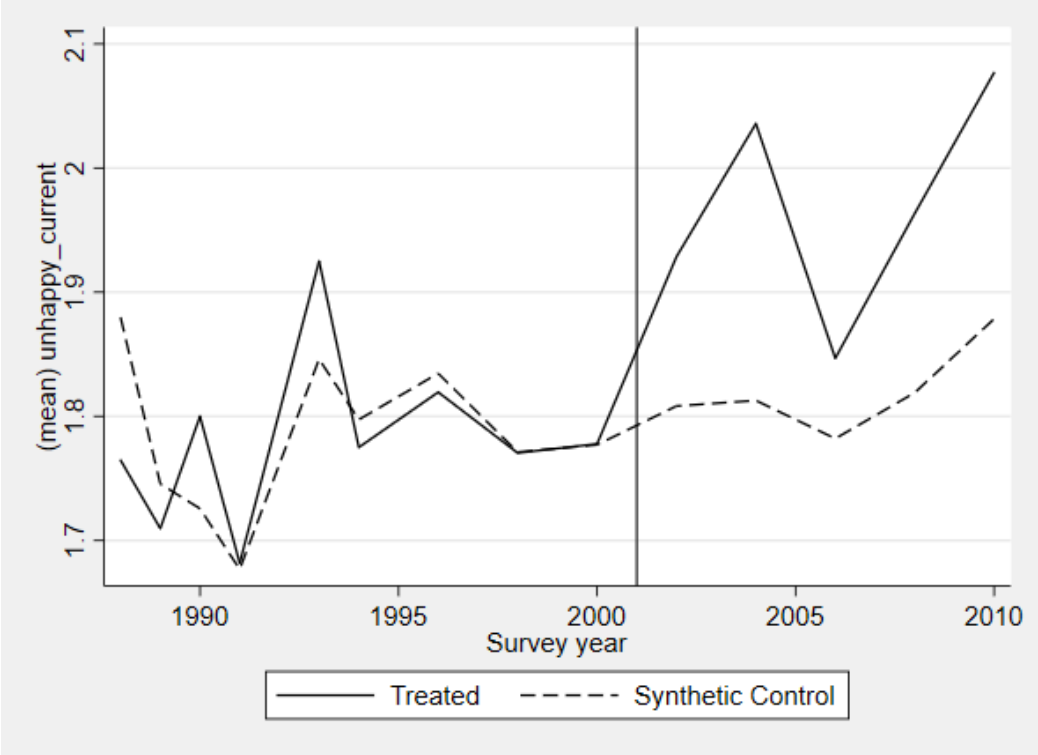


Figure 6.3 demonstrates that this specification follows the trend of this data very well. Similar to the total population, although this model also fails to fully encapsulate the extent of large positive shocks in unhappiness, such as in 1993 and 1990, it does successfully match the negative shock in unhappiness in 1991 and very closely matches the level between 1998 and 2000. Overall, the synthetic does an excellent job of matching the pre-treatment series with a pre-treatment RMSE of 0.055. Looking at the post-treatment, although the synthetic value is consistently lower than

Table 6.4: Estimated Effects on the Blue-Collar Population

Year	Estimated Effects	p-value
2002	0.1202903	0.1176471
2004	0.2230018	0.0588235
2006	0.0647202	0.4117647
2008	0.1443952	0.5294118
2010	0.1983743	0.0588235

the observed value, it still follows the basic upward and downward trends. This is demonstrated as well through Figure 6.4, which shows only positive values for the effect of these RTW laws, and while none of the individual estimates have a p-value under five percent, both the estimates for 2004 and 2010 fall under the six percent significance level. These significance levels, and the general trend seem to show that there is both a short-term and a long-term positive (negative) effect of RTW on the unhappiness (happiness) of blue-collar workers.

6.2.1 Inferential Capabilities

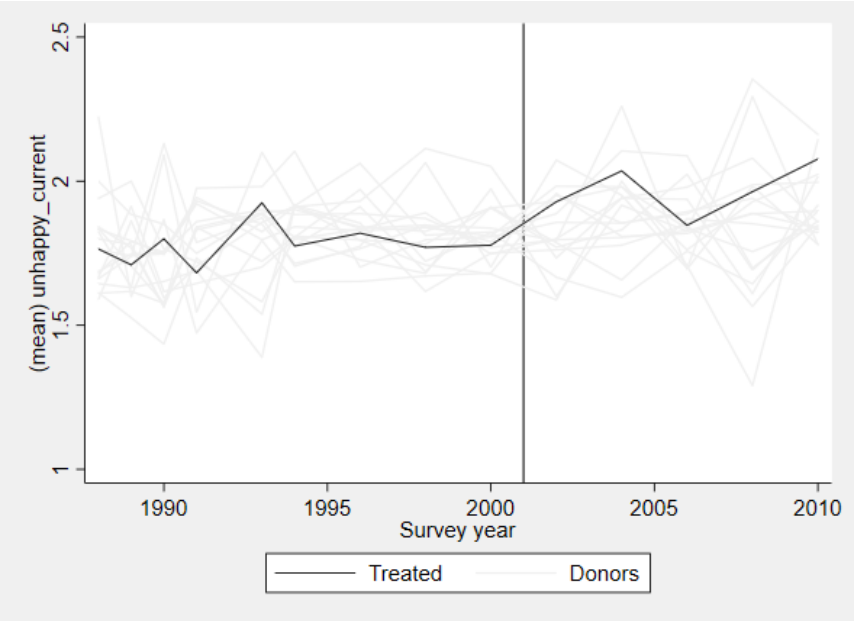
Looking at the reliability of this model on blue-collar and non-college-educated individuals has a joint p-value of zero meaning, that zero percent of the placebos have a higher proportion of post-treatment RMSPE and pre-treatment RMSPE. Additionally, this falls below the five percent confidence interval meaning that the predicted effects are statistically different from 0. This test can also be reinforced by looking at the results of the "in-place" placebo test in Figure 6.4a, with the synthetic Oklahoma never falling outside of the bounds of the other placebos, further demonstrating that this model is a valid counterfactual. Looking then at the quality of fit of this model, the average pre-treatment RMSPE is .941, meaning that its pre-treatment RMSPE outperforms 94.1 percent of the other placebos, demonstrating a better relative fit for

Oklahoma.

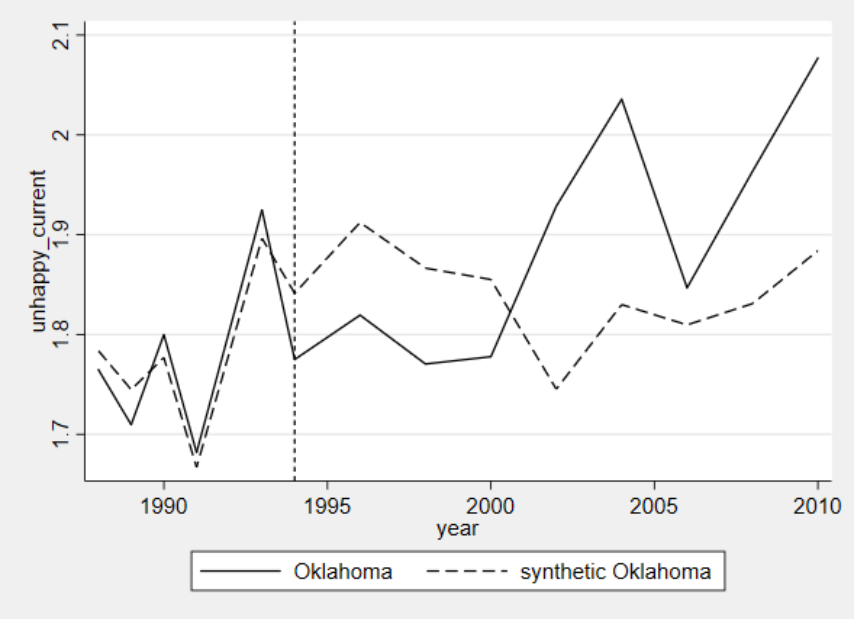
Figure 6.4b plots the "in-time" placebo test for the blue-collar and non-college educated SCM. For this plot the important time frame is from 1994 to 2000. This model follows the trend of this time frame very well; however it is over predicting unhappiness by around .05. While during this time frame, the model doesn't match the level it still shows that this model is a valid counterfactual. The magnitude of the estimated effects, however may be underestimated.

Figure 6.4: Placebo Tests for the Blue-Collar Population

(a) "in-Place" Placebo



(b) "in-Time" Placebo



CHAPTER 7:

DISCUSSION AND IMPLICATIONS

The results presented in Chapter 6 indicate that the entire population of Oklahoma as well as the blue-collar workers and non-college-educated individuals experience a long term increase in unhappiness in the post-RTW law implementation period. blue-collar workers and non-college-educated individuals in particular also seem to experience a more consistent increase in unhappiness with a small but immediate effect after the law was adopted, with a significant increase in unhappiness over the next four years. The overall delayed response is likely caused by the fact that RTW policies cause a drop in dues for unions which in turn reduces their ability to lobby for employee rights as well as reduces their ability to bargain on a level footing with the employers directly collectively. The weakening of unions leads individuals to stop paying union dues as the union will be unable to affect change which begins a vicious cycle. This snowball effect is why it is expected that the impact on unhappiness will increase as time continues.

Comparing these findings with the previous research by Makridis (2019) cited in Chapter 3, the results of the current study show some differences, The main thrust of the analysis in Makridis the entire population of the U.S, and finds a 0.025 SD increase in life satisfaction between states with RTW policies (Makridis, 2019). However, when the author looked at more homogeneous groups through border counties across the

nation, his results are not statistically significant (Makridis, 2019). However, we find statistically significant result showing a lowering of SWB. Specifically, when we convert the results in Table 6.4 and Table 6.2 to SD, we find that even ten years after the adoption of these laws, unhappiness increase by 1.656 SD for the blue-collar and non-college-educated population and 1.597 SD for the total population. Makridis (2019) also uses only a few years of post-legislation data to derive his results. It is reasonable to consider that significant labor law changes take a while to fully integrate into the economy. In this respect, results reported here are more reliable since we use data over a much longer time period in our analysis. It is important to note here, Chen and Islam (2021), which use a similar border-county methodology as Makridis (2019), find that there is a positive correlation of .04 SD between unhappiness and RTW laws (Chen & Islam, 2021). Which is a lower magnitude effect than what is reported in this study. This difference could potentially be caused by the fact that border counties are rural the majority of the time, and, therefore, may not be capturing the effect of RTW laws on the more urban state centers.

7.1 Policy Implications

The results of this current analysis suggest that RTW policies significantly negatively impact the SWB of blue-collar and non-college-educated individuals as well as having an insignificant negative effect on the overall SWB. Repealing the law, however, is challenging with the only case being the NIRA in 1934. NIRA however, hadn't been in place long enough to fully enact its policies so the effect of it's removal would not encompass the full impact of removing a fully integrated RTW law. Additionally, it occurred at an already unique time, during the Great Depression, further biasing any outcomes that could be predicted. Therefore, direct research on the removal of

RTW policies is limited.

Beyond evidence of RTW's effect solely on the well-being of individuals, we can also look at the quality of life for the overall people living in the state. From Figure A.3e, there is a clear gap between RTW states and non-RTW states, with non-RTW states providing approximately a dollar higher hourly wage, and the argument against this is that the increased wages also come with union dues counteracting them; however, in 2014, according to data from the Labor Management Reporting and Disclosure Act, the highest union dues were 830 dollars for the year which comes out to 0.216 dollars per hour so while union dues do negatively impact the raise that comes with unions it still results in a 0.784 dollar per hour raise (Brenner, 2007). Additionally, looking at Figure A.2a, the average number of hours that an employee works is also reduced for states without RTW policies, though the gap between them is less consistent than wages. Combining these two statistics could lead to the assumption that household income may be going down with reduced hours; however, Figure A.1e demonstrates that equivalised income for nonRTW states is also higher than for RTW states. These trends continue to point to the idea that RTW laws negatively impact everyone in the affected states; however blue-collar and non-college-educated individuals are merely hurt more.

7.2 Critiques

One of the most prominent critiques of this model is the lack of external validity; external validity is the ability of a model to relate to other populations outside of the directly measured (Findley *et al.*, 2021). So in the case of this report, external validity is the ability to apply the findings to either other states or the entire U.S population. While SCM is very good at providing information on a specific population, in this case,

the population is Oklahoma. There are expansions on SCM which include multiple treated units which aim to provide more external validity but these methods were not applied in this report. There is, however some argument to be made regarding the external validity of the population estimates for Oklahoma to other states; this is because there is a large amount of variation within the state as a whole which makes it an aggregation of effects behind these RTW policies. This agglomeration will likely have similar trends in other states as well, especially since Oklahoma should have a relatively small impact of RTW policies due to its low unionization rates.

Another possible critique regarding the methodology used in this current study is the relatively small number of interviewed parties in the GSS. However, the GSS interviews include information regarding individuals in close social proximity to the interviewee. This allows the researcher to glean far more information regarding the population than the base number of interviews would imply. Additionally, the GSS is a nationally recognized survey that has been used in numerous studies and therefore its credibility is well-established.

A final critique is that our model captures the residual effects of other policies, not just the adoption of the RTW law. This critique represents a valid concern regarding the implementation of quasi-experimental studies, as while our attempts to control for as many determinants as possible, the real world has too many connections to remove entirely. However, through the usage of SCM we control for policies put into place in the pre-treatment. There are no attempts to control for any policies put into place in the post-treatment as they may be an indirect result of this RTW amendment which we examine both the direct and indirect impact over time.

CHAPTER 8:

CONCLUDING REMARKS

In today's rapidly changing sociopolitical environment, policies like RTW can sometimes be swept out of the way for more pressing topics such as gun violence or racism; however, that does not make them any less critical. Especially with the continued attempts to pass national RTW policies finding the actual effect matters more than ever. This study adds to the extensive literature by looking at the effect of these policies on SWB utilizing data from the GSS. Using SCM, this report finds that RTW policies substantially and statistically significantly harm blue-collar and non-college-educated individuals' SWB in the short and long term. Additionally, results also suggest a negative effect on the entire population's SWB however, the magnitude of the impact is unclear. Both models passed both "in-place" and "in-time" placebo tests demonstrating reliable and robust estimations.

The analysis presented in this study includes an examination of the important psychological implications through SWB. The usage of SWB while growing in popularity in the U.S has already been accepted as a valuable measure to assess the effects of policies internationally. It's advantageous in that rather than relying on the rationality assumption to assess the population's reaction to a policy, we can directly see the effect on their perceived quality of life. Through this SWB we provide evidence of a significant negative effect of RTW laws on individuals well-being and happiness.

While this paper looks at SWB it does not look at the further implications of the change such as increased drug use, suicide, or migration. Additionally, further research can be done to improve the external validity of the modeling strategies used in the analysis; for example using a multi-treatment implementation of SCM.

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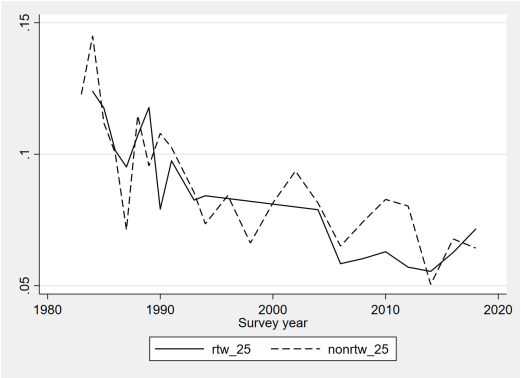
APPENDIX A:

RTW VS. NON-RTW STATES

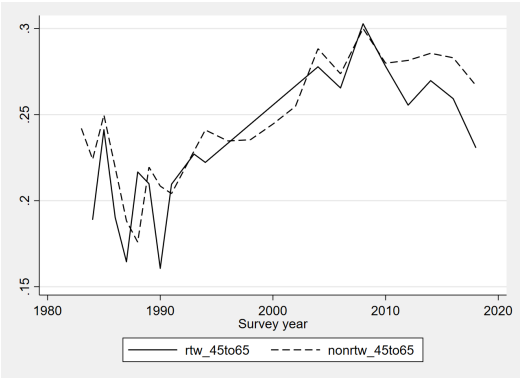
Figure A.1: Comparison Plots for RTW Vs. non-RTW

(a) Proportion of White Age Under 25

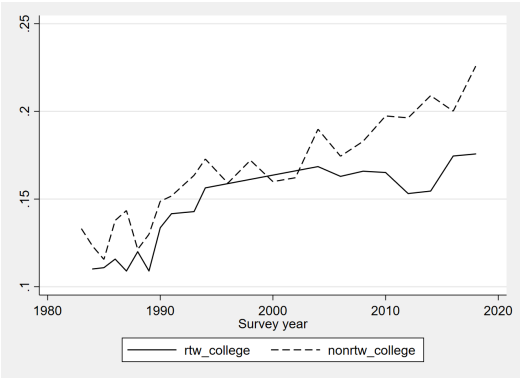


(b) Proportion of White Age 25-45

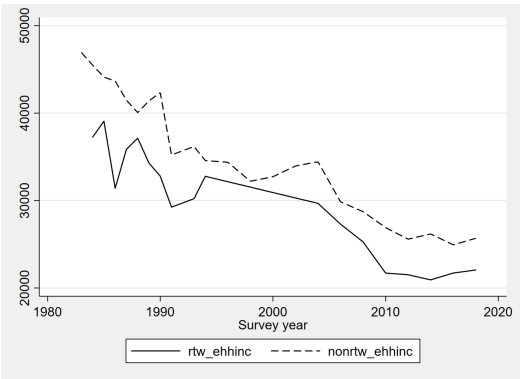
(c) Proportion of White Age 45-65



(d) Proportion of College Graduates



(e) Equivalized Income



(f) Proportion of GFPHealth

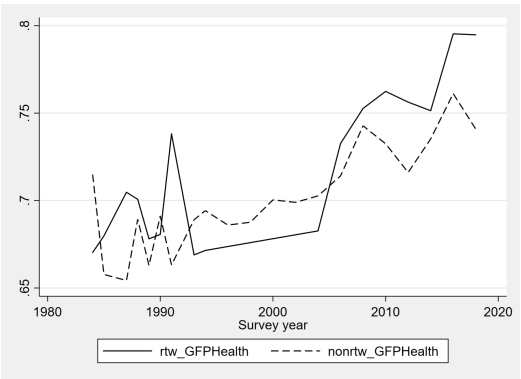
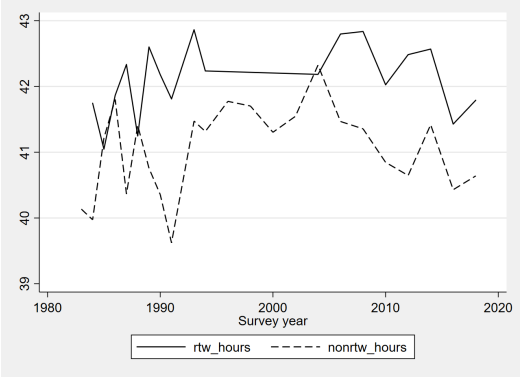


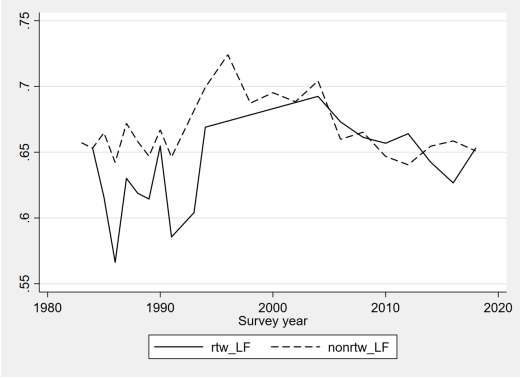
Figure A.2: Comparison Plots 2

(a) Number of Weekly Hours

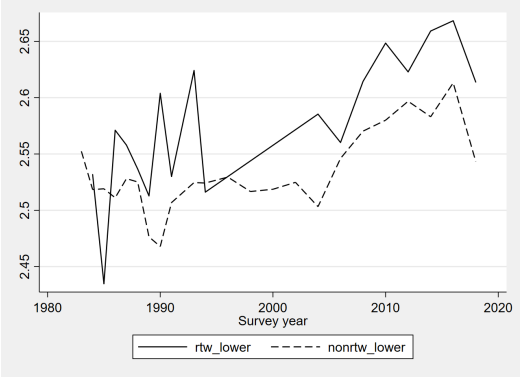


(b) Proportion of High School Graduates

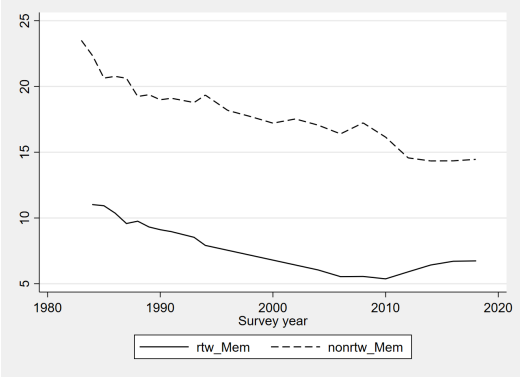
(c) Proportion of In Labor Force



(d) Proportion of Lower Class Individuals



(e) Percentage of Union Membership



(f) Proportion of Individuals in Other Service Industries

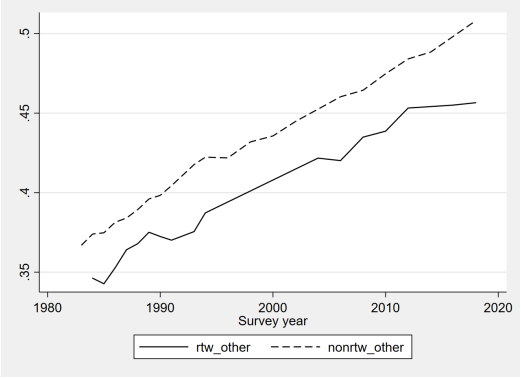
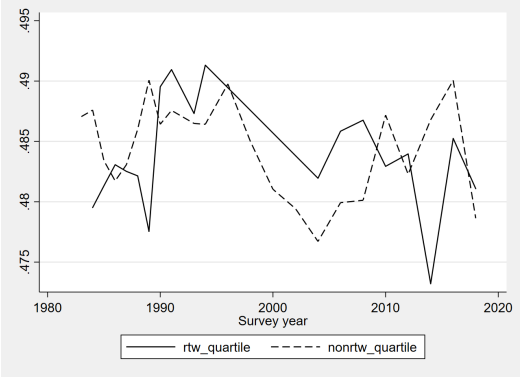
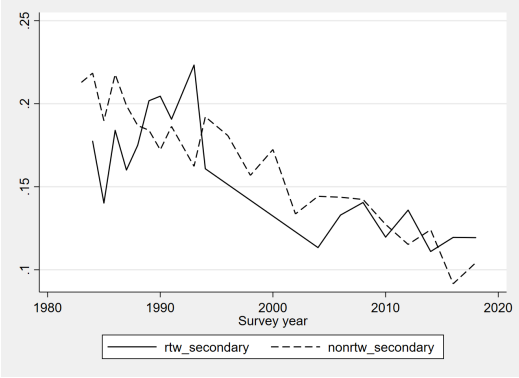


Figure A.3: Comparison Plots 2

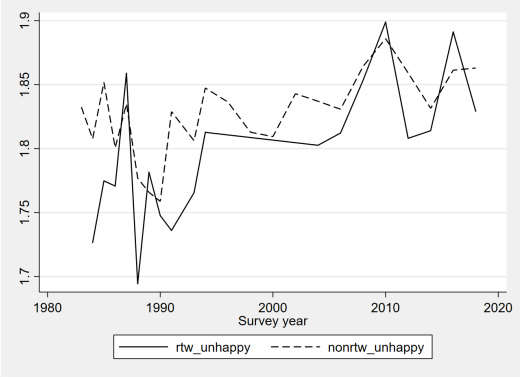
(a) Proportion of Lower Quartile Income Individuals



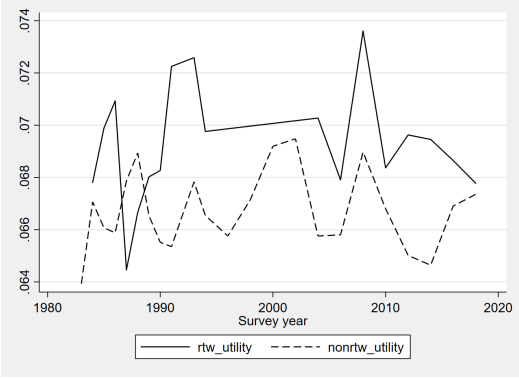
(b) Proportion of Individuals in Secondary Industries



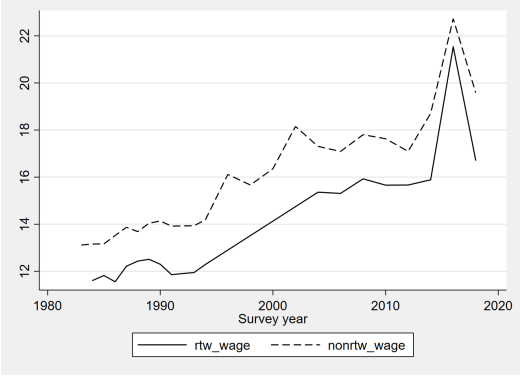
(c) Current Unhappiness



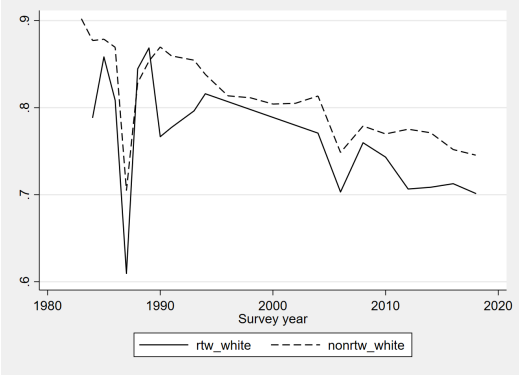
(d) Proportion of Individuals in Utility Transportation or Information Industries



(e) Hourly Wage



(f) Proportion of White Individuals



APPENDIX B:

V MATRICES

Table B.1: V Matrix for Total Population

Variable	V_Matrix Weight
unhappy_current (1993)	0.04328283
unhappy_current (1989)	0.28633427
unhappy_current	0.25345448
std_unhappy_current (1989)	0.10658479
GFPHealth (1993)	0.05808436
lower_quartile (1994)	0.0085583
Mem (1996)	0.01024033
secondary (1988)	0.03139087
other_service_c (1996)	0.07930459
weekly_hours (1993)	0.05453703
inLF (2000)	0.06822814

Table B.2: V Matrix for Blue Collar Population

Variable	V_Matrix Weight
unhappy_current (1996)	0.04048268
unhappy_current (1994)	0.08156341
unhappy_current (1993)	0.14051813
unhappy_current (1991)	0.06844268
unhappy_current (1989)	0.05201012
unhappy_current	0.20885655
white (1993)	0.16829784
lower_class (1990)	0.04186895
utility_trans_info_c (1990)	0.07780863
white _age_45to65 (1994)	0.01370499
white_age_25to45 (1989)	0.00659161
white_age_25under (1990)	0.02546266
weekly_hours (1988)	0.06981294
white_cld_under6 (2000)	0.0045788